

ŁUKASZ SIENKIEWICZ

lukasz.sienkiewicz@zie.pg.edu.pl

Gdańsk University of Technology, Faculty of Management and Economics

11/12 G. Narutowicza St., 80-233 Gdańsk, Poland

ORCID ID: <https://orcid.org/0000-0002-0653-8755>

Algorithmic Human Resources Management – Perspectives and Challenges

Keywords: human resources management; HR analytics; algorithms; HRM ethics

JEL: M12; M54; O33

How to quote this paper: Sienkiewicz, Ł. (2021). Algorithmic Human Resources Management – Perspectives and Challenges. *Annales Universitatis Mariae Curie-Skłodowska, sectio H – Oeconomia*, Vol. 55, No. 2.

Abstract

Theoretical background: Technology – most notably processes of digitalisation, the use of artificial intelligence, machine learning, big data and prevalence of remote work due to pandemic – changes the way organizations manage human resources. One of the increasing trends is the use of so-called “algorithmic management”. It is notably different than previous e-HRM or HRIS (human resources information systems) applications, as it automates HR-related duties. Algorithms, being autonomous computational formulae, are considered objective and mathematically correct decision-making mechanisms. Limiting human involvement and oversight of the labour process might lead to serious ethical and managerial challenges. Many areas – previously being sole responsibility of managers (including HR managers), like employment relations, hiring, performance management, remuneration – are increasingly affected, or even taken over, by algorithmic management.

Purpose of the article: The purpose of this article is to review the development, perspectives and challenges (including possible biases and ethical considerations) of algorithmic human resources management. This novel approach is fuelled by the speeding processes of digitalisation, the use of artificial intelligence, big data and increased analytical capabilities and applications used by contemporary companies. Algorithms are formulas that autonomously make decisions based on statistical models or decision rules without human

intervention. Therefore, the use of algorithmic HRM automates decision-making processes and duties of human resources managers, thereby limiting human involvement and oversight, which can have negative consequences for the organization.

Research methods: The article provides a critical literature review of theoretical sources and empirical evidence on the application of algorithmic human resources management practices. Scientific journals in the field of human resources management and technology applications have been reviewed, as well as research reports from academic institutions and renowned international organizations.

Main findings: Applications of algorithmic human resources management are an emerging field of study that is currently not extensively researched. Little is known about the scale of use as well as consequences of this more automated approach to manage human work. Scarce evidence suggests possible negative consequences, including ethical concerns, biases leading to discriminatory decisions and adverse employees' reactions to decisions based on algorithms. After the review of possible future developments and challenges connected to algorithmic HRM, this article proposed actions aimed at re-humanisation of the approach to managerial decision-making with the support of algorithms, ensuring transparency of the algorithms construction and functionalities, and increasing reliability and reduction of possible biases.

Introduction

Technology – most notably processes of digitalisation, the use of artificial intelligence, machine learning, big data and prevalence of remote work due to pandemic – changes the way organizations manage human resources. One of the increasing trends is the use of so-called “algorithmic management”. It is notably different than previous e-HRM or HRIS (human resources information systems) applications, as it automates HR-related duties and functions traditionally undertaken by human managers (Duggan, Sherman, Carbery, & McDonnell, 2020). Algorithms as computational formulae that autonomously make decisions based on statistical models or decision rules without explicit human intervention (Eurofound, 2018) are presented as objectively and mathematically correct. Duggan et al. (2020) define algorithmic management as a system of control where self-learning algorithms are given the responsibility for making and executing decisions affecting labour, thereby limiting human involvement and oversight of the labour process. Many areas – previously being sole responsibility of managers (including HR managers), like employment relations, hiring, performance management, remuneration – are increasingly affected, or even taken over, by algorithmic management. Therefore, the purpose of this article is to review the development, perspectives and challenges (including possible biases and ethical considerations) of this relatively novel means of human resources management.

Literature review

The analytical process starts with the foundation of accurate, consistent, integrated, accessible and relevant data (Davenport, Harris, & Morrison, 2010). Therefore, the antecedents of the algorithmic HRM are the human resources information systems

(HRIS). The HRIS is basically a system used to collect and store employees' data at the organizational level. In large enterprises and especially multi-national companies, its use is currently widespread. Such companies collect large volumes of data on their employees, such as, for example, salary information, performance reviews, and education level (Kapoor, 2010). Data – depending on its scope and application by the use of corresponding sub-systems through their functionalities – can play various roles in supporting and facilitating human resources management at company level.

Data applications – through more advanced, analytical applications – support the decision-making processes in the organization. As noted by Fahey (2009) analytics are never conducted for their own sake – they are intended to shed light on some business issue. Executives usually do not have time to read and review the reams of data outputs – what they need is insight – a new understanding, complete with its implications relevant to the specific business issue or topic. Therefore, the critical capability is to produce a reasoned explanation of how the findings generate new understanding and what that understanding implies for action. On the basis of such understanding, the decision can be made that is justified and informed, serving the business purpose in question. Therefore, HR analytics is an evidence-based approach for improving individual and organizational performance by making better decisions on the people side of the business (Bassi, 2011).

Davenport et al. (2010) conclude that developed IT architecture makes it easier to weave analytics into ongoing work processes in three ways, through (1) automated decision applications, (2) business applications for operational and tactical decision making, and (3) information workflow, project management, collaboration, and personal productivity tools. These approaches can be applied to make better on-the-spot decisions, even in situations where there is little time for extensive data collection (Levenson, 2011).

According to Pfeffer and Sutton (2006), “evidence-based management is based on the belief that facing the hard facts about what works and what doesn't, understanding the dangerous half-truths that constitute so much conventional wisdom about management, and rejecting the total nonsense that too often passes for sound advice will help organizations perform better”. Analytical approach to human resources management allows to help manage the business in turbulent times, anticipate changes and manage risk, leverage previous investments in IT and information to get more insight, cut costs and improve efficiency and have a basis for improving decisions over time (Davenport et al., 2010).

HR analytics comprises a broad area of practices. In some cases, the term only means a process for systematically reporting on an array of HR metrics – time to hire, turnover, compensation, employee engagement (Bassi, 2011). At the other end of the spectrum, HR analytics can mean only those activities or processes that involve “high-end” predictive modelling (e.g., “what-if” scenarios that forecast the consequences of changing policies or conditions). Bassi and collaborators regard both approaches too narrow, defining HR analytics as “the application of a method-

ology and integrated process for improving the quality of people-related decisions for the purpose of improving individual and/or organizational performance” (Bassi, Carpenter, & McMurrer, 2010).

Lal (2015) indicates five areas of HRM, where analytics can be particularly useful: workforce planning; management and improvement of business performance; learning and development; retention; compensation. Harris, Craig and Light (2011) provide a hierarchical representation of analytical HR applications from employee database – to keep data in order, up to talent supply chain – that allows near to real-time optimization of talents and skills for the entire organization.

HR analytics enables making informed decisions, based on insights supported by scientific evidence, that are not only descriptive, but also predictive and prescriptive. Descriptive analytics reveals current data patterns, while predictive analytics gives meaning to those patterns for the future, expressing them in terms of probabilities (Fitz-enz, 2010). As noted by Fitz-enz, no analytic application can predict the future with absolute certainty, but when properly applied, it can substantially reduce variability. An example can be a predictive model of effectiveness, based on traits, skills and experiences, that can increase the probability of selecting the right people to hire, train and promote. Predictive analytics enables more-effective development structures, harmonizes performance management, leads to more-efficient and more-equitable rewards systems, and lays a strong foundation for talent identification, retention and succession (HR Magazine, 2015).

Research methods

As described above, the need for evidence-based management, advanced (predictive and prescriptive) analytical applications, combined with the growing data processing powers offered by the use of artificial intelligence in management¹ form the backbone of the algorithmic approach to human resources management (Figure 1).

Algorithmic HRM is a step further, going beyond simple analytics (Jarrahi & Sutherland, 2019) as the decision-making functions are elevated from the management role. Essentially, an algorithm is a computational formula that autonomously makes decisions based on statistical models or decision rules without explicit human intervention (Eurofound, 2018). Duggan et al. (2020) define algorithmic management as a system of control where self-learning algorithms are given the responsibility for making and executing decisions affecting labour, thereby limiting human involvement and oversight of the labour process.

¹ As noted by Mann and O’Neil (2016), technological advances allow organizations to utilise artificial intelligence that simultaneously learn and solve problems in increasingly complicated domains, often towards autonomous management of business processes.

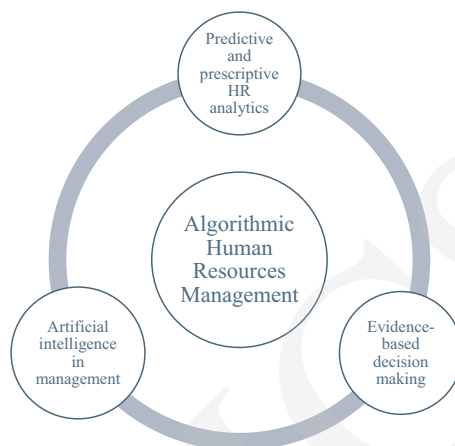


Figure 1. Foundations of algorithmic human resources management

Source: Author's own study.

The use of algorithms in decision-making process presents an opportunity to organizations (Newman, Fast, & Harmon, 2020) as the research evidence indicates that such decisions outperform human management decisions in more than 80% of cases in the common workload context (Yu, Miao, Chen, Fauvel, Li, & Lesser, 2017). One of the key arguments behind such reasoning is the use of probabilistic applications for predicting complex relationships, eliminating unconscious human bias (Cheng & Hackett, 2021).

On the basis of these assumptions the author of this article formulates the research problem that the further development of algorithmic human resources management defined as automated approach to decision making-processes and duties of human resources managers, can have negative consequences for the organization and requires supervision to overcome possible biases and ethical concerns.

However, little is known of the scale of application of algorithmic human resources management practices in organizations. Therefore, the author has undertaken a critical literature review of theoretical sources and empirical evidence on the application of algorithmic human resources management practices. Scientific journals in the field of human resources management and technology applications have been reviewed, as well as research reports from academic institutions and renowned international organizations.

Results

Evidence on the scale of the use of algorithmic human resources management practices is highly limited. The review of literature and existing research did not reveal any significant sources or direct estimates of the scope of its use in global

economy or for selected countries. As Falletta (2014) notes, little is even known about the extent to which the Fortune 1000 and selected global companies are performing broader HR research and analytics practices beyond simple descriptive metrics and scorecards, and more importantly how such activities are being used to facilitate HR strategy, decision making, and execution. Therefore, we have to rely on the indirect indicators of the scale of use. Some current research allows to estimate the potential use of such practices, as presented below.

One of the most recent sources for such estimates is the fourth European Company Survey (ECS) undertaken jointly by Eurofound and Cedefop in 2019. The ECS 2019 collects data in over 20,000 establishments on workplace practices with regard to work organization, human resource management, skills use, skills strategies, digitalisation, direct employee participation and social dialogue (Eurofound and Cedefop, 2020). The European Company Survey findings allow to determine the extent to which establishments in the EU27 have digitalised their operations. The ECS 2019 questionnaire includes several questions on the use of technology.

For example, the survey asked respondents whether their establishment uses digital tools for analysing data collected within the establishment or from other sources (data analytics) to improve the production process or service delivery or to monitor employee performance. In terms of process improvement, 46% of establishments reported the use of data analytics to improve production or service delivery processes. This use of data analytics was most prevalent in Spain (61%) and Italy (59%) and least prevalent in Bulgaria, Czechia, Ireland and Portugal (33%). Managers in other services and financial services were most likely (49%) to report the use of data analytics for this purpose, and managers in construction the least likely (29%) (Eurofound and Cedefop, 2020). In terms of monitoring employee performance, 27% of establishments reported using data analytics for these purposes. This was reported most in Romania (50%) and Croatia (45%) and least in Germany (13%) and Sweden (17%). Data analytics are used for monitoring employees most in the transport sector (36%) and least in construction (20%). Moreover, 22% of establishments use data analytics for both purposes. When asked about changes in the use of data analytics, 52% of managers in establishments where data analytics are used reported that it had increased in the past three years, 47% reported that it had stayed the same, and only 1% reported decreased use. Those using the technology for both process improvement and employee monitoring were most likely to report increased use (60%); those who reported using it for employee monitoring only were least likely (40%) to do so (Eurofound and Cedefop, 2020).

Another useful source for the estimate of the scale of possible applications of analytical use of employee-related data is the Third European Survey of Enterprises on New and Emerging Risks (ESENER, 2019) prepared by the European Agency for Safety and Health at Work. The survey of 2019 covered a total of 45,420 establishments – across all activity sectors and employing at least five people – in the 33 countries: the EU Member States as well as Iceland, North Macedonia, Norway,

Serbia, Switzerland and the United Kingdom. In majority, this study centres around management of health and safety risks at the workplace, with particular focus on psychosocial risks. However, issues covered include questions on the use of the digital technologies at work (see Table 1).

The study covers the use of:

- machines, systems or computers determining the content or pace of work,
- machines, systems or computers monitoring workers' performance,
- wearable devices, such as smartwatches, data glasses or other (embedded)

sensors,

- robots that interact with workers.

These technologies, as described earlier, can provide data for automated decision making in employee-related applications, thus, providing a basis for algorithmic HRM.

Table 1. Work-related digital technologies used by establishments in the EU27 and Poland (by size)

| Establishment size (number of employees) | Geographical scope | % of establishments answering "yes" | | | |
|---|--------------------|--|--|--|-----------------------------------|
| | | Machines, systems or computers determining the content or pace of work | Machines, systems or computers monitoring workers' performance | Wearable devices, such as smartwatches, data glasses or other (embedded) sensors | Robots that interact with workers |
| All sizes | EU27 | 11.8 | 8.2 | 4.8 | 3.7 |
| | Poland | 6.7 | 8.8 | 3.0 | 4.2 |
| 5–9 | EU27 | 9.5 | 6.5 | 3.8 | 2.8 |
| | Poland | 4.5 | 6.8 | 3.3 | 2.9 |
| 10–49 | EU27 | 12.8 | 9.1 | 5.4 | 3.8 |
| | Poland | 7.6 | 9.9 | 2.4 | 5.2 |
| 50–249 | EU27 | 17.1 | 12.3 | 6.4 | 6.9 |
| | Poland | 11.7 | 11.6 | 2.9 | 5.2 |
| 250 or more | EU27 | 26.1 | 18.7 | 11.5 | 13.1 |
| | Poland | 26.8 | 25.9 | 9.5 | 12.6 |

Source: Author's own study based on (ESENER, 2019 [Question: "Does your establishment use any of the following digital technologies for work?"]).

As indicated in the table, the scale of the use of different work-related digital technologies varies, according both to geographical scope² and size of establishment. As regards the use of machines, systems or computers determining the content or pace of work, as well as the use of wearable devices (smartwatches, data glasses or

² For the purpose of this article, comparative data for Poland and the EU27 have been extracted from the database by the author.

other sensors), Poland lags far behind EU average. In Poland, only the share of large (over 250 employees) establishments, that make the use of machines, systems or computer determining the content or pace of work is higher than EU average (26.8% as compared to 26.1%). It lags far behind leading countries like Malta (45.2%), Finland (50.2%) or Hungary (50.6%), but is significantly higher than in Italy (14.9%), Slovakia (15.5%) or France (16.3%). However, the use of machines, systems or computers monitoring workers' performance in Poland is more widespread in establishments of almost all sizes (excluding medium-sized enterprises). It is most evident for large companies (over 250 employees), where 25.9% employ such technologies.

Generally speaking, the scale of use of work-related digital technologies in Europe (and Poland) is growing, providing fertile grounds for the development of algorithmic HRM applications. The future direction of these developments is unknown, which calls for an analysis of potential challenges of this approach to employees' management.

Discussion

Algorithmic HRM is characterised by a number of uncertainties and challenges. Tambe, Cappelli, and Yakubovich (2019) identify four challenges in using artificial intelligence in HRM: (1) complexity of HR phenomena, (2) constraints imposed by small data sets, (3) accountability questions associated with fairness and other ethical and legal constraints, (4) possible adverse employee reactions to management decisions via data-based algorithms. As Duggan et al. (2020), citing Greenwood (2013), argue, HRM may be sleepwalking into the eradication of ethical responsibility, for example, in relation to the level of protection and use of individual data, transparency and accountability of algorithmic processes, and worker well-being. Gal, Jensen, and Stein (2020) argue that despite algorithmic management is often perceived as supportive to evidence-based, bias-free, and objective decisions, it might lead to serious ethical challenges. Use of people analytics in organizations might result in algorithmic opacity, datafication, and nudging, which limit people's ability to professionally flourish.

Most notably, an algorithmic approach to management is often referred to as a "black box"³, as the transparency of algorithms themselves (their internal construction, variables or relationships) or their outcomes (people-related decisions made on the basis of algorithms) is limited – both for the employees themselves, as well as for managers. Davenport and colleagues (2010) note that a purely analytical and dispassionate approach to human resources decisions might lead to what they call "analysis paralysis". The amount of data, stemming from descriptive, predictive and

³ However, Cheng and Hackett (2021) argue that widely criticised "black box" nature of the HR algorithms is not entirely appropriate. Based on the extensive literature review of academic papers and practitioner-oriented articles, they conclude that HRM-related algorithms are best characterised as heuristics.

prescriptive analytical applications might be overwhelming to managers, who might be more eager to make more automated decisions, solely based on the outcomes of the algorithm calculations, not taking into consideration contextual information. There might be a tendency to “let the algorithms decide” as the responsibility for (wrong) decisions can be perceived as lifted from the managers themselves. On the other end of the spectrum, making critical HR decisions solely based on prior experience, intuition, or gut feelings could have disastrous effects (Falletta, 2014). Therefore, it is crucial to steer algorithmic management towards a “decision supporting tool” rather than the decision-making mechanism.

Moreover, as noted by Angrave, Charlwood, Kirkpatrick, Lawrence, and Stuart (2016), this significantly data-dominated approach moves work into an inhuman form, with algorithms undertaking roles that were traditionally the preserve of HR professionals. This might result in de-humanisation of human resources management, negating currently well developed interpersonal and empathetic aspects of people management (*ibid.*). Emerging evidence indicates that algorithmic management is contributing to uncertainty and anxiety among workers (Rosenblat & Stark, 2016). Newman et al. (2020), on the basis of four laboratory experiments and large-scale randomized experiment in organizational setting, confirm their hypothesis that while HR algorithms positively affect human bias in decision making, they are perceived as reductionist by those being evaluated, as they believe certain qualitative and contextual information is not taken into account. This reduces the perception of procedural fairness of HR algorithm use for evaluation purposes, as the information base for such decisions is deemed less accurate. This, in turn, affects negatively organizational commitment, with perceptions of unfairness mediating this adverse effect.

Conclusions

Review of theoretical background and available research undertaken by the author has its limitations, mostly due to the scarcity of empirical evidence on outcomes of algorithmic human resources management implementation on organizations and employees. Therefore, the research problem focused on in this study can only be answered to a limited degree and requires further empirical investigation. Undoubtedly, the existing evidence – mostly theoretical considerations, but also growing body of research findings – support the assumption that in cases where algorithmic management is fully automated, it leads to serious negative consequences for organizations.

There is a growing body of evidence and debates over the possible significant biases of the algorithms, which calls for a need of algorithm auditing (Guszcza, Rahwan, Bible, Cebrian, & Katyal, 2018). It might lead to the development of new HR-related organizational functions as an “HR algorithm auditor”, being either a separate role or a responsibility of HR Business Partners. The role of these professionals should be manifold, focusing in the first place on:

– re-humanisation of the approach to managerial decision-making with the support of algorithms,

- ensuring transparency of the algorithms construction and functionalities,
- increasing reliability and reduction of possible biases.

Only in such a way can the use of algorithmic HRM be steered towards an approach that supports informed and evidence-based decisions, without losing the humanistic elements of people-focused management in modern organizations.

Further research in this field should be undertaken, focused on ethical and managerial challenges of both private and public organizations. This new research should focus on employees' perceptions, fairness of algorithm-based decisions, as well as influence on organizational culture, climate and trust in organizations making extensive use of an algorithmic approach to management.

References

- Angrave, D., Charlwood, A., Kirkpatrick, I., Lawrence, M., & Stuart, M. (2016). HR and Analytics: Why HR Is Set to Fail the Big Data Challenge. *Human Resource Management Journal*, 26, 1–11. <https://doi.org/10.1111/1748-8583.12090>
- Bassi, L. (2011). Raging Debates in HR Analytics, *People & Strategy*, 34(2).
- Bassi, L., Carpenter, R., & McMurrer, D. (2010). *HR Analytics Handbook: Report of the State of Knowledge*. Amsterdam: Reed Business.
- Cheng, M.M., & Hackett, R.D. (2021). A Critical Review of Algorithms in HRM: Definition, Theory and Practice. *Human Resources Management Review*, 31(1). <https://doi.org/10.1016/j.hrmr.2019.100698>
- Davenport, T.H., Harris, J.G., & Morison, R. (2010). *Analytics at Work. Smarter Decisions, Better Results*. Boston: Harvard Business Press.
- Duggan, J., Sherman, U., Carbery, R., & McDonnell, A. (2020). Algorithmic Management and App-Work in the Gig Economy: A Research Agenda for Employment Relations and HRM. *Human Resources Management Journal*, 30, 114–132. <https://doi.org/10.1111/1748-8583.12258>
- Eurofound. (2018). *Automation, Digitalisation and Platforms: Implications for Work and Employment*. Luxembourg: Publications Office of the European Union. Retrieved from https://www.eurofound.europa.eu/sites/default/files/ef_publication/field_ef_document/ef18002en.pdf
- Eurofound and Cedefop. (2020). *European Company Survey 2019: Workplace Practices Unlocking Employee Potential*. Luxembourg: Publications Office of the European Union.
- European Survey of Enterprises on New and Emerging Risks (ESENER). (2019). *Managing Safety and Health at Work. European Risk Observatory Report*. Bilbao: European Agency for Safety and Health at Work.
- Fahey, L. (2009). Exploring “Analytics” to Make Better Decisions – the Questions Executives Need to Ask. *Strategy & Leadership*, 37(5), 12–18. <https://doi.org/10.1108/10878570910986434>
- Falletta, S. (2014). In Search of HR Intelligence: Evidence-Based HR Analytics Practices in High Performing Companies. *People & Strategy*, 36(4).
- Fitz-enz, J. (2010). *The New HR Analytics. Predicting the Economic Value of Your Company's Human Capital Investments*. New York: American Management Association.
- Gal, U., Jensen, T.B., & Stein, M.K. (2020). Breaking the Vicious Cycle of Algorithmic Management: A Virtue Ethics Approach to People Analytics. *Information and Organization*, 30(2). <https://doi.org/10.1016/j.infoandorg.2020.100301>

- Greenwood, M. (2013). Ethical Analyses of HRM: A Review and Research Agenda. *Journal of Business Ethics*, 114, 355–366. <https://doi.org/10.1007/s10551-012-1354>
- Guszcza, J., Rahwan, I., Bible, W., Cebrian, M., & Katyal, V. (2018). Why We Need to Audit Algorithms. *Harvard Business Review*. Retrieved from <https://hbr.org/2018/11/why-we-need-to-audit-algorithms>
- Harris, J.G., Craig, E., & Light, D.A. (2011). Talent and Analytics: New Approaches, Higher ROI. *Journal of Business Strategy*, 32(6), 4–13. <https://doi.org/10.1108/02756661111180087>
- HR Magazine. (2015). *Should Companies Have Free Rein to Use Predictive Analytics?* Retrieved from <https://www.shrm.org/hr-today/news/hr-magazine/pages/0615-predictive-analytics.aspx>
- Jarrah, M.H., & Sutherland, W. (2019). Algorithmic Management and Algorithmic Competencies: Understanding and Appropriating Algorithms in Gig Work. In N. Taylor, C. Christian-Lamb, M. Martin, & B. Nardi (Eds.), *Information in Contemporary Society. Lecture Notes in Computer Science*, Vol. 11420, (pp. 578–589). Cham: Springer. https://doi.org/10.1007/978-3-030-15742-5_55
- Kapoor, B. (2010). Business Intelligence and Its Use for Human Resource Management. *The Journal of Human Resource and Adult Learning*, 6(2), 21–30.
- Lal, P. (2015). Transforming HR in the Digital Era. *Human Resource Management International Digest*, 23(3), 1–4. <https://doi.org/10.1108/HRMID-03-2015-0051>
- Levenson, A. (2011). Using Targeted Analytics to Improve Talent Decisions. *People & Strategy*, 34(2).
- Mann, G., & O’Neil, C. (2016). Hiring Algorithms Are Not Neutral. *Harvard Business Review*. Retrieved from <https://hbr.org/2016/12/hiring-algorithms-are-not-neutral>
- Newman, D.T., Fast, N.J., & Harmon, D.J. (2020). When Eliminating Bias Isn’t Fair: Algorithmic Reductionism and Procedural Justice in Human Resource Decisions. *Organizational Behavior and Human Decision Processes*, 160, 149–167. <https://doi.org/10.1016/j.obhdp.2020.03.008>
- Pfeffer, J., & Sutton, R. (2006). *Hard Facts, Dangerous Half-Truths and Total Nonsense: Profiting from Evidence Based Management*. Boston: Harvard Business Press.
- Rosenblat, A., & Stark, L. (2016). Algorithmic Labor and Information Asymmetries: A Case Study of Uber’s Drivers. *International Journal of Communication*, 10, 3758–3784.
- Tambe, P., Cappelli, P., & Yakubovich, V. (2019). Artificial Intelligence in Human Resources Management: Challenges and a Path Forward. *California Management Review*, 61(4), 15–42. <https://doi.org/10.1177/0008125619867910>
- Yu, H., Miao, C., Chen, Y., Fauvel, S., Li, X., & Lesser, V.R. (2017). Algorithmic Management for Improving Collective Productivity in Crowdsourcing. *Scientific Reports*, 7(1), article no. 12541.