

Introducing a Multi-Stakeholder Perspective on Opacity, Transparency and Strategies to Reduce Opacity in Algorithm-Based Human Resource Management

Markus Langer^a & Cornelius J. König^a

Universität des Saarlandes

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^a Fachrichtung Psychologie, Universität des Saarlandes, Saarbrücken, Germany

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Abstract

Artificial Intelligence and algorithmic technologies support or even automate a large variety of human resource management (HRM) activities. This affects a range of stakeholders with different, partially conflicting perspectives on the opacity and transparency of algorithm-based HRM. In this paper, we explain why opacity is a key characteristic of algorithm-based HRM, describe reasons for opaque algorithm-based HRM, and highlight the implications of opacity from the perspective of the main stakeholders involved (users, affected people, deployers, developers, and regulators). We also review strategies to reduce opacity and promote transparency of algorithm-based HRM (technical solutions, education and training, regulation and guidelines), and emphasize that opacity and transparency in algorithm-based HRM can simultaneously have beneficial and detrimental consequences that warrant taking a multi-stakeholder view when considering these consequences. We conclude with a research agenda highlighting stakeholders' interests regarding opacity, strategies to reduce opacity, and consequences of opacity and transparency in algorithm-based HRM.

Keywords: Explainable Artificial Intelligence, Opacity, Transparency, Human Resource Management, AI ethics

Introduction

Artificial Intelligence (AI) and algorithmic technologies to support or even automate human resource management (HRM) activities are a key driver of innovation in HRM (Kellogg et al., 2020; Makarius et al., 2020). In line with Kellogg et al., (2020; p.366), we consider AI and algorithmic technologies (following we subsume them under the term algorithm) to encompass “computer-programmed procedures that transform input data into desired outputs in ways that tend to be more encompassing, instantaneous, interactive, and opaque than previous technological systems.” As this understanding suggests, opacity is a key characteristic associated with current algorithms and can thus render algorithm-based HRM activities opaque. Opacity in this regard means that (a) the inputs used in algorithm-based HRM remain unknown or not understandable, (b) relations between inputs and outputs remain hidden, and (c) there is no further explanation for a given output (e.g., prediction or classification) (Arrieta et al., 2020; Burrell, 2016; Sokol & Flach, 2020). Consequently, opacity can be located on the opposite end of a continuum, with transparency at the other end, and can contribute to a lack of understandability of algorithm-based processes and outputs.

Previous work has highlighted the potential for both negative and positive implications of opacity for algorithm-based HRM. For instance, for people working with algorithm-based systems, opacity can undermine adequate trust in system outputs, thus diminishing decision-making performance (Yeomans et al., 2019) and at the same time opacity can increase efficiency due to not being distracted by unnecessary additional information (Tintarev & Masthoff, 2007). Similarly, for people affected by algorithm-based HRM decisions (e.g., applicants), opacity can either negatively or positively affect reactions to algorithm-based decisions (Langer et al., 2018; Newman et al., 2020). For companies using algorithm-based systems to control worker activities, opacity

can serve to uphold control mechanisms but at the same time may conflict with legal regulations requiring a certain level of transparency (Goodman & Flaxman, 2017; Kellogg et al., 2020).

Although previous work has already investigated implications of opacity for single stakeholders in HRM and has highlighted that opacity can have negative and positive consequences for single stakeholders, a comprehensive analysis of the implications associated with opacity from the perspectives of diverse stakeholders in algorithm-based HRM is still missing (Kellogg et al., 2020). Specifically, advantages and disadvantages associated with opacity only become apparent and especially important when considering the perspectives of the main stakeholders in algorithm-based HRM simultaneously. Additionally, previous work on algorithm-based HRM has predominantly focused on reasons for opacity or the implications of opacity without considering strategies to reduce opacity and promote transparency. As there are benefits and downsides associated with opacity, stakeholders in HRM need to actively consider whether and to what extent algorithmic opacity aligns with their goals and needs regarding algorithm-based HRM and also need to have the tools to potentially increase transparency when they conclude that the downsides of opacity outweigh the benefits.

In this paper, we argue that opacity is a central aspect of algorithm-based HRM and can contribute to promises and perils associated with algorithm-based HRM. We thus present the key reasons for opacity in algorithm-based HRM and emphasize the necessity to take a multi-stakeholder view when considering the implications of opacity in algorithm-based HRM as advantages and disadvantages associated with opacity only become apparent when simultaneously considering these perspectives. Moreover, our paper contributes to the literature on algorithm-based HRM by providing an overview on strategies to reduce opacity (technical solutions, education and training, regulation and guidelines) that address the main reasons for opacity (system-based opacity, opacity due to illiteracy, and intentional opacity; Burrell, 2016). To our

knowledge, this paper is the first to highlight the strategies that HRM researchers and practitioners could use to deliberately reduce opacity. Finally, we emphasize that there are trade-offs associated with the strategies to reduce opacity and provide an agenda for future research investigating consequences of opacity and strategies to reduce opacity from a multi-stakeholder view.

Algorithm-Based HRM

HRM involves a large variety of activities that could be supported or even fully automated by algorithm-based systems (M. M. Cheng & Hackett, 2021; Kellogg et al., 2020). For instance, Lepak et al. (2005) categorize HR activities ranging from transactional to transformational. Transactional activities reflect administrative components of HR aimed to maintain the organizations' HR infrastructure, whereas transformational activities contribute to strategic organizational goals. Importantly, the same HR task can be transactional or transformational depending on how central the task is to the organizations' strategy (Lepak et al., 2005). For instance, whereas compensation might be more transactional for traditional organizations with full-time employed workers, algorithm-controlled, dynamic compensation is at the core of the gig economy's business model where workers are considered independent contractors (e.g., Uber; M. K. Lee et al., 2015; Möhlmann et al., in press).

For each HRM activity, there is then a variety of possible development strategies regarding algorithm-based systems to support or automate HR activities (M. M. Cheng & Hackett, 2021). Broadly, we can distinguish them into manual development, self-learning, and continuous learning. Manual development involves human developers who formalize tasks in a way that they can be automatically fulfilled by algorithm-based systems (M. M. Cheng & Hackett, 2021). For instance, for well-defined tasks in scheduling, systems could follow an explicitly programmed set of rules to determine shifts and schedules for employees. However, a large share of tasks and outcomes in HRM are less well-defined and thus self-learning development strategies might be more promising

to automate (parts of) these tasks (M. M. Cheng & Hackett, 2021; Makarius et al., 2020; Möhlmann et al., in press). In such cases, human developers set up the initial instance of a system's algorithm and then feed it with training data to allow the algorithm to learn relationships between inputs and outputs. In other words, depending on the task or strategy, developers can choose from various different machine learning methods. For instance, screening applicant job interviews through algorithm-based systems could follow this strategy where the respective algorithm would learn to distinguish more or less suitable applicants based on a database of previous applicant interviews and interviewer ratings (Hickman et al., 2021; Naim et al., 2018). Based on a self-learning strategy, developers would then distribute a system that was tested on a training dataset but that would not adapt to changing environments. In contrast, certain HRM tasks are more dynamic and might require adaptive systems (Kellogg et al., 2020; Möhlmann et al., in press). Consequently, a continuous learning development strategy might be appropriate where a system is set up with the capacity to learn from newly incoming data. An example of such a system is Uber's algorithmic management system where it assigns tasks, determines compensation, and manages ongoing evaluation processes of their large driver workforce (M. K. Lee et al., 2015).

Algorithms resulting from these different development strategies can then be implemented in HRM as descriptive, predictive, or prescriptive algorithms (Leicht-Deobald et al., 2019). Descriptive algorithms analyze historic data and try to provide insights regarding their implications for present organizational states (Leicht-Deobald et al., 2019). For example, such algorithms could analyze employee behavior and customer satisfaction outcomes to find patterns of behavior that have positively influenced customer satisfaction in the past that they can then learn from and use in future customer interactions (Leicht-Deobald et al., 2019). Predictive algorithms are those that analyze past or real-time data in order to predict future outcomes. For instance, such systems could analyze applicant behavior in job interviews to predict their future job performance. This could

result in a score that HR managers use as additional information supporting their hiring decisions (Langer et al., 2021). Finally, prescriptive algorithms go beyond predictive ones by providing simulations of what would happen if one decides on a specific course of action, including explicit suggestions to human decision-makers and maybe even automatically implement decisions. For instance, such algorithms could be used to implement automated task assignment or compensation for workers (M. K. Lee et al., 2015; Ravenelle, 2019).

Reasons and Implications for the Opacity of Algorithm-Based HRM

Three Reasons for the Opacity of Algorithm-Based HRM

Independent of HRM activity, algorithms' development strategy, and the implementation of algorithm-based systems, one underlying topic is the opacity of algorithm-based systems (Kellogg et al., 2020; Leicht-Deobald et al., 2019). In fact, a large share of papers that investigate algorithm-based HRM highlight the potential for opacity of algorithm-based HRM (M. Cheng & Foley, 2019; Griesbach et al., 2019; Höddinghaus et al., 2020; Jarrahi & Sutherland, 2019; Kellogg et al., 2020; M. K. Lee et al., 2015; Leicht-Deobald et al., 2019; Möhlmann et al., in press; Möhlmann & Zalmanson, 2017; Myhill et al., 2021; Veen et al., 2020). In line with recent research (Kellogg et al., 2020), we consider opacity as a key characteristic and even as the default for algorithm-based HRM.

Specifically, there are three broad reasons that contribute to opacity in algorithm-based HRM scenarios: system-based opacity, opacity due to illiteracy, and intentional opacity (Burrell, 2016). *System-based opacity* refers to opacity resulting from characteristics of systems in use. There are several factors that contribute to this form of opacity and we exemplify those factors with the use of a system for the automatic evaluation of job interviews. (a) Algorithm-based systems that support information processing and decisions usually consist of a combination of systems (Burrell, 2016), and this will likely be the case for a system automatically evaluating interviews:

There might also be a subsystem extracting nonverbal and content related information from interview videos, and another subsystem that is trained on previous applicant information to distinguish the most suitable applicants from the less suitable. Making the decision logic of one subsystem transparent does not necessarily affect transparency of another subsystem (Raghavan et al., 2020). (b) Algorithm-based systems usually analyze a large number and variety of features (predictors) in order to arrive at their outputs (Kellogg et al., 2020). In the case of a video interview recording, every word applicants use can serve as a potential feature to determine their suitability for a job (Campion et al., 2016), every frame of a video produces additional features to use for prediction (Liem et al., 2018), and every second of audio data provides additional applicant information (e.g., about applicants voice pitch). In order to make this large number of features useful for algorithms, they have to be condensed from a raw to a preprocessed format and during these preprocessing steps, opacity may increase due to features losing a directly graspable meaning (Burrell, 2016). (c) Finally, some kind of algorithm is needed to detect patterns in features and to link features to outcome variables. One of the most commonly cited class of opaque algorithms are artificial neural networks often used for self- and continuous learning development strategies (Arrieta et al., 2020; Felzmann et al., 2019). Heavily simplified, developers determine the initial structure of artificial neural networks and then feed them with training data. Neural networks then detect patterns in the data and adjust their weights associated with input variables in order to be better able to classify or predict target variables. This happens without human programming involved, making artificial neural networks opaque even to their developers. Furthermore, neural networks use internal representation of data that do not readily translate to human semantics and to human ways of problem solving (Ananny & Crawford, 2018; Burrell, 2016). This means, even if a human could peek into the “decision-making” process of neural networks, the representation of information, and the decision processes might not reduce opacity. This also indicates that

system-based opacity might be more or less pronounced for different development strategies (Burrell, 2016). Specifically, in contrast to self- and continuous learning, system-based opacity will usually be lower if a system was manually developed as human developers might have explicitly programmed a set of rules that a respective algorithm-based system would follow to arrive at its outputs.

Opacity due to illiteracy, is the second reason for opacity and is a result of illiteracy in regard to algorithm-based systems and their underlying mathematical or developmental foundations (Burrell, 2016). With the spread of algorithm-based systems in HRM, there are more and more stakeholders who may have little knowledge of the general logic of algorithm-based processes and solutions. For instance, people who work in HRM are usually not trained in programming (Burrell, 2016; Oswald et al., 2020) but are now more than ever required to understand system outputs and processes, scrutinize when to rely on system recommendations, or evaluate the usefulness and validity of algorithm-based solutions for decisions (Höddinghaus et al., 2020; Langer et al., 2021). Without a basic level of programming literacy, reducing algorithm-based opacity might remain a hopeless endeavor independent of the HR activity for which an algorithm is used, and independent of the development or implementation strategy. In fact, even linear regressions can be opaque to stakeholders with no background in statistics (Páez, 2019).

Finally, *intentional opacity* means that it can be an intentional choice to keep algorithm-based systems, processes, and outputs opaque. On the one hand, this choice lies in the hands of developers who might favor system performance over system transparency when developing systems (Brock, 2018). On the other hand, deployers of systems (e.g., upper-level managers deciding to use algorithm-based systems for certain HRM activities) can purposefully reduce available information regarding systems. Reasons for this can be that organizations want to protect their intellectual property, keep their competitive advantage, or uphold information asymmetries

for exercising control over workers (Rosenblat & Stark, 2016; Schnackenberg & Tomlinson, 2016). Making code details of algorithms openly available or decision-processes more transparent could make it easier for competitors to copy the companies' approaches (Sokol & Flach, 2020). Relatedly, providing workers or the public with insights into the decision-logic of algorithms may undermine their usefulness and can lead to people using the information to game the system (Rosenblat & Stark, 2016; Schnackenberg & Tomlinson, 2016).

Implications of Opacity for HRM Stakeholders

The reasons for opacity and their combination have important implications with respect to algorithm-based HRM. In fact, there are daily high-stake decisions where algorithm-based HRM determines the future of more and more people of whom only a small number have experience in working with such systems (M. M. Cheng & Hackett, 2021). Consequently, algorithm-based systems used for HRM activities are opaque to an increasing number of people who consequently will not or only partially be able to understand the reasons for algorithm-based decisions. These are people who use algorithm-based systems as decision support and who may want to understand the logic of algorithm-based recommendations (Dhaliwal & Benbasat, 1996), people who are affected by algorithm-based HRM and who may want to understand the rationale behind algorithm-based decisions affecting their lives (M. K. Lee et al., 2015), or people who deploy algorithm-based systems in HRM and may need to understand whether these systems and their outputs align with company strategy and comply with legislation (Arrieta et al., 2020). Whereas this indicates that opacity can be detrimental because it prevents stakeholders from better understanding algorithm-based processes and outputs, opacity can also be beneficial as it can increase efficiency for users of systems, or can be used by organizations to prevent insights in algorithm-based systems that may be used in an adversarial way. In the case of HRM, there are advantages and disadvantages associated with opacity that become especially apparent when considering the diversity of key

stakeholders with potentially diverging interest with respect to opacity. Figure 1 shows the relation of algorithm-based systems in HRM for the five main classes of HRM stakeholders – users, affected people, deployers, developers, and regulators – and the implications of opaque algorithm-based systems in HRM associated with these stakeholders.

Opacity for users of algorithm-based systems in HRM. Users of algorithm-based systems in HRM might be HR managers or general managers who use systems with the goal of increasing decision-making efficiency and quality (Kellogg et al., 2020; Langer et al., 2021). Opacity of algorithm-based systems can affect the efficiency and quality (e.g., decision quality) of human-system teams (Yeomans et al., 2019). Specifically, with opaque systems, users may miss insights regarding decision outputs that could help them adequately consider system outputs in their decision-making (Lai & Tan, 2019). However, opacity can also contribute to efficient processes because the system would provide streamlined information (Tintarev & Masthoff, 2007). Furthermore, through a technology acceptance lens, opacity can impact perceived usefulness and ease of use of a system (Venkatesh et al., 2003; Yang et al., 2012). Opacity can decrease these variables by not having enough insights into system decision processes to adequately use the system (Yang et al., 2012). At the same time, opacity could make processes easier as system outputs may focus on the most important information thus preventing information overload. Further contributing to user-system collaboration, it is commonly assumed that opacity undermines the possibility to build adequate trust in systems and their outputs (Endsley, 2017; Hoff & Bashir, 2015). For example, in the case of systems supporting performance evaluations, only providing a numeric value for employee evaluations might not be enough to trust the system recommendation. This can lead to issues with under- or over-trusting the system (Glikson & Woolley, 2020; Parasuraman & Manzey, 2010; Parasuraman & Riley, 1997). In the case of under-trust, users would not incorporate recommendations by the system in their decision-making process, making the

system redundant. In the case of over-trust, users would not adequately supervise systems or would rely too much on outcomes given by the system without challenging their adequacy (Langer et al., 2021). Furthermore, opacity can affect users' well-being at work, job satisfaction, and motivation (Hackman & Oldham, 1976; Morgeson et al., 2012). For instance, it has been assumed that opacity can undermine human self-determination and autonomy (Jobin et al., 2019). As well, according to work characteristics research, opacity would relate to perceived responsibility for work results and to outcomes such as job motivation (Hackman & Oldham, 1976; Morgeson et al., 2012; Parker & Grote, 2020). Finally, users such as HR managers can be in the role of explainers and sustainers of algorithm-based systems (Kellogg et al., 2020; Makarius et al., 2020; Wilson et al., 2017). The explainer role involves being able to explain algorithm-based systems and their outputs to other stakeholders (e.g., upper management or to people affected by algorithm-based decisions, such as applicants in personnel selection, employees in performance evaluation situations). The sustainer role involves continuous monitoring of algorithm-based systems to ensure they are operating as intended (e.g., whether continuous learning systems produce fair outputs) or whether they need to be updated. For both roles, opacity undermines users' abilities to successfully fulfill these roles as they might not be able to explain system outputs to other stakeholders or have no insight into system processes to monitor potentially unwanted changes in a system's decision logic over time (Kellogg et al., 2020).

Opacity for people affected by algorithm-based HRM. People affected by algorithm-based HRM are those who usually cannot choose whether they want to be affected by algorithm-based decisions but on which the outcomes of algorithm-based decision have wide-ranging effects on their everyday life in an organization (e.g., through algorithm-based scheduling or algorithm-based task assignment), or even their future career (e.g., through algorithm-based promotion decisions) (Langer & Landers, 2021; Leicht-Deobald et al., 2019). This class of stakeholders

consists, for instance, of applicants or employees affected by personnel selection decisions, performance evaluation, or scheduling outcomes. For them, opacity is especially associated with decision-processes and outputs of using algorithm-based systems in HRM and wanting to understand if decisions based on algorithm-based processes and their outputs were fair (Arrieta et al., 2020; M. K. Lee et al., 2015; Myhill et al., 2021). Similar to reactions to managers who explain why a particular team member got promoted to a team leader position over others, reactions to decisions made in collaboration with algorithm-based systems might be negative when lacking transparency (Schnackenberg & Tomlinson, 2016; Shaw et al., 2003). In general, people affected by algorithm-based HRM might want to evaluate justice and fairness of algorithm-based processes and outcomes (M. K. Lee, 2018; Ötting & Maier, 2018). This highlights the importance of opacity for HRM in relation to organizational justice (Colquitt et al., 2001). Most directly, opacity could reduce informational justice which could also impair insight into other facets of justice (i.e., procedural and distributive justice) (Gregor & Benbasat, 1999; Schlicker et al., 2021). Yet, opacity could also positively affect justice perceptions as sometimes less information is better than too much information (Langer et al., 2018; Newman et al., 2020). Especially salient are the implications of opacity for gig and platform workers who are directed, evaluated, and disciplined by algorithm-based systems (Kellogg et al., 2020; Rosenblat & Stark, 2016). Directed means that workers receive tasks and recommendations by algorithm-based systems which then steer their behavior; evaluated is when algorithm-based systems use worker behavior to curate ratings of workers on which payment and future work opportunities might depend; and disciplined means that workers might automatically be fired and replaced when not following algorithm-based instructions (Kellogg et al., 2020). For all those procedures, opacity can undermine perceived control and autonomy at work as workers may have no insight into the algorithmic decision-making processes and outputs that structure their everyday work experience (Kellogg et al., 2020; Myhill

et al., 2021). However, opacity can also potentially be beneficial for workers with respect to control and autonomy as it may enable them to detect and take advantage of system features that are not even known to system developers or deployers (Kellogg et al., 2020; Langer & Landers, 2021).¹ Furthermore, although opaque, gig workers seem to sometimes prefer algorithmic management over human bosses as they feel more autonomous in the former case (Langer & Landers, 2021; Möhlmann et al., in press).

Opacity for deployers of algorithm-based systems for HRM. Deployers of algorithm-based systems consist of two subgroups. First, deployers can be organizations providing algorithm-based solutions for HRM; second, deployers can be decision-makers in organizations who decide which system to implement and how to implement a system within an existing process. These stakeholders need to ensure that the algorithm-based systems they deploy adhere to a level of transparency that legal guidelines (e.g., in the European Union *General Data Protection Regulations 2018 [GDPR]*) demand in relation to the use of algorithms in decision-making (Burrell, 2016; Goodman & Flaxman, 2017). In this regard, deployers are in a unique role as they can directly influence system opacity and need to consider its advantages and disadvantages. Specifically, they might make strategic decisions regarding which information to disclose to other stakeholders affected by algorithm-based HRM (Felzmann et al., 2019). For instance, deployers in the area of algorithmic management may keep their systems intentionally opaque to maintain control over workers managed by the respective algorithm-based system (Kellogg et al., 2020; Rosenblat & Stark, 2016). Furthermore, deployers may decide to hide what kind of inputs algorithm-based systems for HRM take as this can impact acceptance among users or people affected by HRM systems (Langer et al., 2018). This way, they may also attempt to protect their intellectual property from competitors or their systems from adversarial attacks (Arrieta et al.,

¹ We thank an anonymous reviewer for highlighting this possibility.

2020; Kellogg et al., 2020). Similarly, deployers need to consider whether reducing opacity will foster or undermine systems' usefulness (Gregor & Benbasat, 1999; Kellogg et al., 2020). For instance, whereas for users, less opacity can foster the utility of such systems as decision-support, for people affected by HRM systems any insights into system functioning can make systems useless if it enables them to game the system (e.g., by revealing how applicants can influence their scores; by informing how workers can get a higher payment; Möhlmann et al., in press; Raghavan et al., 2020; Rosenblat & Stark, 2016).

Opacity for developers of algorithm-based HRM systems. Behind every algorithm-based system there are developers developing, maintaining, and updating systems. For instance, those might be developers of a third-party provider of algorithm-based solutions or developers within a data science team of an organization. This class of stakeholders is mostly interested in better ways to design, improve, and update algorithm-based systems. Although opacity is usually associated with high-performance systems (Burrell, 2016), opacity of system processes and outputs can complicate improving, debugging, and inspecting systems (Miller et al., 2017) as it can undermine finding out how to provide better outputs (e.g., more validly predict job performance) or how to prevent biased outcomes. At the same time, opacity makes it harder to maintain systems. Specifically, it is unlikely that algorithm-based systems in HRM will work as intended without recurring human intervention (Kellogg et al., 2020). HRM operates in a dynamic environment where systems need to be adapted to changing demands and contexts. For instance, as applicant pools or job requirements change, algorithm-based systems for personnel selection need to be examined and possibly updated to uphold predictive accuracy as well as to prevent unfair bias. Opacity might prevent realizing issues at an early point in time and may thus delay the detection that a system needs an update. Simultaneously, opacity may reduce the likelihood that other stakeholders (e.g., HR managers in their role of sustainers of algorithm-based systems) report

issues with algorithm-based systems. Moreover, opacity can hinder tracing of reasons for system failures. Note that developers of algorithm-based systems are (like deployers) in a unique role as they can deliberately alter systems' opacity (e.g., by deciding for more transparent system design), although the extent of their influence on opacity might be restricted by technical constraints (Ananny & Crawford, 2018).

Opacity for regulators of algorithm-based HRM. Regulators will be predominantly interested in opacity due to legal and ethical reasons (Arrieta et al., 2020). For instance, this class of stakeholders consists of employee representatives (e.g., work councils), juries, lawyers, and policy-makers who provide the regulatory frame for algorithm-based HRM. Opacity can protect intellectual property and can thus also be a deliberate regulatory strategy that enables companies to maintain their competitive advantages (Arrieta et al., 2020, Burrel, 2016). However, opacity might also make it harder to perform system auditing to determine whether algorithm-based systems follow legal and ethical standards (Kellogg et al., 2020). Similarly, opacity might make it harder to determine who is accountable in case of unfavorable outcomes of algorithm-based HRM (e.g., in discrimination lawsuits that might arise due to systems producing biased outputs; Dastin, 2018). Jobin et al. (2019) analyzed the global landscape on ethics guidelines on AI algorithms to which regulators (but also deployers) of algorithm-based systems contribute. Their analysis showed that those guidelines converge towards transparency as the most important principle surrounding the use of algorithms in high-stakes decision-making. This is due to the fact that there is hope that transparency improves monitoring and auditing of algorithm-based systems, empowers people to act against algorithm-based systems (e.g., enables whistleblowing), and promotes other ethical principles in the application of algorithm-based systems (e.g., autonomy, justice, trust) (Jobin et al., 2019). Although those ethical guidelines calling for transparency are not legally binding, legislation such as the European Union's GDPR as well as the European proposal for AI-

specific legislation (AI Act) show that considerations surrounding opacity and transparency will be central for future legal considerations in algorithm-based HRM (Floridi, 2021; Goodman & Flaxman, 2017).

How to Promote Transparency in Algorithm-Based HRM

The fact that there are various stakeholders with their own perspectives and interests regarding algorithm-based HRM makes considerations surrounding opacity and transparency in algorithm-based HRM especially challenging. For some stakeholder goals, reducing opacity and promoting transparency will be necessary to fulfill those goals, whereas for other goals, maintaining opacity can be beneficial. Similarly, some stakeholders might want algorithm-based HRM to be more transparent whereas others want to preserve opacity. Considering all stakeholders perspectives as well as the advantages and disadvantages associated with opacity and transparency seems necessary for effective and accepted use of algorithm-based HRM.

However, research on algorithm-based HRM has so far predominantly focused on reasons for opacity as well as their implications without providing strategies to reduce opacity and promote transparency. Being aware of possible strategies to reduce opacity is crucial as it gives stakeholders in algorithm-based HRM the opportunity to consider these strategies when dealing with the advantages and disadvantages of opacity. In the following section, we introduce suggested strategies to reduce system-based opacity, opacity due to illiteracy, and intentional opacity in order to promote transparency.

Technical solutions to reduce system-based opacity. There is a variety of technical solutions to address system-based opacity (Adadi & Berrada, 2018; Arrieta et al., 2020). The literature on technical solutions is vast and a comprehensive review of this research is beyond the scope of the current paper (we refer readers to Adadi & Berrada, 2018; Arrieta et al., 2020; Guidotti et al., 2019; Lipton, 2018, for overviews on those methods). Broadly speaking, the two big classes

of technical solutions to reduce system-based opacity are transparency-by-design and post-hoc interpretability or explainability methods (Guidotti et al., 2019; Lipton, 2018). Transparency-by-design is to implement algorithm-based solutions using (at least partly) transparent algorithmic models and features for prediction and classification. Transparency-by-design therefore relates to the actual transparency of algorithmic models used in algorithm-based systems. It could mean models whose entire logic is transparent to people, models where single components (e.g., inputs, parameters, calculations) are transparent, and models where at least the underlying algorithm is transparent (e.g., that linear regression describes linear relations; Arrieta et al., 2020; Lipton, 2018).

Post-hoc interpretability and explainability methods play a crucial role when there is low or virtually no model transparency (Lipton, 2018). In such cases, researchers (mostly computer scientists) attempt to design technical solutions that make system processes or outputs less opaque. For instance, post-hoc interpretability and explainability methods can augment black-box models with methods to generate text or symbols to explain functioning of a system or the rationale behind outputs of a system (e.g., “these applicants were rejected because they did not respond to question 2”). Further examples for post-hoc interpretability and explainability methods provide visual information or feature relevance information that give intuition regarding the importance of a respective feature for a given output. As another example, there are methods that try to derive information regarding what would have happened if there would have been different input information (e.g., what would have happened if an applicant would have been male instead of female) or methods that inform the user on what would have needed to be different for a different outcome (e.g., this applicant would have been invited for a job interview, if they would have had 1 more year of job experience) (Karimi et al., 2021; Mittelstadt et al., 2019). As a final example, post-hoc interpretability and explainability methods could provide further representative data examples that relate to a respective output. For instance, this could mean that in addition to the

recommendation regarding an applicant (e.g., “this applicant received 8 out of 10 points”), other applicants who are representative for a given recommendation category (i.e., for the category “8 out of 10 points”) could be presented together with their input information (see Arrieta et al., 2020, for an overview on post-hoc interpretability and explainability methods).

The extent to which these technical solutions reduce opacity without considering other reasons for opacity is still up for debate. Specifically, opacity due to illiteracy will likely undermine the positive effects that those technical solutions can realistically achieve (Langer et al., 2021). For instance, understanding an inherently transparent system still requires basic knowledge on how algorithms generally work. Similarly, highlighting the most influential predictors in an algorithm still requires an understanding of what this means for the outputs of the respective algorithm. Furthermore, technical solutions can be designed intentionally opaque. For instance, deployers can decide to implement technical solutions that only reveal parts of a system’s actual decision-making process otherwise they could overwhelm users with additional information (Chromik et al., 2019). Thus, it might be necessary to implement regulations that prevent the misuse of technical solutions to opacity.

Education and training as strategies to reduce opacity due to illiteracy. To address the issue of opacity due to illiteracy, it is necessary to educate and train stakeholders (Oswald et al., 2020). Beginning in primary school, policy is attempting to bring programming literacy to the broad public (Lepri et al., 2018). Furthermore, online courses to teach people the basics of programming and machine learning are booming and could be used as training methods within organizations that want to enable their HR staff to become more knowledgeable regarding algorithm-based systems (Oswald et al., 2020). However, it is still unknown what the effects of education and training are on the use of algorithm-based systems in practice (Kellogg et al., 2020).

Again, we need to consider interaction effects with the other reasons for opacity and strategies to reduce opacity. For example, implementing technical solutions could make algorithm-based systems and their outputs less opaque without the need for strong algorithmic literacy. However, the development of technical solutions so far was mostly focused on methods that benefit the goals of developers (e.g., increasing developers' understanding to help them improve system quality) (Brock, 2018; Miller et al., 2017). This implies that research is necessary to make technical solutions helpful for people with limited algorithmic literacy. Eventually, technical solutions that are tailored to the needs of people with low algorithmic literacy could lower the bar for knowledge necessary to effectively use algorithm-based systems in practice (e.g., Doshi-Velez & Kim, 2017; Sokol & Flach, 2020). Unfortunately, research on the effects of technical solutions for non-experts in applied settings (Liao et al., 2020; see Tonekaboni et al., 2019, for an exception in the medical domain) is particularly rare and practically non-existent for the current applications of algorithm-based systems in management. This makes it questionable whether existing technical solutions would even align with stakeholder needs in applied settings or with regulation that was set in place to address algorithmic opacity (Goodman & Flaxman, 2017).

Regulation and ethical guidelines as strategies to reduce intentional opacity. In the case of intentional opacity, reasons for opacity lie in the hands of developers and deployers (Felzmann et al., 2019). In such cases it might be necessary to legally require developers and deployers to reduce opacity and implement means of increasing algorithmic transparency. For instance, the GDPR clearly taps into issues surrounding opacity and transparency. Particularly relevant in this regard are Articles 12, 13, 14, 22 and Recital 71 of the GDPR (Goodman & Flaxman, 2017). Article 12 builds the foundation for the use of “transparent, intelligible, and easily accessible” information and communication in the other articles. Articles 13 and 14 refer to providing “meaningful information about the logic involved” when using automated decision-making and profiling (i.e.,

using automated processing of personal data to evaluate people's characteristics and to evaluate and predict human behavior). Article 22 puts restrictions on the use of completely automated profiling and calls for safeguards in cases where automated profiling is used (e.g., right to contest and right for human intervention). Finally, Recital 71 includes what is commonly discussed as a "right to an explanation" (Goodman & Flaxman, 2017): "[automated] processing should be subject to suitable safeguards, which should include specific information to the data subject and the right to obtain human intervention, to express his or her point of view, to obtain an explanation of the decision reached after such assessment and to challenge the decision."

Whereas those parts of the GDPR aim towards more transparency of algorithm-based decision processes, there is still a lot of room for interpretation with the right to explanation and with other parts of the GDPR (which is also a reason for recent proposals on more specific European legislation with respect to transparency requirements of algorithm-based systems; Floridi, 2021).² How deployers will implement those aspects in algorithm-based HRM is an open question. For instance, deployers could implement technical solutions or make source code openly available. However, this might not be especially helpful to reduce opacity for people with low algorithmic literacy. Additionally, there are cases where this is not practically feasible. In such cases, it might be possible to invite independent auditors. Those could audit respective algorithms and disclose their inner workings to, for instance, regulators to ensure ethical and legal standards (Burrell, 2016) and at the same time preserve an organization's intellectual property by maintaining opacity regarding competitors.

² See <https://eur-lex.europa.eu/legal-content/EN/TXT/HTML/?uri=CELEX:52021PC0206&from=EN> for the Regulation of the European Parliament and of the council laying down harmonised rules on artificial intelligence (Artificial Intelligence Act) and amending certain union legislative acts.

Aside from legal regulations, there has been a recent upsurge in ethical guidelines calling for increased transparency of algorithm-based systems (Jobin et al., 2019). Although those are not legally binding, they can influence decision-makers in organizations to invest in increasing algorithmic transparency (Jobin et al., 2019; Kellogg et al., 2020). However, even though most ethical guidelines call for transparency, they are less uniform regarding their interpretation and definition of transparency and how it should be implemented. Additionally, the content of those guidelines might reflect the underlying motivation and goals of the respective institution that developed the guidelines. For instance, Jobin et al. (2019) emphasize that ethical guidelines developed by private companies differ from those of non-profit organizations or policy makers (e.g., private companies support technical solutions to reduce opacity whereas other institutions call for more legal regulation and auditing). This indicates that interests with regard to (intentional) opacity might be reflected in ethical guidelines that actually aim to address respective issues of opacity.

Trade-offs Associated with the Strategies to Reduce Opacity for HRM Stakeholders

Up to this point, we have presented the centrality of opacity for algorithm-based HRM, and we have considered implications of opacity for the main stakeholders, and provided an overview on strategies to reduce opacity and promote transparency. Throughout the paper we have seen that opacity can be beneficial for certain desired outcomes in algorithm-based HRM and detrimental for others, and opacity can be in the interest of or can undermine the interests of different stakeholders. Similarly, there are possible trade-offs to be aware of when considering strategies to reduce opacity in order to promote transparency from the perspectives of the involved stakeholders.

Trade-offs for users. Augmenting algorithm-based systems with technical solutions to reduce opacity can reduce efficiency of processes as users need to process additional information (Adadi & Berrada, 2018; Gregor & Benbasat, 1999; Tintarev & Masthoff, 2007). If users want to

quickly fulfill daily tasks and routines, any additional information that accompanies system outputs might lead to negative reactions and decreasing efficiency (Gregor & Benbasat, 1999; Tintarev & Masthoff, 2007). However, additional information (and training) can also enhance efficiency of decision-making as system outputs become more convincing or more easily integrable into users' decision-making processes (Langer et al., 2021). There is another trade-off associated with the faithfulness and simplicity of information generated by technical solutions. Although people prefer simple explanations (Lombrozo, 2007), these might not cover the full rationale of an algorithm-based outcome and thus will not faithfully represent the reasons for an algorithm-based decision. Thus, if technical solutions only reveal parts of the reasons for an outcome, there might be cases where users falsely assume that a system-based recommendation is based on, for instance, fair processes (Ribeiro et al., 2016; Sokol & Flach, 2020). Similarly, getting information that faithfully informs about the reasons for the outputs of algorithm-based systems is a task for future research in computer science. To date, it is not really possible to verify whether advanced systems provide insights into their decision-making processes that actually reflect what the reasons for respective outputs were (Schölkopf, 2019). Furthermore, a considerable number of users will need more and better education and training to address opacity due to illiteracy. Although there will hopefully soon be an emerging generation of HR professionals equipped with data scientific foundations, developing evidence-based training for more algorithmic illiteracy might pose a challenge if individuals and organizations do not have resourcing for the associated training costs.

Trade-offs for people affected by algorithm-based HRM. Increasing transparency of algorithm-based processes might overwhelm people affected by algorithm-based HRM. For instance, Lee et al. (2019) argue that if the complexity of a decision-making process is made transparent, people might think that system outputs are the best possible solution – after seeing the complexity of system-based decision processes, they might not even consider that there could have

been a fairer solution. This speculation is, for instance, in line with Bigman et al. (2020) whose findings indicate that moral outrage is less likely for outcomes provided by systems and with findings by Elsbach and Stigliani (2019) showing that people believe novel technologies are just too complex to understand. Additionally, affected people might not even expect information or explanation in relation to algorithm-based decisions (Schlicker et al., 2021). In some cases, providing clarifying information on algorithm-based decision processes can even detrimentally affect reactions to algorithm-based processes (Langer et al., 2018).

Trade-offs for deployers. There is a trade-off between information leakage and endeavors to make algorithm-based systems more transparent (e.g., technical solutions and legal regulations) (Sokol & Flach, 2020). Every piece of information that increases transparency of algorithm-based systems can help competitors to unravel and potentially copy a system. Furthermore, reducing opacity can help people to game systems (M. K. Lee et al., 2015). In machine learning, this issue is discussed in relation to adversarial attacks on machine learning models meaning that people try to unravel a model's decision process to manipulate the process to their own advantage (Arrieta et al., 2020). Especially in algorithmic management contexts, the trade-off between transparency and gameability becomes apparent (Kellogg et al., 2020; M. K. Lee et al., 2015; Möhlmann et al., in press). For instance, Uber drivers commonly try to exchange information about how the Uber algorithm determines compensation for rides in order to be better able to control their compensation (Möhlmann & Zalmanson, 2017). Similarly, Upwork workers (people working on the freelancing platform Upwork) try to find out how Upwork monitors their work or determines work performance in order to find ways to circumvent monitoring or to enhance their performance evaluation (Jarrahi & Sutherland, 2019). For deployers, those situations are likely undesirable, thus motivating them to maintain or even increase opacity. We can also imagine systems that are able to tailor provided information in a way that will more likely increase outcomes deployers find

desirable. For instance, systems could learn what kind of explanation they have to provide to users in order to increase users' trust in a system or workers on algorithmic management platforms' commitment to follow the rules of the platform provider (Ravenelle, 2019). This, again, points to the potentially conflicting interests of different stakeholders regarding algorithm-based HRM, and again emphasizes considerations regarding opacity as a strategic lever for deployers (Ananny & Crawford, 2018; Schnackenberg & Tomlinson, 2016). For instance, deployers can strategically increase or decrease system transparency. In the case of algorithm-based systems for HRM, this means that deployers of algorithm-based solutions might provide users with overly detailed information which occludes actually relevant information and can decrease motivation to even consider the provided information (Ananny & Crawford, 2018). Similarly, making transparent certain parts of the algorithmic prediction models (e.g., inputs) while ignoring others (e.g., outputs) might be another strategic decision in relation to the transparency of algorithm-based systems in HRM. Another trade-off for deployers is associated with education and training as a way to reduce opacity due to illiteracy. On the one hand, deployers might want to train users to be better able to provide high-quality decisions in collaboration with algorithm-based systems (Oswald et al., 2020). On the other hand, they might want to keep some opacity as transparency can also lead to less efficiency (Gregor & Benbasat, 1999) or to users being better able to game systems (Kellogg et al., 2020).

Trade-offs for developers. First, when trying to make systems less opaque, there are important technical limitations. Specifically, completely solving the issue of system-based opacity seems challenging if not impossible (Ananny & Crawford, 2018; Zerilli et al., 2018). For instance, it might never be fully possible to translate internal representations of deep neural nets into human semantics and for continuous learning systems, any explanation might just reflect a snapshot of a system's current state of internal decision logic (Ananny & Crawford, 2018). Second, there is a

trade-off that concerns system accuracy and transparency with potentially strong implications for the implementation of algorithm-based systems in practice. Previous research frequently refers to an accuracy-transparency trade-off in machine learning (Arrieta et al., 2020; Yarkoni & Westfall, 2017): Higher accuracy in machine learning algorithms (e.g., classification or prediction accuracy) often goes hand in hand with lower transparency. Transparency-by-design (i.e., using transparent models) can be a roadblock for accuracy because more transparent models (e.g., rule based, tree based) tend to be less accurate than less transparent models (artificial neural networks). As another example, preprocessing (e.g., deleting improbable data values) can boost prediction accuracy but will reduce transparency (Burrell, 2016). This likely requires purposeful decision-making, balancing prediction accuracy and transparency of an algorithm-based system. Beyond research to find (mathematically) pareto-optimal solutions, it might be fruitful to study how much prediction accuracy one is ready to lose for improving transparency in algorithm-based HRM. The answer to this question likely depends on the application context of algorithm-based systems (Arrieta et al., 2020; Felzmann et al., 2019; Kellogg et al., 2020; Leicht-Deobald et al., 2019). For instance, using algorithm-based systems for transactional activities (e.g., everyday work scheduling; Lepak et al., 2005) might call for less transparency than for ethically sensitive, transformational decisions in promotion, personnel selection, or organizational development.

Trade-offs for regulators. Many ethical guidelines refer to transparency in relation to algorithm-based systems in practice, assuming that more transparency is better (Jobin et al., 2019; Martin, 2019). However, transparency might be achievable for only certain algorithm-based systems, and given that transparency does not automatically ensure understandability (e.g., for people with low algorithmic literacy), it might be necessary for some activities but not for others, and might be in the interest of only some stakeholders. Thus, regulators have to consider conflicts and trade-offs between different interests in relation to opacity (Langer et al., 2021; Sokol & Flach,

2020). Whereas developers more likely call for technical insights into systems in order to improve systems, affected people might call for easily accessible information increasing their controllability of algorithm-based systems. Furthermore, deployers might call for transparency because they want their systems to adhere to legal regulation, whereas developers either cannot provide a certain level of transparency due to technical constraints or would need to significantly lower the performance of systems to provide such transparency. Addressing specific stakeholders' interests in a given situation requires context-aware technical solutions, training and education, or regulation tailored to stakeholders' needs (Mittelstadt et al., 2019). With respect to technical solutions, this is already an active field of research. However there are scholars questioning whether it will be possible to develop technical solutions with this kind of responsiveness, adaptability, interactivity, and context-awareness in the near future (Ananny & Crawford, 2018; Burrell, 2016).

Future Research Directions

In summary, there is a strong need for research on the basic issue of opacity, on proposed strategies to reduce opacity (technical solutions, training and education, regulation and guidelines), and on consequences of opacity and transparency with respect to stakeholder perspectives in algorithm-based HRM. To holistically address opacity in algorithm-based HRM, it is crucial to investigate the three reasons for opacity and strategies to reduce opacity from the perspective of each type of stakeholder, and with regard to potential advantages, disadvantages, and trade-offs. Furthermore, our analysis of the consequences of opacity and transparency shows that they cover various topics central to the area of algorithm-based HRM such as work design (Parker & Grote, 2020), control (Kellogg et al., 2020), decision-making (Grove et al., 2000), trust (J. D. Lee & See, 2004; Mayer et al., 1995), justice and fairness (Ötting & Maier, 2018), acceptance of algorithm-based systems in HRM (Newman et al., 2020), improvement of the performance of algorithm-based systems in HRM (Tambe et al., 2019), as well as legal and ethical issues (Goodman &

Flaxman, 2017; Jobin et al., 2019). Table 1 provides an overview on future research directions from the perspective of the stakeholders in HRM and with respect to the strategies to reduce opacity as deliberate activities to address the reasons for opacity and balance the advantages and disadvantages associated with opacity and transparency.

Regarding technical solutions to system-based opacity, some of the most pressing research questions arise from the fact that technical solutions have rarely found their way into real world settings. Within the increasing use of algorithm-based systems for HRM (M. M. Cheng & Hackett, 2021; Tambe et al., 2019) there lies opportunity to investigate the outcomes of different technical solutions on stakeholders involved. Depending on the stakeholder, the respective HRM activity, and further contextual variables (e.g., time pressure), there is a strong need for a structured research agenda to investigate how technical solutions contribute to the implementation of algorithm-based HRM in practice. Specifically, this means (a) investigating the use of different technical solutions for different application areas, (b) exploring the effects of technical solutions on a variety of possible outcomes (e.g., fairness, trust, autonomy, responsibility, work satisfaction, and human-AI team performance), (c) scrutinizing the processes of how technical solutions affect those outcomes, (d) examining contextual influences and individual differences as moderators of the relation between technical solutions, stakeholders and outcomes, and (e) iteratively improving technical solutions and their use in applied settings (see also Langer et al., 2021).

Regarding education and training as strategies to reduce opacity due to illiteracy, it seems particularly important to develop and validate educational and training efforts regarding the use of algorithms in management. Although there have been calls for more education and training (Oswald et al., 2020), it is not yet clear how to effectively and efficiently implement them. Furthermore, there is a lack of research showing that education and training really affect intended outcomes for the respective stakeholders such as human-system team performance in HRM,

adequate trust in systems, acceptance of algorithm-based decisions, or risk assessment for deploying algorithm-based systems in HRM.

Regarding regulation and guidelines as strategies to reduce intentional opacity, there has been a recent boom in ethical guidelines and legislation addressing the use of algorithms in practice (for an overview see Hagendorff, 2020; or Jobin et al., 2019). However, their effects on the behavior of developers and deployers are unclear. Will developers perceive those regulations as necessary or do they believe them to be ignorable? In the case of deployers, it is conceivable that they could creatively interpret regulation and ethical guidelines (e.g., similar to privacy statements required by the GDPR; Degeling et al., 2019) to keep the strategic lever of opacity and transparency. Furthermore, it is an open question as to whether other stakeholders (i.e., users, affected people) feel empowered by those regulations and if they would react favorably to organizations adhering to ethical guidelines regarding the use of algorithm-based systems in HRM.

In Table 1, we present technical solutions, education and training, as well as regulation and guidelines as possible strategies to reduce opacity. However, regarding the aforementioned possible trade-offs, those solutions might be confronted with issues in practice. For instance, although there are various ethical guidelines, legal regulations, and a variety of scholars promoting to increase transparency of algorithm-based systems (Adadi & Berrada, 2018; Jobin et al., 2019), there are also authors criticizing previous research emphasizing that, for instance, increasing transparency does not always lead to the expected or even positive outcomes (Ananny & Crawford, 2018; Felzmann et al., 2019), or claiming that there is a double standard in relation to transparency emphasizing that human decisions basically also are black boxes (Zerilli et al., 2018). Furthermore, there is already research showing that there could be “dark pattern” of technical solutions to opacity (Chromik et al., 2019). For instance, technical solutions could be designed to confuse or divert affected people in a way that they would not question algorithm-based decisions, or in a way to

convince regulators that algorithm-based decisions adhere to legal regulations when it is the algorithm-based decision process that is problematic. Consequently, there is a need for a systematic research agenda investigating how to successfully, legally, ethically, and effectively balance opacity and transparency while considering stakeholders' individual perspectives.

Conclusion

Algorithm-based HRM will continue to play a central role in organizational practices (M. Cheng & Hackett, 2021; Möhlmann et al., in press; Tambe et al., 2019). With the spread of algorithm-based HRM, there will be increasing demands from a variety of stakeholders to make algorithm-based HRM more efficient, useful, trustworthy, ethical, fair, legal, and accountable (Floridi et al., 2018). In this paper we have emphasized that opacity is a key characteristic of algorithm-based HRM activities that might affect all of these demands. We have also shown that considerations between opacity and transparency are complex when implementing algorithm-based HRM and that there are different reasons for opacity, different strategies to reduce opacity, and different stakeholders with (partly) conflicting interests. Furthermore, depending on the HR activity, stakeholders' perspectives, and the application context will inform whether a system should be designed in a less opaque way, whether users need to be better trained in working with systems, or whether we need regulation to promote transparency. Opacity seems to be the default when implementing algorithm-based HRM and any strategy to reduce opacity needs to be examined with respect to the various stakeholders and their (strategic) interests regarding algorithm-based HRM.

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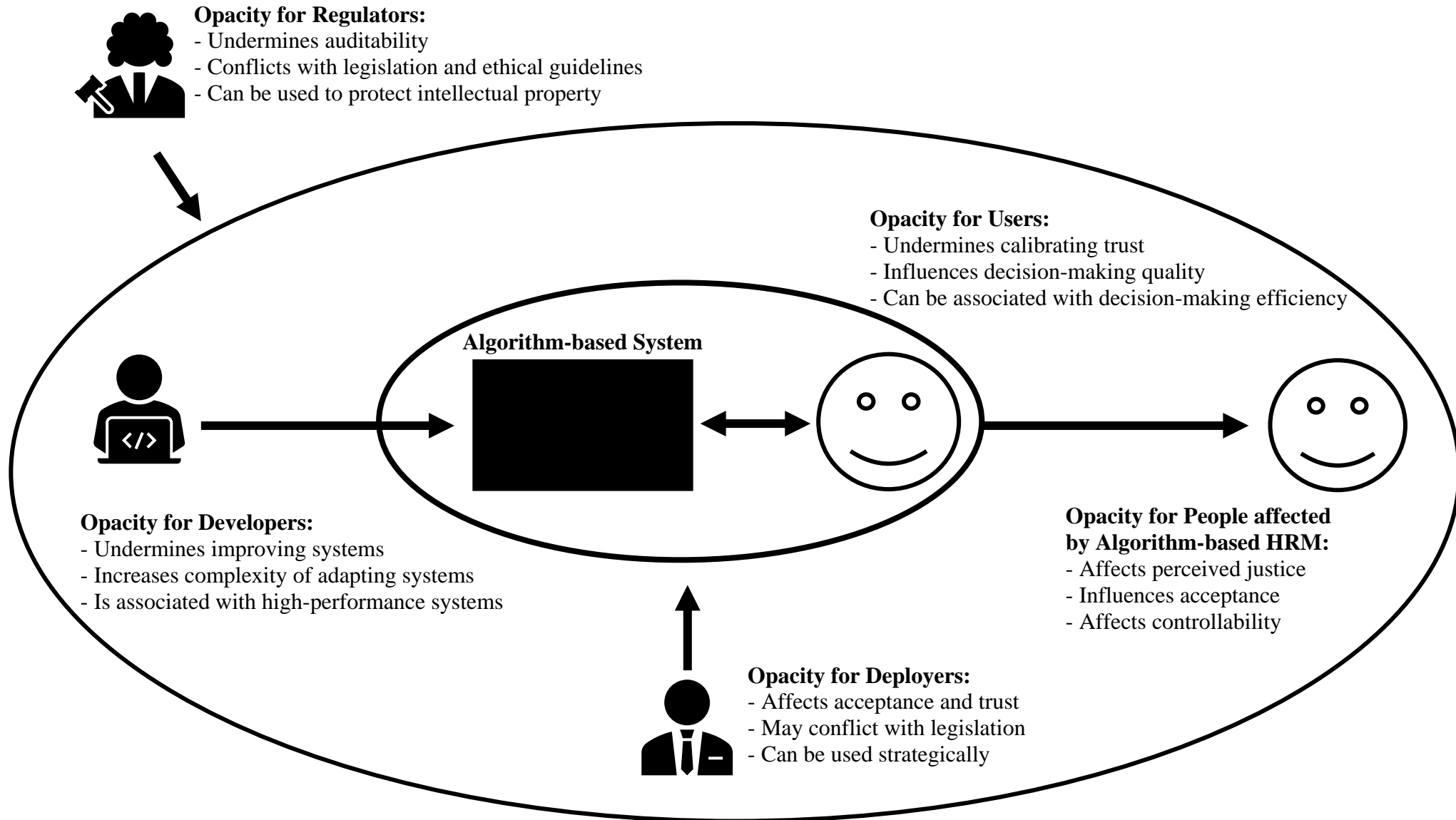


Figure 1. Overview of stakeholders and their relationships to algorithm-based system in HRM, and sample implications of opacity of algorithm-based HRM (figure adapted from Langer et al., 2021).

Table 1.

Research questions in algorithm-based HRM resulting from the perspective of the main stakeholders in algorithm-based HRM, from the proposed strategies to reduce opacity, and from the trade-offs associated with the strategies to reduce opacity

	Technical solutions to reduce system-based opacity	Education and training as strategies to reduce opacity due to illiteracy	Regulation and guidelines as strategies to reduce intentional opacity
Users	<p>How do users react to technical solutions (e.g., trust, acceptance)?</p> <p>How do technical solutions contribute to work design when implementing algorithm-based HRM?</p> <p>How do technical solutions affect performance of human-system teams (e.g., decision-making performance)?</p> <p><i>Are there trade-offs with respect to efficiency and performance when implementing technical solutions?</i></p>	<p>What are the effects of training and educating users (e.g., regarding perceived usefulness, decision-making quality)?</p> <p>How to train HR employees on the use of algorithm-based systems in HRM?</p> <p>How to efficiently implement user training?</p> <p><i>What are the costs associated with user training?</i></p>	<p>What are effects of regulation and guidelines for users (e.g., regarding autonomy)?</p> <p>How do users react to regulations and guidelines?</p> <p><i>How to ensure that users perceive regulations and guidelines as impactful?</i></p>
Affected people	<p>How do affected people react to technical solutions (e.g., justice, fairness, controllability)?</p> <p>Do technical solutions promote justice in algorithm-based decisions?</p> <p><i>Do technical solutions have side effects for affected people (e.g., overwhelm people, allow gaming systems)?</i></p>	<p>What are the effects of training and educating affected people (e.g., regarding acceptance, controllability)?</p> <p>How to educate the public regarding algorithm-based HRM?</p> <p><i>Does education and training of affected people influence system gameability?</i></p>	<p>What are the effects of regulation and guidelines for affected people (e.g., regarding worker autonomy, applicant reactions)?</p> <p><i>Will regulation and guidelines increase bureaucracy (e.g., for gig workers)?</i></p>
Deployers	<p>How do deployers react to technical solutions (e.g., anticipating acceptance, trust)?</p> <p>Do technical solutions contribute to algorithm-based HRM strategy (e.g., only with technical solutions will algorithm-based HRM be used for transformational HRM activities)?</p> <p><i>Do deployers use technical solutions strategically (e.g., to keep opacity high)?</i></p>	<p>What are the effects of training and educating deployers (e.g., regarding risk assessment of algorithm-based HRM)?</p> <p>Do more algorithmic literate deployers implement algorithm-based systems differently?</p> <p><i>Will deployers develop trainings that keep certain information intentionally opaque?</i></p>	<p>How do deployers respond to regulation (legal and ethical guidelines)?</p> <p>How do regulations and guidelines affect algorithm-based HRM strategy?</p> <p><i>Will deployers try to circumvent regulation and guidelines to keep the strategic lever of opacity?</i></p>
Developers	<p>Do technical solutions improve the development of algorithm-based HRM?</p> <p>Do technical solutions help to realize issues with algorithm-based systems earlier?</p> <p><i>How to treat accuracy-transparency trade-offs?</i></p>	<p>Can developers be made aware of other stakeholders' perspectives to be better able to improve systems?</p> <p><i>How to train developers in weighing different stakeholders' perspective, advantages and disadvantages of opacity?</i></p>	<p>How do developers implement regulation in algorithm-based systems?</p> <p><i>How to prevent regulation and guidelines from negatively affecting system quality?</i></p>
Regulators	<p>How do regulators react to technical solutions? (e.g., evaluation of auditability, adherence to regulation of algorithm-based HRM activities)</p> <p><i>How to ensure that technical solutions are designed to the benefit of users, affected people and not only in the strategic interests of deployers?</i></p>	<p>What are the effects of training and educating regulators (e.g., more practically implementable regulation)?</p> <p>How to train regulators?</p> <p><i>Does literacy affect the demands and interests of regulators regarding algorithm-based HRM?</i></p>	<p>How do regulators in companies (e.g., employee representatives) enforce regulations and guidelines?</p> <p><i>How to prevent overregulation and bureaucracy?</i></p>

Note. Italicized sentences represent sample trade-offs to investigate that are associated with the strategies to reduce opacity.