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*Document Version*

Accepted author manuscript

*Published in:*

Information and Organization

*DOI:*

[10.1016/j.infoandorg.2020.100301](https://doi.org/10.1016/j.infoandorg.2020.100301)

*Publication date:*

2020

*License*

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*Citation for published version (APA):*

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), Article 100301. <https://doi.org/10.1016/j.infoandorg.2020.100301>

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Download date: 09. Dec. 2024



# **Breaking the vicious cycle of algorithmic management: A virtue ethics approach to people analytics**

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## **Abstract**

The increasing use of People Analytics to manage people in organizations ushers in an era of algorithmic management. People analytics are said to allow decision-makers to make evidence-based, bias-free, and objective decisions, and expand workers' opportunities for personal and professional growth. Drawing on a virtue ethics approach, we argue that the use of people analytics in organizations can create a vicious cycle of ethical challenges - algorithmic opacity, datafication, and nudging - which limit people's ability to cultivate their virtue and flourish. We propose that organizations can mitigate these challenges and help workers develop their virtue by reframing people analytics as a fallible companion technology, introducing new organizational roles and practices, and adopting alternative technology design principles. We discuss the implications of this approach for organizations and for the design of people analytics, and propose directions for future research.

## **1. Introduction**

In recent years, a growing number of organizations have started using People Analytics (PA) to manage their workforce. PA refer to computational techniques that leverage digital data from multiple organizational areas to reflect different facets of members' behavior. Utilizing algorithmic technologies, PA analyze these data for patterns and present decision-makers with more granular views of organizational resources, processes, people, and their performance (Huselid, 2018). This can help decision-makers to expand their visibility into the functioning of the business, and consequently make more informed and objective decisions (Barrett and Oborn, 2013; Zarsky, 2016).

Like other AI-based tools, PA are based on algorithmic technologies that rely on large datasets for their operation. Their application raises ethical questions that have been discussed in relation to algorithmic technologies in different fields, such as the potential of algorithms to promote bias in

medicine (Joy and Clement, 2016), unduly influence political discourse (Mittelstadt, 2016), and engender racial discrimination in predictive policing practices (Jefferson, 2018).

Unlike other applications of algorithmic technologies (e.g., for financial trading, data security, weather forecasting, or identifying terrorists), PA are aimed at developing the behavior and character of people (Isson and Harriott, 2016) through a quantitative analysis of their conduct and psychological makeup. Their underlying logic can be traced back to principles that were originally elaborated through work conducted within the human relations movement (Bodie et al, 2016); their application is intended to improve the work experience of organizational members, reduce their stress levels, increase their job satisfaction, and expand their opportunities for personal and professional growth and development (Guenole et al, 2017; Isson and Harriott, 2016; Levenson, 2015; Marr, 2018)<sup>1</sup>.

Because of their focus on developing people's behavior and wellbeing, the application of PA in organizations is inherently related to human virtue, which refers to the cultivation of personal excellence that moves an individual towards the accomplishment of a good life (Aristotle, 1987; MacIntyre, 1967); that is, "a morally admirable life [characterized by] the development and exercise of our natural capacities, and especially those which characterize us as humans" (Hughes, 2003, p. 183); a life "worth seeking, choosing, building, and enjoying" (Vallor, 2016, p. 12). This understanding of virtue is elaborated in the moral philosophy of virtue ethics (MacIntyre, 1967), which focuses on people's character and emphasizes their capacity to exhibit good behavior in challenging situations. It places morality in embedded dispositions that individuals can acquire over time through involved participation in social practices and immersion in their community,

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<sup>1</sup> <https://osf.io/wxcqp>; <https://newsroom.cisco.com/feature-content?type=webcontent&articleId=1790568>; <https://www.entrepreneur.com/article/289042>; <http://www.hcamag.com/features/people-analytics-the-key-trend-in-employee-engagement-228113.aspx>

and in individuals' voluntary and reflective effort to cultivate their moral character and fulfil their human potential (Aristotle, 1987). Thus, when people are hindered in developing their virtue, they are also hindered in pursuing a fulfilling life that is worth seeking.

Among the many ethical challenges arising from the application of algorithmic technologies, there are three, in particular, that may inhibit people from developing their virtue and are, thus, relevant in the context of PA: algorithmic opacity (Burrell, 2016), datafication of the workplace (Tsoukas, 1997), and the use of nudging to incentivize certain behaviors (Mateescu and Nguyen, 2019). Opacity, datafication, and nudging have been explored in the literature. For example, Pasquale (2015), O'Neil (2016) and Mittelstadt et al. (2016) identified the use of opaque algorithms as a concern which may create information asymmetries and inhibit oversight. Zwitter (2014), Baack (2015), and Mai (2016) discussed the adverse impacts of datafication on privacy. Sunstein (2015), Tufekci (2015), and Tene and Polonetsky (2017) described the harmful effects of nudging when used to manipulate people's behavior without their consent, for illicit purposes, or against their interests.

While these works make useful contributions in highlighting prominent issues arising from opacity, datafication, and nudging, we know little about their potential effects on people's ability to develop their character. The identified harmful aspects (e.g., information asymmetries and behavior manipulation) point to potential barriers to people's ability to cultivate their virtue, but these links have not been systematically explored. This is particularly problematic because while PA usage is intended to aid workers' growth and wellbeing, practices stemming from wide-spread application of PA that may adversely affect people's virtue are on the rise; for example, using algorithmic decision-making tools in organizations that curtail workers' capacity for voluntary action (Beer, 2017) and personal integrity (e.g., Leicht-Deobald et al, 2019).

To address this problem, we examine the use of PA in organizations from a virtue ethics approach and observe the effects of algorithmic opacity, datafication, and nudging on people's ability to cultivate their virtue. We find that the use of PA can create a vicious cycle of ethical challenges that adversely impact people's efforts to develop their virtue by pursuing internal goods, acquiring practical wisdom, and acting voluntarily. We maintain that these effects are not a necessary consequence of using PA. Rather, they are likely to manifest when organizations enact a set of frames of PA as a technology that is epistemologically superior to its human counterparts. The framing of technology can shape people's understanding of the nature of the technology, what it can be used for, and the likely outcomes of its utilization. Therefore, it can influence organizational action regarding the design and implementation of the technology (Orlikowski and Gash, 1994). Accordingly, we propose that organizations can mitigate the adverse effects of PA and help workers develop their virtue by reframing PA as a fallible companion technology, which in turn can give rise to new organizational roles and practices, and alternative technology design practices. The rest of the paper is organized as follows. First, we describe the lens of virtue ethics. Then we examine how the ethical challenges of opacity, datafication, and nudging hinder organizational members' ability to develop their virtue. Next, we discuss a view of PA as a fallible companion technology that can inform a more ethical use of this technology. We finish by proposing avenues for future research.

## **2. An introduction to virtue ethics**

In order to detail and understand the ethical consequences of PA, we draw on a *virtue ethics* approach, which was developed by Aristotle. Virtue ethics highlight personal characteristics in determining the ethical nature of individuals and their actions (Aristotle, 1987). Virtue ethics focus on the virtuous agent rather than on right actions or on what anyone should do. They are therefore

different to utilitarian ethics, which emphasize the consequences of actions – specifically their capacity to maximize good – in determining their ethical nature, and to deontological ethics, which propose that ethical behaviors are those which conform with a correct moral rule or principle (Hursthouse, 1999). Below, we elaborate on the virtue ethics lens by describing its major thematic components: an individual’s ability to pursue internal goods, acquire practical wisdom, and act voluntarily (table 1).

<b>Thematic Component</b>	<b>Definition</b>	<b>Manifestations</b>
Pursue internal goods	Internal goods are valued for their own sake and integral to the practice that people engage in. By pursuing internal goods, virtuous agents move towards realizing their human potential and achieving their telos.	Pursuing internal goods manifests in achieving excellence of products or outcomes.  Pursuing internal goods manifests in a sustained effort to improve one’s competencies, thereby pushing the boundaries of one’s field of practice.
Acquire practical wisdom	Practical wisdom is the ability to reason correctly about moral issues; it guides the virtuous agent towards ethical behavior by recognizing and responding to the particularities of any given situation.	Practical wisdom manifests in doing the right thing within uncertain circumstances that require courage, honesty, or restraint.  Practical wisdom manifests in reflecting on whether a given course of action is worthy of and conducive to a good life, both for the agent and the community.
Act voluntarily	Voluntary action implies that agents behave in a virtuous way with full and reasoned recognition of their actions and the circumstances within which they act, recognizing that their action is the right one for its own sake given the circumstances.	Acting voluntarily manifests in doing something for the right reason and not out of compulsion or for ulterior reasons.  Acting voluntarily manifests in agents’ ability to provide a coherent explanation for their actions and why they seemed appropriate within certain circumstances.

*Table 1. Summary of the three thematic components of virtue ethics*

### *2.1. Virtue as the pursuit of internal good*

To Aristotle, a virtue is a quality which enables an individual to move towards the achievement of their human telos. Telos can be understood as a final end or goal towards which individual actions are performed, and from which their meaning is derived (MacIntyre, 1967). A final end must be something that is chosen for its own sake rather than as a means for achieving something else. For

example, the final end of an architect is to design structures, of a composer to create music, of an academic to discover and disseminate new knowledge, of a worker to perform their work well. Thus, it is within the totality of the telos that human qualities emerge as virtues (MacIntyre, 2007). As the examples above indicate, virtue is expressed in social practice, which from an Aristotelian perspective is understood as a complex and cooperative human activity through which “goods internal to that form of activity are realized in the course of trying to achieve those standards of excellence, which are appropriate to, and partially definitive of, that form of activity, with the result that human powers to achieve excellence, and human conceptions of the ends and goods involved, are systematically extended” (MacIntyre, 2007, p. 187).

By engaging in social practice, the virtuous agent continually tries to improve and excel at something, thereby pushing forward their own practice as well as the activity itself. For instance, through repeated training, the architect develops both her own skills and the field of architecture. In the process of so doing, the agent can be said to pursue good that is internal to her practice. Two kinds of *internal goods* can be achieved this way. The first manifests in the excellence of products or outcomes, for example, well-designed houses. The second manifests in a sustained effort to improve and hone one’s competencies in order to become a better practitioner. The pursuit of internal goods inheres in a life that is dedicated to learning and improvement and that reflects a moral commitment that requires humility and hard work (MacIntyre, 1967). Through the quest for such a life, we can achieve eudaimonia, a state of fundamental well-being and flourishing, within which we are able to realize and expand our human potential (Aristotle, 1987).

Internal goods are valued for their own sake and are integral to the practice that we engage in such that we can only experience them in relation to this practice and identify them by the experience of participating in this practice (MacIntyre, 2007). Their achievement confers benefits both to the

practitioner as well as for the entire community that participates in the practice. Conversely, *external goods* do not derive from the practice and are only associated with it within certain circumstances. For example, successful athletes are extremely well-paid today, but not 100 years ago. Goods such as power, recognition, money, and influence can be said to be practice-agnostic because they are not unique to any one practice and there are always alternative ways to achieve them. According to Aristotle, external goods are a scarce resource; whereas the achievement of internal goods is beneficial to everyone who is involved in a practice, one's attainment of external goods means that less of them will be available to other participants (Aristotle, 1987).

## *2.2. Practical wisdom as a fundamental virtue*

In order to pursue goods that are internal to a social practice, and to navigate complex and variable situations by taking morally-sound actions, it is crucial to acquire and develop practical wisdom. To have practical wisdom is to have the ability to properly recognize and respond to morally salient elements in any given situation, thereby exercising virtue. Practical wisdom thus goes beyond possessing and utilizing practical skills, which are aimed at producing desired ends or products. It aims at doing the right thing within certain circumstances that require courage, honesty, or restraint (MacIntyre, 1967).

Knowing general moral principles is not sufficient to exhibit virtue. Because our world is dynamic and complex, any abstract principle is likely to provide indeterminate guidance within a concrete situation (Tsoukas, 2018). For instance, to be a 'good employee', a 'model citizen', or a 'loving parent' can vary and translate to different actions across situations. Practical wisdom orients the virtuous person towards good behavior by attending to the particularities of each situation, recognizing areas where no existing technique or policy apply, and specifying courses of action



wherein the virtuous person exhibits humility, justness, courage, etc. Accordingly, it involves reflecting on whether a given course of action is worthy of and conducive to a good life, both for the agent and the community (Beabout, 2012).

Practical wisdom is a stable disposition that allows people to form good judgements about actions within morally difficult and ambiguous situations, where the best decision is not obvious. According to Aristotle, it is a fundamental virtue whereby we cultivate our minds to become excellent at deliberating the specifics of a given situation, appropriately applying moral principles in response to the situation, and acting in ways that are internally good to the practice in which we engage (Hughes, 2003).

Practical wisdom – as any other virtue – is not innate and cannot be learned in a theoretical fashion; rather, it is the consequence of training that involves performing virtuous acts (MacIntyre, 1967). It is acquired through habituation and repetition: a person becomes brave by repeatedly performing brave acts. One brave action does not make the person brave; but doing so repeatedly will inculcate the habit of acting bravely such that we call not only the actions, but also the person brave (MacIntyre, 1967). To be virtuous, therefore, is not a choice in a specific situation, but a choice for life: a life dedicated to understanding the virtues and following them, as well as to developing one's character. This process is not an individual effort but takes place through a socialization into a community. It involves interacting with and observing others who possess practical wisdom, thereby learning the moral codes that underpin the community's collective life. In this process, a person develops the capacity to exercise virtue - courage, humility, temperance - in a way that fits the situation at hand (Tsoukas, 2018).

### 2.3. *Virtue and voluntary action*

Acquiring practical wisdom is a necessary but insufficient condition for acting virtuously. For an act to be rightly called virtuous, three conditions need to be met (Aristotle, 1987). The first and most elementary condition is that the *act must be of a virtuous kind* (Hursthouse, 1999): telling the truth, exhibiting bravery, helping others. However, doing those things alone does not necessarily mean that a person has acted virtuously. It could be that someone was truthful because they were forced to tell the truth, or that they told the truth when they thought they were lying, or that they did so unintentionally, for instance while they were intoxicated.

Hence, a second condition is needed that *the agent must act for the right reason*, or that the agent does not act for the wrong reasons, such as out of ignorance, to comply with a threat, or to avoid punishment. For example, if someone acted honestly because they were afraid that they might get caught lying, then they did not act virtuously. The virtuous person recognizes that telling the truth is the right thing to do under the given circumstances and acts accordingly. Thus, the ‘right reason’ necessitates that the agent must choose their actions for their own sake. This excludes acting out of compulsion or for ulterior reasons.

To this we add a third and final condition that the *agent must know what they are doing*; that they are telling the truth, exhibiting courage, or helping others. This requires that if we asked the agent why they told the truth, acted bravely, or helped others, they would be able to articulate an honest answer that allowed us to appreciate what it was about their understanding of the situation and their action that made this action seem like the right thing to do in this situation.

These conditions, the second and third in particular, indicate how central the notion of voluntary action is in Aristotle’s philosophy. To Aristotle, virtues can only manifest in voluntary action because we cannot reasonably assign praise or blame to actions that we did not volunteer to

undertake (MacIntyre, 1967)<sup>2</sup>. For any act to be considered virtuous requires that the agent must not only act in a way that can be described as virtuous, but also that they do so with full and reasoned recognition of their actions and the circumstances within which they act, and that they do so because they recognize that their action is the right one for its own sake given the circumstances.

Having described the basic tenets of virtue ethics, we next apply them to examine three broad ethical challenges that arise from using PA. We describe these challenges in terms of how the use of PA affects people's ability to pursue internal goods, acquire practical wisdom, and act voluntarily.

### **3. An ethical consideration of PA: A virtue ethics perspective**

As we described at the outset of the paper, the application of PA is intended to help workers achieve personal and professional growth. Therefore, it engenders ethical issues that are particularly pertinent to people's ability to cultivate their character and exhibit virtue: algorithmic opacity, datafication of the workplace, and the use of nudging. Despite the extant discussion of these issues in the literature, their significance has not been examined either in the context of PA or in relation to people's ability to develop their character and fulfil their human potential. Therefore, we next examine these ethical challenges from a virtue ethics perspective. We summarize the challenges in table 2 and elaborate on them below.

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<sup>2</sup> Aristotle's notion of voluntarism is different to the ideal of a rational decision-maker. It does not require that people critically reflect on each decision that they make, but rather that, when asked (by others or themselves), people can coherently articulate some reasons for their actions.

Ethical challenge	Impact of PA on workers' ability to pursue internal goods	Impact of PA on workers' ability to acquire practical wisdom	Impact of PA on workers' ability to act voluntarily
<b>Opacity</b>	Algorithmic opacity can diminish organizational members' ability to understand the logic of the decisions made about them and their practices, hindering their ability to hone and develop their craft.	Unclear feedback reduces organizational members' visibility into the assumptions and norms that underpin the organization, hindering their ability to socialize into the organization.	Algorithmic opacity makes it difficult for members to genuinely understand their organizational landscape and the appropriateness of their actions.
<b>Datafication of the workplace</b>	Failing to understand how their work contributes to the organization hinders members' ability to reflect on the assumptions that underlie their actions and recognizing which ones need to be revised and improved.	One-sided or reductionist feedback can impair members' ability to be meaningfully socialized into the organization, and develop an understanding of its norms, values, and culture.	Oversimplified representations of members' behavior may prevent them from meaningfully reflecting on their actions, the circumstances within which they take place, and their effect.
<b>Nudging</b>	Manipulative practices prevent organizational members from pursuing personal outcomes and drive them to focus on achieving outcomes that are external to their practice and reflective of third-party interests.	Nudging towards certain thoughts and behaviors can prevent members from meaningfully reflecting on and understanding complex situations and develop good ethical judgments.	Manipulative practices prevent members from deliberating about meaningful choices and reduce their ability to provide a coherent explanation to themselves or others for why they have acted in a certain way.

*Table 2. Three ethical challenges that arise from PA use: A virtue ethics perspective*

### 3.1. Opacity

PA rely on an algorithmic analysis of large quantities of data to facilitate evidence-based, objective decisions that are meant to make organizations more transparent, fair, efficient, and productive (Minbaeva, 2018). These algorithms can be used to optimize, filter, rank, and classify data to recommend courses of action to decision-makers: who to hire and fire, who to promote, how to optimize resource-allocation across projects, how to construct work teams to maximize their productivity, etc.

However, algorithms do more than objectively detect subtle associations in large datasets to provide actionable recommendations. Algorithms have the power to govern their environment because they act as data filters in some cases and amplifiers in others, they plan and carry out analyses on data to render it meaningful, and they legitimize this meaning by producing results

with apparent accuracy, simplicity, and objectivity (Ananny, 2016). Algorithms can therefore affect how we conceptualize the world, modify its social structure, and alter our relationship to it (Floridi, 2014).

This process is complex, unpredictable, and laden with subjective evaluations, reflective of patterned institutional and organizational practices. Hence, it is important that the data used in the process are made visible (i.e., their scope, type, and quality) and that the connection between the data and conclusions is open to assessment (Pasquale, 2015). This way it is possible to evaluate whether the recommendations algorithms make are reasonable and fair (e.g., that they do not discriminate against job applicants based on their race) (Sandvig et al, 2014) and that the outputs they produce are consistent with their input data (e.g., that they do not imply causal relationships when only correlations can be established).

However, in many instances, the data used by algorithms and the manipulations performed on them are inscrutable and untraceable (Asadi-Someh et al., 2016; Mittelstadt et al, 2016). Hence, the first ethical challenge that arises from the use of PA involves the *opacity* of algorithmic decisions. When decision-makers act on PA output, impacted workers often do not have access into the logic that guided the decision. Because of their elusive and inscrutable nature, algorithms can be too complex to be fully understood by those who are impacted by their application and by those applying them (Faraj et al., 2018). Frequently, they are protected by corporate confidentiality, and the data they rely on for input remain unknown (O’Neil, 2016). Therefore, workers cannot follow the decision-making process and have no way of responding or contributing to it. Consequently, algorithmic decisions can be encountered as arbitrary and nonsensical and leave workers with no recourse when they impact them negatively (cf. Zarsky, 2016). This

situation can become worse when recommendations are delivered in a formulaic fashion that is divorced from the local discourse that characterizes the algorithm's context of application.

This may not always be resolved by increasing access to algorithmic data. For instance, algorithms based on neural networks, which are commonly used for voice and image recognition, cannot be simply understood because of the multiple layers of hidden mathematical neurons they contain and the complex interactions between them. Even when increasing algorithmic transparency can allow us to understand their built-in logic, doing so may have the paradoxical effect of generating so much information that workers can experience information fatigue, lack of interpretive skills, and meaninglessness (Stohl et al., 2016).

This poses a serious challenge from a virtue ethics standpoint. In the absence of visibility into how decisions are made about them, organizational members can lose the ability to understand how their actions are perceived by others, whether their skills are satisfactory and improving, and how they contribute to the work of other members as well as to the performance of the organization as a whole. For instance, when teachers' performance is assessed by opaque algorithms, it can lead to situations where they are considered to be high performers by their peers and managers, but are poorly assessed by the algorithm (Man and O'Neil, 2016; O'Neil, 2016). When such algorithms are designed by third-party vendors, their logic remains obscure and teachers cannot know what led to their poor assessment or what they need to do to improve their skills meet algorithmic expectations.

Without clear and timely feedback, organizational members are denied the possibility of reflecting on their actions and on the assumptions that underlie them, and therefore of continually improving their skills. In other words, the opacity of PA diminishes members' ability to pursue goods that are internal to their practice. Such a pursuit requires the ability to monitor our performance and

progress based on feedback from other experts that guide us through our training process. However, even well-intentioned members who are dedicated to their practice would find it difficult to continually push forward their practice in the face of unintelligible feedback.

The lack of detailed feedback can also make it difficult for members to develop a refined awareness of the assumptions, norms, and values that guide the collective life of the organization. Rich, personally-tailored, and varied feedback provides more than practice-specific technical details to allow for professional development; it also contains explicit and implicit cues regarding an organization's formal and informal social codes, expectations, and morals: acceptable dress code, forms of addressing colleagues, expectations regarding work-life balance, etc.

When feedback is provided - primarily or exclusively - by opaque algorithms, the ability of members to tap into organizational norms and values can be severely hampered. In organizations where inter-personal relationships and communications are mediated by algorithms (e.g., the bulk of Uber drivers' interactions with the company takes place through the Uber app and is governed by algorithms that determine drivers' pay rate, work placement, status, and ratings), the ability of employees to integrate into the communal life of the organization and become fully-fledged members is diminished. As a result, their ability to acquire practical wisdom is damaged.

Algorithmic opaqueness can also reduce members' ability to act voluntarily. Above we maintained that in an algorithmically-mediated environment, the relationship between members' actions and an organization's reactions can appear arbitrary, inexplicable, or unreasonable. Therefore, it becomes difficult for members to genuinely understand their organizational landscape and the likely outcomes of their behaviors. This may lead to Kafkaesque situations where the relationship between cause and effect are so blurred that an action performed to produce one outcome brings about the opposite outcome. For example, in our research we have come across a highly productive

consultant who was almost fired from her work because the utilization algorithm employed by her company's PA platform classified her as 'under-performing' due to extended periods of 'inactivity', which only occurred because she had finished her work well ahead of schedule. The work that she did whilst 'inactive' was not recorded by the algorithm and therefore not taken into consideration. Involuntary "algorithm games" that result from this, where organizational member's "fake" behaviors because they are registered by the algorithm, are well-documented (Bambauer and Zarsky, 2018).

### *3.2. Datafication of the workplace*

The second ethical challenge arising from the use of PA is the *datafication of the workplace*. In datafied organizations, members are not treated as fully-fleshed, subjective beings. Instead, they are reconstituted and known as collections of objective digital data that they produce actively and passively as they go about their work (Constantiou and Kallinikos, 2015). These data can be gleaned from performance evaluations, personality and psychological analyses, online activities, and relationships with colleagues. Once collected, these data can be systematically aggregated, analyzed, and fed to algorithmic decision-making technologies which are used to hire and fire members, allocate work, assess performance, assign financial rewards, and manage in-company communications.

When applied across an organization, such management-by-metrics becomes an all-encompassing exercise in quantifying and measuring members' practices. Moreover, it signals a behavioristic cause-and-effect approach to human conduct that ignores the idiosyncratic meanings and motivations that underlie members' actions. For example, one analytics platform classifies members into one of five pre-specified personas ("the engager", "the catalyst", "the responder",



“the broadcaster”, and “the observer”) based on their behavior on enterprise social networks<sup>3</sup>. This analysis is done by counting the frequency in which members engage in several predefined types of behavior (e.g., start conversations, comment, like). Once classified, members can be acted upon based on the assumed characteristics of their persona.

Such an approach raises considerable challenges from a virtue ethics perspective. First, a datafied understanding of members and their work risks oversimplifying both. In the example above, the vast richness of human variation is reduced to five pre-specified models and people are categorized based on a limited amount of secondary data. When members are fed back oversimplified representations of their behavior, they may find it difficult to identify themselves in them. Furthermore, when they are treated based on these representations, they are unlikely to be able to meaningfully reflect on their actions and their effects, and on their work and its contribution. This diminishes their capacity to continually develop and extend their skills and potential, and therefore to pursue goods that are internal to their practice. Members’ inability to meaningfully reflect on their actions and likely consequences also diminishes their capacity to act voluntarily, which requires that we understand our actions, the circumstances within which they take place, and their effect.

These ethical problems can become aggravated when the scope of datafication broadens and when how we are known is based not only on our own activities, but also on the activities of others. For instance, several PA platforms include an ‘organizational network analysis’ functionality<sup>4</sup>. By processing data from email, phone, and instant messaging, these platforms can map and visualize

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<sup>3</sup> <http://www.swoopanalytics.com/personas/>

<sup>4</sup> <https://www.trustsphere.com/organizational-network-analytics/>

<https://docs.microsoft.com/en-us/workplace-analytics/use/explore-metrics-internal-networks#network-size-and-network-breadth>

relationships between individuals and groups. Within a digital universe thus constructed, who we are and how we are known, is a function not only of our own activities, but also of the activities and relationships of others with whom we are connected. In this scenario, our digital persona may be even further removed from our own perception of ourselves and we may find any interactions based on it even less meaningful.

In highly datafied organizations, human interactions are mediated, regulated, and at times controlled by algorithmic technologies. Companies such as Uber and Deliveroo are designed to reduce unmediated interactions among workers and between workers and managers. Instead, digital data and algorithms are applied to construct representations of members and their work, which form the basis for all decisions made about workers. Whenever feedback is given to workers about their performance, it is brief, quantitative, and one-sided. Such a reductionist mode of communication can severely impair their ability to be meaningfully socialized into the organization, and develop an understanding of organizational norms, values, and culture. Consequently, this can reduce their ability to develop practical wisdom, which is predicated on rich interactions and ongoing habituation into a community.

### *3.3. Nudging to incentivize certain behaviors*

A third ethical challenge occasioned by PA concerns the use of nudging to incentivize the behaviors of organizational members (Mateescu and Nguyen, 2019). The utilization of PA relies on systematic collection of data that aims to cover the full scope of workers' activities. These data far exceed in scope, depth, and level of granularity conventional KPI data traditionally used by organizations, such as employee revenue, sales targets, billable hours, and 360 feedback scores. For instance, location data from employees' mobile devices can be used to track their physical

location and monitor who they interact with; Internet browsing patterns can be used to gauge workers' emotional states, political views, and moral stances; email and phone records, as well as activity on enterprise social networks, can be used to assess social engagement; data from sociometric badges can be used to examine the content of conversations between employees<sup>5</sup>; and biometric data can be collected from wearable health tracking devices that employees are encouraged to use<sup>6</sup>.

These data collection practices can create a work environment where online and offline activities are constantly tracked for analysis, prediction, and modification. Often such practices are one-sided as employees are unaware of the extent and nature of data collected about them and they profoundly diminish workers' privacy.

Privacy is commonly understood as one's ability to have "control over knowledge about oneself" (Introna and Pouloudi, 1999, p. 29) and decide how much information to reveal about oneself in each situation (Zuboff, 2015). Privacy can be also understood as the protection of the ability to lead a voluntary life (Alfino, 2001); to be able to think and plan without deliberate informational interruptions, distortions, and misrepresentations of people, things, and events. This ability can be undermined by manipulative practices that are characteristic of nudging.

A nudge is defined as "any aspect of the choice architecture that alters people's behavior in a predictable way without forbidding any options or significantly changing their economic incentives" (Thaler and Sunstein, 2008, p. 6). A common nudge in computer environments is the setting of defaults, which are pre-set courses of action that take effect if nothing is specified by the decision-maker (Gill, 2018). But nudging can also take more elaborate and sinister forms. For

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<sup>5</sup> <https://dupress.deloitte.com/dup-us-en/focus/internet-of-things/people-analytics-iot-human-resources.html>

<sup>6</sup> <https://www.abiresearch.com/press/mhealth-wearables-help-employers-achieve-higher-co/>

example, in 2017, it became known that advertisers on Facebook could target advertisements at teenagers during moments of psychological vulnerability. By monitoring posts, pictures, and interactions in real-time, Facebook helped advertisers identify moments when teenagers felt stressed, insecure, anxious, and overwhelmed, to influence them into buying their products<sup>7</sup>.

This kind of nudging can also be employed by organizations through the use of PA and other algorithmic systems to encourage ‘appropriate’ behaviors. For instance, one PA platform<sup>8</sup> uses a natural language processing algorithm to conduct a sentiment analysis and create individual and team happiness ratings to help decision-makers craft their interactions with them to achieve favorable outcomes – e.g., increase people’s productivity and compliance. Similarly, enterprise social networks (e.g., Slack and Yammer) recommend to workers others within the organization that they may have shared interests with thereby shaping future interactions and associations.

These practices are manipulative and ethically questionable when they are aimed at covertly subverting people’s decision-making capacity by exploiting their psychological, cognitive, or emotional vulnerabilities to change their beliefs, thoughts, or behaviors. Such manipulative practices limit people’s capacity for voluntary action: because they are hidden, we are unaware that our choice architecture has been restructured to take advantage of our emotional or cognitive make-up in order to facilitate an outcome that would not have otherwise occurred. Hence, when influenced in this way, our ability to deliberate about meaningful choices is undermined, as is our ability to explain to ourselves or to others why we have acted in a certain way.

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<sup>7</sup> <https://www.forbes.com/sites/paularmstrongtech/2017/05/01/facebook-is-helping-brands-target-teens-who-feel-worthless/#74249eda344e>

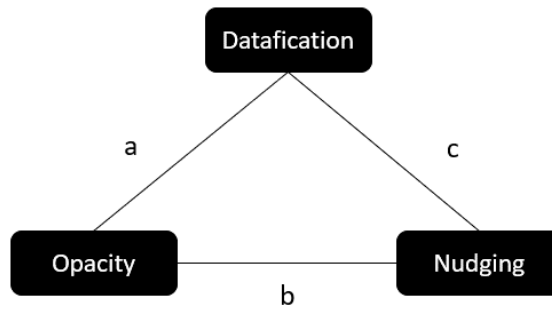
<sup>8</sup> <https://intellihr.com.au/features/people-management/performance-issues-management/>

These manipulative practices can also reduce our ability to pursue internal goods. As described above, internal goods are valued for their own sake and integral to the practice that we engage in. Therefore, they are deeply personal in the sense that they are an expression of one's unique engagement in this practice. On the other hand, manipulations are designed to prompt people to achieve outcomes that are external to their practice and reflective of third-party interests (Mittelstadt et al, 2016): to be more productive, engaged, alert, etc.

These manipulative practices also harm our ability to develop practical wisdom, which entails the ability to form good judgements about actions within morally ambiguous situations, where the best decision is not obvious. When our circumstances are deliberately manufactured to nudge us towards certain thoughts and behaviors, our ability to meaningfully reflect on our circumstances and on our actions within them is reduced. Consequently, our power to understand complex situations and develop good ethical judgments within them is compromised.

### *3.4. The vicious cycle of ethical challenges*

Above we presented each of the three ethical challenges as a standalone issue. However, they are, in fact, bound in mutually-reinforcing relationships, which, if go unchecked, can create a vicious cycle wherein each challenge enables or intensifies the consequences of other challenges (see Figure 1). While a full exploration of all the interrelationships among datafication, opacity, and nudging is beyond the scope of this paper, we provide three illustrative examples of these interrelationships below.



*Figure 1. The interrelationships of opacity, datafication, and nudging*

First, datafication of the workplace enables and amplifies the effects of opacity (arrow a) because datafied representations of workers are likely to be divorced from workers’ own understanding of themselves and consequently perceived as incomprehensible, especially when they are used as the basis for recommendations for action. For instance, Microsoft’s MyAnalytics is a productivity dashboard that provides information to workers about how they spend their time and who they spend it with so that they can become more productive. It systematically collects data about workers’ activities from several office 365 applications: email, calendar, Microsoft Teams, and Skype for Business. It then analyzes the data to provide insights to employees about their work routines and suggestions about how they should structure their time, such as; “your calendar is usually less than 30% booked when the week starts; make sure to plan time for focused work into your calendar ahead of time.”<sup>9</sup> However, much of workers’ activity takes place outside of office 365 and the data recorded in the dashboard is likely to be a reductive and potentially misleading representation of their actual practices. Therefore, any recommendations or user-profiles generated based on this data, are likely to be perceived as foreign and have low face-validity.

Second, nudging can enable another layer of opacity (arrow b) because people who are unknowingly nudged are unaware not only of the logic algorithm that underlay the nudge, but also

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<sup>9</sup> Taken from one of the authors’ MyAnalytics dashboard.

of the fact that an algorithm was used to nudge them at all. Nudges can be transparent when the individuals being nudged are aware that someone is attempting to alter their behavior and of the purpose of the nudge (Bruns et al, 2018), even if they do not understand the structure of the algorithm that produces that nudge. For example, one PA platform’s “nudge engine”<sup>10</sup> uses machine-learning technology to analyze large swaths of granular data and generate personalized emails to employees to suggest behavioral changes to increase organizational effectiveness and inclusion.

In other instances, users are not aware that they are being nudged. For example, an Australian bank has recently taken steps to curb gambling behavior among its customers. The bank uses a machine-learning algorithm to identify problem gamblers and provides friction in any customer’s decision to spend or withdraw money that is likely to be used for gambling. This effort includes covertly changing default product offerings on the bank’s mobile app such that problem gamblers are shown products that the bank deems to be safer (e.g., low interest credit cards and loans) than offers shown to other customers.

Third, datafication of the workplace can enable the practice of nudging (arrow c) because the creation and categorization of datafied profiles is the basis for nudging. Microsoft’s MyAnalytics is again a case in point. As the platform collects more data about workers’ activities, it compiles increasingly detailed employee profiles, which in turn serve as the basis for generating personalized nudges that are designed to change the behavior of these employees. Nudges in MyAnalytics hold the promise of “providing friendly, data-driven collaboration tips that surface

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<sup>10</sup> <https://humu.com/product/>

as you get work done in Office 365.”<sup>11</sup> For example, workers will get a notification through MyAnalytics if a meeting invite conflicts with a block of focus time that they had already scheduled, hence nudging them to decline the meeting request.

#### **4. Mitigating the adverse effects of PA and fostering an ethical approach to their utilization**

Above we examined the possible adverse effects of PA from a virtue ethics perspective. Our analysis of the ethical challenges associated with PA should not be misconstrued as an outright repudiation of this technology or as a deterministic statement that using PA will always have detrimental effects. We maintain that the ethical challenges described above are neither a necessary outcome of the use of PA nor a true manifestation of their ‘spirit’ (DeSanctis and Pool, 1994). Rather, they are likely to arise if organizations hold certain conceptions, or frames (Orlikowski and Gash, 1994), of PA and what they are capable of.

Below we propose that in order to break the vicious cycle we described above, organizations should reframe PA in a way that more accurately describes these technologies and what they can do, and is reflective of the principles and values of virtue ethics. Since the framing of technology informs organizational action regarding its implementation and design (Orlikowski and Gash, 1994), reframing of PA can open up alternative approaches to their implementation (through new roles and practices) and design. Consequently, this can help organizations apply PA in an ethically-informed way which, rather than have an adverse effect on workers, will allow them to expand their capacity to exhibit virtue and flourish in the workplace. We summarize these ideas in table 3 and elaborate on them below.

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<sup>11</sup> <https://www.microsoft.com/en-us/microsoft-365/blog/2018/07/12/introducing-workplace-analytics-solutions-and-myanalytics-nudging>



<b>Ethical challenge</b>	<b>Reframing PA</b>	<b>New organizational roles and practices</b>	<b>Alternative technology design principles</b>
<b>Opacity</b>	Humanizing PA portrays them as technologies that are capable of making mistakes, and that therefore should be scrutinized and held up to account	Algorithmists can sharpen human oversight in algorithmic decision-making, including a balanced emphasis on human-machine input	Revealing PA’s reasoning, including their shortcomings and uncertainty, makes them more readily interpretable and less opaque
<b>Datafication of the workplace</b>	Acknowledging the complexity of moral situations highlights the need to mitigate datafication and cultivate human interpretations	Algorithmists can advocate for adding breadth and multiplicity to algorithmic accounts, counteracting reductionism and one-sided representations	Exposing shortcomings in algorithmic reasoning highlights the need for additional, non-datafied insights
<b>Nudging</b>	Universal nudging can result in a morally-deficient workforce; organizations should limit the scope of nudging and allow members to reflect, and exercise human judgement to develop their practical wisdom	Algorithmists can ensure that nudging is transparent and consistent with workers’ pursuit of their internal goods, which is aided by the incorporation of rich and intuitive accounts of workers and their actions	The introduction of ambiguity and accountability into PA design can lead to probabilistic context-based nudging rather than deterministic and decontextualized nudging

*Table 3. Mitigating the adverse ethical effects of PA and espousing virtue in organizations*

#### *4.1. Foster new technological frames: PA as a fallible companion technology*

At the outset of the paper we described PA as computational techniques that are used to analyze large datasets and inform managerial decision-making. Admittedly, this is a reductive description because PA are not just a technology; they represent a quantitative, evidence-based, and data-driven approach to management (McAfee and Brynjolfsson, 2012). This approach portrays people as passive recipients of algorithmic authority, intervention, and modification (Norozov, 2013); as individuals fully knowable through their data traces (Zuboff, 2015) that live within an organizational reality which can be accurately modelled and efficiently acted upon thanks to the power of algorithms (Vallor, 2016).

These views of PA can be understood as a set of technology frames (Barrett, 1999; Davidson, 2002; Orlikowski and Gash, 1994). Orlikowski and Gash defined technological frames as “the assumptions, expectations, and knowledge [that people] use to understand technology in

organizations. This includes not only the nature and role of the technology itself, but the specific conditions, applications, and consequences of that technology in particular contexts” (Orlikowski and Gash, 1994, p. 178). As Orlikowski and Gash note, frames can influence the decisions people make regarding the design and use of technologies, and therefore their implementation trajectory and organizational consequences.

Accordingly, we suggest that the ethical challenges we described above arise from a particular set of frames of PA and what they can be used for. These frames have been propagated by technology vendors, which offer “seductive visions of data analytics” (Beer, 2018, p. 466) that can render organizations transparent and intelligible in new ways (Zuboff, 2015). Analytics packages like PA are portrayed as providing readily-interpretable insights to organizations in real-time. These insights are unbiased, accurate, and revealing truths about previously-unexposed organizational areas, thereby enabling a detailed exposition of past events and prediction of future occurrences (Beer, 2018).

Common to these visions is a view of PA as enhancing the work of decision-makers by imbuing them with rationality (Cascio and Boudreau, 2008; Davenport, 2009; Van Knippenberg et al, 2015), objectivity (Oswald and Putka, 2016; King et al., 2016), and prophetic abilities (Bersin et al, 2016; Mishra et al, 2016; Schiemann et al, 2018), thus positioning PA as an external epistemological agent. In many ways, this agent is superior to humans (Hong, 2016; Saffer, 2014) who have limited cognitive abilities and who commonly make irrational and biased decisions (e.g., Gershman et al, 2015; Gigerenzer, 2004; Koch et al, 2015; Simon, 1947; Sullivan, 2014; Waber, 2013).

When we accept these frames, the broad-scale application of PA, along with the collection and analysis of vast amounts of quantitative data that are required for their operation, seem logical and

desirable. However, as we described in section 3, this approach can increase algorithmic opacity, datafication, and nudging, and ultimately lead to the emergence of a vicious cycle of ethical challenges. In order to break this cycle and incorporate PA into organizations in a way that allows their members to exhibit virtue requires reframing PA: from a superior epistemological agent to a fallible companion technology (Saffer, 2014) that is designed by humans, co-evolves with us, and is reflective of our imperfect cognitive makeup and complex social surroundings. Framing PA as a fallible companion technology implies: (1) that PA are co-constituted with humans rather than an external epistemological agent to humans (Haraway, 2003); (2) expectations that PA should function as an expert assistant characterized by competence, adaptability, cooperativeness, and trustworthiness (Biundo and Wendemuth, 2017), and; (3) knowledge that PA can make mistakes, have flaws, and require care if they are to be trusted companions to us (Latour, 2011).

Such a perspective derives from three realizations about PA. First, algorithms embedded in PA are designed by people and mirror the institutional structures within which they live and the biases inherent in the data they use (Ananny and Crawford, 2016; Faraj et al., 2018; O’Neil, 2016). Second, while PA are thought to enhance the quality of decisions because they are based on extensive valid data (Togt and Rasmussen, 2017), in practice, when faced by time or financial constraints, organizations may use algorithms that leverage inexpensive or readily available data as simplistic proxies for multi-faceted human behavior or skills (O’Neil, 2016)<sup>12</sup>. This practice can lead to the creation of over-simplified models of a complex reality and degrade the quality of the decisions that are based on them (Dery et al, 2013; Macnish, 2012; Schermer, 2011). Third, the predictive power of PA should be questioned because acting on algorithmic predictions, decision-makers can create the conditions to realize these very predictions, thereby facilitating self-fulfilling

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<sup>12</sup> <https://www.financialeducatorsCouncil.org/financial-background-check-surveys>

prophecies (cf. Wang, 2012), which in turn, make it difficult to accurately assess the predictive power of PA and the algorithms that they use (Gal et al, 2017).

This framing of PA conceptualizes them as socio-technical entities that are profoundly and inescapably mutually-constituted with their social and organizational surroundings, and with the people that inhabit them. The data that they process, the design and training of their embedded algorithms, and their use are infused with the values, norms, and practices that characterize their environments. Consequently, we suggest framing PA not a superior epistemological agent but as a fallible companion technology that reflects our own cognitive limitations and the messy social environments that we live within.

Reframing PA can have positive implications for people's ability to exhibit virtue and flourish in their organizations. First, reframing PA as a fallible companion technology mitigates opacity by humanizing them, thereby opening up possibilities for organizational members to question their underlying logic. For instance, most of us do not understand how the medicine we take help us get better, but we take them anyway because we trust the expertise of pharmaceutical companies when it comes to concocting chemicals and understanding how the human body functions. However, evidence of corrupt and negligent practices in the pharmaceutical industry<sup>13</sup> can make us aware that they are run by humans who exhibit the same logical and character flaws that the rest of us do, and who therefore should be regularly scrutinized and held up to account. Likewise, reframing PA as a companion technology that is susceptible to the same cognitive limitations as us, can encourage organizational members to question the inherent logic of algorithms, and seek to understand how decisions about them are made.

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<sup>13</sup> <https://bit.ly/2GgokJp>; <https://bit.ly/36lHvw3>; <https://abcn.ws/2NTDnx0>

Second, reframing PA as a fallible companion technology highlights that the drive for *datafication* needs to be moderated because PA and their embedded algorithms do not meaningfully understand the data that they consume, the world that this data represents, and do not have a relationship of care with the people that generate this data (Tsoukas, 1997). All-encompassing datafication privileges evidence-based ‘truth’ – however decontextualized – over other moral values, such as empathy, wisdom, or justice: it is better to know who our best consultant ‘really’ is than to allow an overworked employee to catch up on their sleep and turn up late to work one morning without the risk of being exposed. However, reality, particularly moral reality, is always richer and more complex than any concrete representation of it and the ethical response to this limitation is not to broaden the evidential base for these representations by collecting more data. Rather, it is to help people cultivate better ways of interpreting, questioning, and thinking about them (Morozov, 2013); to help people perceive moral situations in a subtle and judicious manner. In other words, to help them develop their practical wisdom.

Third, reframing PA as a fallible companion technology brings to the fore the perils of the practice of *nudging* and the need to limit its scope. Nudging, as it is currently commonly practiced, involves automating decision-making and delegating the responsibility involved in this process to algorithms. This is morally questionable for two reasons. Firstly, it manipulatively imposes a single and external view of the ‘right’ action or choice, which can curtail people’s ability to act voluntarily. Secondly, it robs people of the opportunity to deliberate the moral significance of their choices and, in many cases, their inherent messiness and ambiguity, thereby limiting their capacity for reflection, practical wisdom, and moral growth (Morozov, 2013). When organizations universally apply the practice of nudging, workers are not able to do the wrong thing because they are always steered towards desirable behavior. However, this can result in a morally-deficient

workforce who may not do the right thing unless the option to do the wrong thing is eliminated by algorithms. Therefore, to help workers develop their virtue, organizations would be well-advised to implement the practice of nudging in a way that allows members to exercise their judgment, which may involve seeking advice from a technology companion.

#### *4.2. Foster new organizational roles and practices: Algorithmists and a hybrid approach*

Reframing PA as a fallible companion technology opens up avenues for new organizational roles and practices in relation to the utilization of this technology. It highlights that organizations should be circumspect in their evaluation and use of PA and make sure to scrutinize their underlying algorithmic technologies and output.

To do so, we suggest that organizations establish the role of *algorithmists* (Cukier and Mayer-Schönberger, 2013); people with a new set of skills who are tasked with monitoring the ecosystem of algorithms and their human companions. Algorithmists will straddle computational and organizational domains and have expertise in both. They will serve as auditors of algorithms, conduct internal quality checks, and examine the impact of algorithmic decisions on human stakeholders in order to increase their credibility and accountability. Algorithmists, therefore, are not just data scientists, but the human translators, mediators, and agents of algorithmic logic. They are on the front line of providing the care (Latour, 2011) needed to bring to fruition the framing of PA as trusted, but fallible companions.

We further propose that organizations implement a *hybrid approach* to using PA, which complements algorithmic processing of quantitative data with an analysis of qualitative data, reflective of workers' subjective experiences and meanings (Saffer, 2014). A hybrid approach can be particularly useful in equivocal settings that are open to multiple interpretations, defy one-

dimensional explanations, and are difficult to codify and quantify. Interestingly, PA are commonly used in exactly such settings – e.g., in the assessment of workers’ mental and emotional states and prediction of future behavior within dynamic organizational environments – which can lead to over-simplifications and errors (Fox, 2015; Rahwan et al, 2019).

The introduction of algorithmists and use of a hybrid approach can help people to exhibit virtue in their organizations. First, the new role and practice can mitigate *opacity* without overwhelming organizational members with too much data (Ananny and Crawford, 2016). Algorithmists sharpen human oversight in algorithmic decision-making (Ananny and Crawford, 2016; Fecheyr-Lippens et al., 2015) in order to increase algorithmic transparency. Thanks to their unique set of skills, which allows them to competently navigate both computational and organizational areas, algorithmists are able to make informed choices about what, and how much, information should be shared with members so that they understand how decisions about them are made without overburdening them with unnecessary data or technical details. Similarly, the hybrid approach to utilizing PA can yield richer and more intuitive representations of members and their actions than purely algorithmic quantitative accounts. Such representations can provide organizational members with a clearer background against which to interpret feedback about their behavior and performance, and help them gain a deeper understanding of the assumptions, norms, and values that underpin the collective life of the organization (Asadi-Someh et al, 2016) in order to cultivate their practical wisdom.

Second, algorithmists and the hybrid approach can restrict excessive *datafication*. Algorithmists, with their in-depth knowledge of both computational and organizational domains, understand the limitations of datafication and the disconnect between people’s lived experiences and their reductive data residues. Therefore, they can be effective advocates for adding breadth and

multiplicity to algorithmic accounts and for curbing datafication practices. This effort, in turn, can be aided by the implementation of a hybrid approach, which provides a practical avenue to developing comprehensive and rich representations of members' behavior to inform the work of decision-makers.

Third, algorithmists and the hybrid approach can mitigate undue *nudging*. The practice of nudging can be harmful when used against people's interests, without their consent, and when opting out is impossible. A hybrid approach, combined with the expertise of algorithmists, can help ensure that nudging is conducted in a more ethically-informed manner. Not all nudges are inherently morally-deficient and some nudging practices are ethically-defensible, for instance when used to empower individuals or promote social transparency (Sunstein, 2015). Algorithmists can monitor nudging practices, their purported objectives, and their impact on workers to guarantee that nudges are transparent and congruent with workers' efforts to pursue their internal goods. Transparent nudging means that workers know when they are being nudged and understand how their choice architecture has been changed and the grounds for these changes. Such transparency calls for hybrid approach for using PA that draws on both quantitative and qualitative data to compile and communicate rich and intuitive accounts of workers and their actions. Furthermore, algorithmists can work to ensure that the design of nudging practices allows for a simple and readily-available opt out option for workers in cases where they perceive nudging to impinge on their autonomy to make their own choices (Sunstein, 2015).

#### *4.3. Foster new technology design principles: Designing for informing and ambiguity*

Reframing PA as a fallible companion technology has ramifications that extend to their development, with a focus on designing PA as companions to virtuous organizational members. Various principles have been suggested to design ethical algorithmic technologies (e.g., Etzioni



and Etzioni, 2016; Kraemer et al, 2011; Mortier et al, 2016). Here we focus on two that are particularly pertinent to the development of virtue in organizations; accountability and responsibility (Dignum, 2017).

Accountability refers to the ability of algorithmic systems to explain how they have arrived at their decisions and place them in a broad context to aid human interpretation (Dignum, 2017). From a virtue ethics perspective, we articulate this as a principle of *designing for informing*. Algorithmic systems designed for informing can provide reasoning and context for the insights or decisions they generate like an expert assistant would. The aim of an expert assistant is not to push us into action based on predefined evaluation criteria, but to facilitate reflection, ask questions, give hints, propose alternative options – thereby cultivating our ability to identify and assess the moral consequences of different options, act voluntarily, and develop practical wisdom. Designing for informing also aligns with the above-mentioned hybrid approach that incorporates algorithmic processing of quantitative data with qualitative analysis of data reflective of workers’ subjective emotions and motivations (Saffer, 2014).

Responsibility denotes the ability of algorithmic systems to answer for their decisions and identify errors and unexpected results. Many algorithmic systems are designed to be over-confident (Clark, 2017). The probabilistic calculations underlying a data-driven insight are usually hidden from users and results are presented as facts. For example, an image recognition system trained to identify pictures of Donald Trump happily presents pictures of chicken filets among actual Donald Trump pictures (ibid.) without revealing how confident it is that a certain picture is of Trump. However, information about confidence levels exists and could easily be included in the design. Figure 2 shows two design alternatives for an image recognition system. The left image is the actual design used by picdescbot (a bot that describes random pictures from Wikimedia commons

using Microsoft Cognitive Services). The image on the right is the proposed alternative design (Clark, 2017) that reveals the system’s certainty level about its insights.

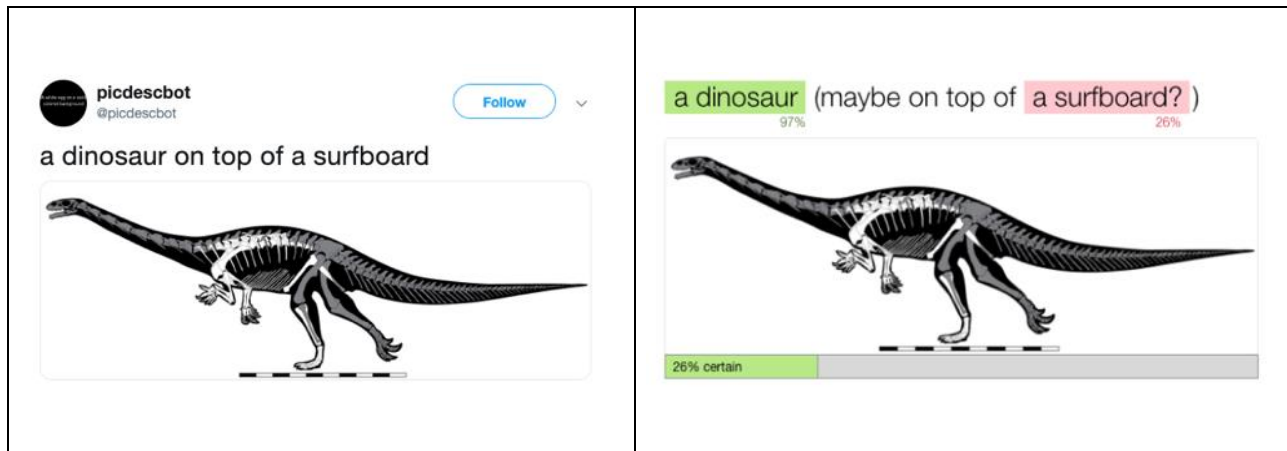


Figure 2. Designing for ambiguity, not certainty

Similar design alternatives would be possible for PA. For instance, instead of receiving a list of top 20 people most likely to quit in the next six months, a system may produce the same top list but with confidence scores. Lower confidence scores then inform the informing principle described above, where the system would explain why the confidence score is low (e.g., contradictory data) and prompt the manager to make further enquiries, add input to the algorithm, or ignore this entry on the list if they wish to. From a virtue ethics perspective, we articulate this as a principle of *designing for ambiguity*, not certainty.

These two design principles (designing for informing and ambiguity) can have positive implications for people’s ability to exhibit virtue and flourish in their organizations. First, they can mitigate *opacity* by facilitating a better understanding among workers of what data is used and how inferences about them are made (Mortier et al, 2016). Particularly, systems that reveal their own internal processing, including its shortcomings and varying certainty levels, are more easily interpretable by workers, especially with the help of expert algorithmists. This can expand organizational members’ ability to understand the logic of algorithmic reasoning and decisions,

allow them to orient themselves within their organizations, develop their skills, thereby cultivating their ability to exhibit virtue.

Second, designing for informing and ambiguity can mitigate *datafication* because revealing shortcomings in algorithmic reasoning highlights the need for additional representations and insights to inform organizational sensemaking and action. These insights may come from qualitative data, or from non-datafied sources such as human intuition (Burton et al, 2019). Revealing shortcomings in algorithmic reasoning also emphasizes the need for organizations to enact a more mindful mindset (Weick et al, 1999) that incorporates a diversity of viewpoints and negotiations as “it takes a complex system to sense a complex environment” (Weick et al, 1999, p. 82). Such a ‘reluctance to simplify’ may prove a useful principle to ensure that insights are evaluated from different perspectives, thereby increasing an organization’s ability to notice, be skeptic, and avoid reductive explanations (Aanestad and Jensen, 2016; Butler and Gray, 2006).

Third, designing for informing and ambiguity can mitigate *nudging*, or change its nature. Revealing uncertainty in algorithmic reasoning highlights the need for further explanation. Manipulative persuasive systems that have an aura of certainty can hinder voluntary action by reducing choice and nudging human behavior in particular and predictable directions in accordance with pre-defined preferences. However, the introduction of uncertainty into the design of PA can lead to probabilistic rather than deterministic nudging. That is, rather than be pushed into specific ways of acting, workers can be given several options from which to choose. Accountable PA can also help workers understand why they were presented with specific possible courses of action by providing them the contextual reasoning that led to the generation of these possibilities. This can increase the possibility for choice among workers and their scope to take voluntary action and cultivate practical wisdom.

## 5. Conclusions and further research

In this paper, we have examined the ethical consequences of PA from a virtue ethics approach. Because virtue ethics focus on people's capacity to develop their character and flourish, they offer a uniquely pertinent perspective from which to ethically evaluate PA, whose implementation and use are commonly justified by the need to expand workers' opportunities for personal and professional growth (Guenole et al, 2017; Isson and Harriott, 2016; Levenson, 2015; Marr, 2018). We have identified the ethical challenges of algorithmic opacity, datafication, and nudging that arise from the use of PA in organizations and observed their effects on people's ability to cultivate their virtue. We have demonstrated how the interrelationships among the three challenges can result in a vicious cycle of adverse ethical effects that hinder organizational members' ability to pursue internal goods, acquire practical wisdom, and act voluntarily. We have argued that these ethical challenges are not a necessary outcome of using PA, but that they are likely to materialize when organizations frame PA as a superior epistemological entity.

We have described how reframing PA as a fallible companion technology can help organizations conceive of new roles, practices, and design principles to restrain the scope and effects of opacity, datafication, and nudging, and help workers to develop their virtue: When organizations mitigate *opacity* by humanizing PA, sharpening oversight, and revealing algorithmic reasoning, they reduce the scope for datafication and nudging because workers are better able to understand how they are viewed by algorithms and why certain courses of action have been proposed to them; When organizations mitigate *datafication* by cultivating human interpretations and drawing on multiple formats and sources of information, including non-datafied insights, they reduce the scope for opacity and nudging because algorithmically-constructed accounts of workers are not as far removed from their own lived experience and these accounts can promote more contextual and

probabilistic nudging practices; When organizations mitigate *nudging practices* by making them more transparent and contextual, they reduce the scope for opacity and datafication because workers know that their choice architecture has been changed, understand the basis for these changes, and are able to bring to bear their subjective experiences into algorithmic attempts to act on their datafied profiles.

These insights suggest four avenues for future research. First, as PA become more common, understanding how their underlying machine-learning algorithms work will become increasingly important in enhancing workers' ability to develop their virtue. The algorithmic literacy of the general public – and dare we say, of many organizational leaders – is still in its infancy (D'Ignazio and Bhargava, 2015), and it is unlikely that many of us will be able to recognize and counteract the current limitations of PA, especially if technology vendors do little to highlight these limitations. We have proposed that trained algorithmists could help surface these limitations and outline ways to mitigate their effects, not only after an algorithmic system has been applied, but also during its design process (cf. D'Ignazio and Bhargava, 2015). Further research is required both to conceptually flesh out in more detail the nature, skills, and potential functioning of algorithmists in organizations, and to empirically examine how their presence can enhance workers' ability to cultivate virtue when relying on algorithmic technologies.

Second, more research is needed to better understand algorithmic sensibilities and rationality (Hong, 2016), paving the way for a more realistic conversation about PA capabilities and allowing organizations to adjust their perceptions and expectations accordingly. For example, while human heuristics have been studied extensively, we know comparatively little about the heuristics of algorithms (Bozdog, 2013). Recent research indicates that data analytics can drive dysfunctions in organizational learning by exacerbating superstitious or ego-centric learning (Pachidi and

Huysman, 2017). Thus, there is a need to examine PA capabilities through algorithm audits (e.g., code audit, scraping audit) (Sandvig et al, 2014) and uncover how algorithms ‘sense’ the world (Rahwan et al, 2019) and impact people’s behavior.

Third, most research on PA to date has been conceptual (Marler and Boudreau, 2017; Tursunbayeva et al, 2018), and there is a pressing need for empirical studies to provide rich descriptions of the implementation and use of PA in organizations; how they are received, understood, incorporated into practice, and how they shape and are shaped by organizational members, roles, routines, and legacy systems. We took an initial step in outlining a set of frames of PA that portrays them as a fallible technology and similar efforts have recently been made by other scholars (e.g., Green and Viljoen, 2020). Examples of harmful algorithmic technologies being banned from use are also starting to appear<sup>14</sup>. Such conceptions of algorithmic technologies and PA offer a counter narrative to the one propagated by many technology vendors (Beer, 2018) and aim to account for the complex realities of social life and algorithmic effects. An empirical body of work is required to develop a more concrete, substantive, and detailed understanding of algorithms-in-practice. Empirical studies can also help to substantiate and further develop and refine the application of ethical frameworks in order to understand the significance of PA for the organizations and people that use them.

Fourth, our study serves as a starting point in illustrating how the use of PA in organizations can create a vicious cycle of mutually-reinforcing ethical challenges - algorithmic opacity, datafication, and nudging - which limit people’s ability to cultivate their virtue and flourish.

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<sup>14</sup> <https://www.theguardian.com/technology/2020/feb/05/welfare-surveillance-system-violates-human-rights-dutch-court-rules>

Additional conceptual and empirical work is needed to further explore and develop those inter-relationships.

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