Proceedings of the 54th Hawaii International Conference on System Sciences | 2021

The Bermuda Triangle of Leadership in the AI Era? Emerging Trust Implications From "Two-Leader-Situations" in the Eyes of Employees

Simon D. Schafheitle
University of St.Gallen
simondaniel.schafheitle@unisg.ch

Antoinette Weibel
University of St.Gallen
antoinette.weibel@unisg.ch

Alice Rickert
University of St.Gallen
alice.rickert@unisg.ch

Abstract

Artificial Intelligence (AI) and machine learning (ML) algorithms are changing the work in many ways. One hitherto little-studied area is how these technologies are impacting leader-employee relationships, particularly employees' trust relationships in their "flesh-and-blood" leaders. In this paper, we discuss how algorithms change the nature of leadership when some leadership functions become automated. As a consequence, employees will often find themselves in a "two-leader-situation" with resulting frictions, that create novel leadership focus areas. Three situations, in particular, can be trust-problematic in the eyes of followers: the triad relationship might (1) make responsibilities blur, (2) create conflicting decisions of human leaders and algorithms, and (3) make employees' voice unheard. We argue that these situations can undermine employee perceptions of leaders' trustworthiness as followers might start to question a leaders' ability, benevolence, and integrity if leaders do not understand these novel situations.

1. Introduction

In a recent VERGE magazine feature, Josh Dzieza (1) raises the question "how hard will the robots make us work" and analyzes how and to what extent AI and ML algorithms already automate leadership functions. Theoretically, management functions like the establishment of stability and control have long been discussed as a potential for automation by AI (2, 3). Leadership functions, on the other hand, like the creation and establishment of goals and motivation have long been believed to be specific human tasks (4, 5) . However, at present AI and ML do not only assist and even automate certain decision-making tasks (e.g., problem diagnosis, information analysis, and integration) but also enlarge their scope of application to typical leadership tasks, such as goal-setting, persuading, motivating, and even sanctioning thereby creating even positive an emotional climate (6, 7). For instance, in gig-economy companies, such as Task Rabbit or Uber, algorithms can independently "deactivate", thus sanction a worker's account based on an opaque algorithmic decision (8). Other companies apply integrated and AI-driven performance management platforms that "optimize" working times, track work procedures, and rate employee productivity in a short-paced manner (1). Finally, AI is also used to improve the employee experience by personalizing HR services and often does this with the promise to be more agreeable than existing services for instance if claimed that "Amelia delivers the best elements of human interaction – conversation, expression, emotion, and understanding" (9).

Expected efficiency gains through the automation of both management and leadership functions seem to be a strong driver for the development of elaborated technological solutions. In their global survey, Kolbjørnsrud and colleagues (10) found that 86% of the surveyed executives plan to use AI for managing and leading their employees, including monitoring, coordinating, gamifying, and controlling their workforce. At the same time, though, human leaders are likely to prevail (see Figure 1); or as David De Cremer (11, ch. 6) recently wrote: human leaders are needed for sensemaking, for looking ahead, for contextualizing and for showing compassion (or other emotions). In a similar vein, Jarrahi (12) stresses the human advantage for decisions under uncertainty and ambiguity, where typically conflicting views and interests of stakeholders need to be balanced. Hence, at least for the present, in those organizations where some leadership tasks are automated employees will still have a human supervisor.

However, such two-leader situations, or more precisely matrix structures, always accentuate trust issues for at least two reasons. First, trust is considered a necessary precondition for coordination and cooperation across the interfaces in such a triad relationship. Secondly, trust is considered to become more tested and frail due to the inherent tensions of such a situation, at the same time (13). This salience of trust for matrix structures will be particularly felt by employees who now find themselves in the position to

URI: https://hdl.handle.net/10125/71285
978-0-9981331-4-0

be dependent on both, an algorithm and the human leader.

In this paper, we define employee trust in his/her leader as a willingness to be vulnerable based on beliefs about the likelihood that his/her leaders' future actions will be beneficial, favorable, or at least not detrimental" (14, p. 576). In a "two-leader-situation", however, vulnerabilities are pronounced often for the following reasons. First, it is often not clear which leader is responsible. On the one hand, this is a wanted design feature in matrix structures to allow for a compromise from two perspectives. On the other hand, this ambiguity is also an inherent feature of AI because self-learning algorithms change their function and "gestalt" over time and their mere application (15). Second, conflicts between these two leaders need to be resolved by the employee – this has been found to be one of the most difficult stumbling blocks in matrix structures (16). Here we will argue that a fight between an algorithm and a human leader is putting a particular strain on the employee-human leader trust relationship. Third, trust problems can also arise if the employee is not given enough voice; this is a likely scenario if algorithms and human leaders come to the same conclusion while the specific context as experienced by the employee was neither factored in by AI nor by the leader.

Thus, this paper aims at clarifying how algorithms impact existing social relationships inside organizations. More precisely, we contribute to a nuanced understanding of the triangle relationship between algorithms enacting leadership functions, human leaders, and employees. We are doing this by devoting special attention to novel leadership focus areas for sustaining employees' trust in leaders. To achieve this goal, we begin with the conceptualization of AI-/ML-algorithm's technological functionalities and theorize how they "can" automate leadership functions and what will be left for humans. Consequently, we address three novel, yet critical focus areas for leadership to sustain employees' trust in the human leader that is so important for effective workplace functioning (17). We conclude by outlining further avenues of research that underline our current work in progress.

2. Avenues of Algorithmic Leadership Automation

To gain a better understanding of the advent of "two-leader-situations", we will outline how and why algorithms automate leadership functions. As a consequence, we will argue that three "Gallic villages" remain, where humans will remain superior to algorithms, hence make "two-leader-situations" emerge in the workplace.

2.1. Technological Functionalities of Algorithms

Building on the work on algorithmic decision-making (e.g., 7, 18), algorithmic leadership (e.g., 19, 20), electronic performance monitoring (e.g., 21), human-machine interaction (e.g., 22), and the more general literature on the impact of technology on workplaces and their inherent social relationships (e.g., 23, 24), we distilled the following two technological functionalities of algorithms that drive leadership automation: (1) *algorithms' foresightedness* (25) and (2) *prescriptive analysis capabilities* (26, 27).

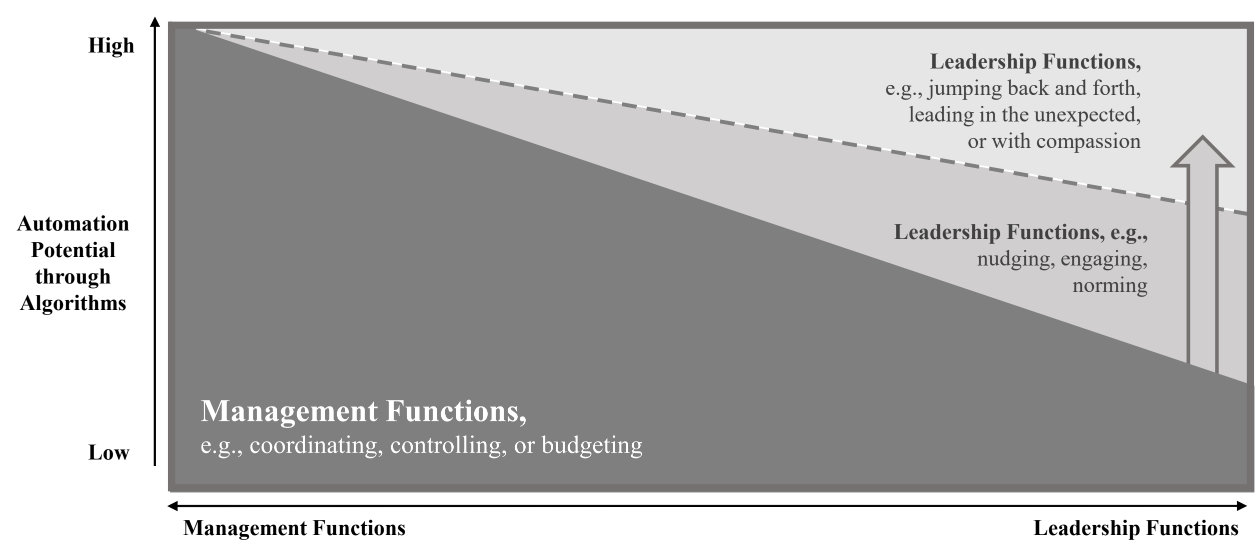

Figure 1. Automation potential of management and leadership functions through algorithms

Foresightedness differentiates algorithms from rather "old technologies", such as first-generation computers, that function more reliable, accurate, and allow augmented data gathering and analysis procedures, compared to humans (i.e., appropriateness, see 25). In combination with foresightedness, algorithms become "intelligent" because it allows algorithms to develop and refine their capabilities from their analyses' enactment and that they can autonomously apply their capabilities to original and novel application areas. For instance, IBM WATSON's foresightedness manifests as it gets better in identifying dog pictures from a vast amount of image data and that this capacity is also applicable to Jeopardy quiz competitions (28). Of course, an algorithm's foresightedness rests on necessary prerequisites of precise, reliable, and augmented data gathering and analysis capabilities, i.e., its appropriateness. Examples of foresightedness of algorithms include Natural Language Processing algorithms, Artificial Neural Networks, or Bayesian Belief Networks (see 27, for an overview). Applied to the automation of leadership, foresightedness means that an algorithm is technically capable of performing leadership functions, i.e. that it "possesses" relevant technological capabilities enabling it to perform leadership functions. Simply put, foresightedness means that an algorithm is *technically capable* of enacting leadership functions.

Secondly, *prescriptive analysis capabilities* mean that algorithms can recommend action based on a likelihood evaluation of existing alternatives. These capabilities comprise the most sophisticated form of automation, compared to descriptive (i.e., static status quo analyses in form of dashboards) or predictive ones (i.e. forecasting outcomes, based on historic or real-time data similar to an OLS regression logic) (26, 29). In line with the review findings of Lepenioti and colleagues (30, p. 58), prescriptive capabilities capitalize on AI and ML to embed predictive findings in a probabilistic context "*to provide adaptive, automated, constrained time-dependent and optimal decisions*". For instance, the Amazon "firing-by-algorithm" practice illustrates how algorithms use "static" predictions on success factors of employee performance to evaluate the likelihood that a particular employee will continue to underperform and that firing might be the cheapest alternative compared to training or development initiatives (31). Examples of an algorithm's prescriptive capabilities include all sorts of sophisticated regression analyses (e.g., ARIMA), or automated Monte Carlo simulation techniques, amongst others (27, p. 33). Applied to the automation of leadership, prescriptive capabilities enable an algorithm to practically apply its foresighted capabilities to HR issues, hence to perform leadership functions. Simply put, prescriptive capabilities mean that an algorithm has what it takes to *actually implement and apply* its foresighted capabilities into business practice.

2.2. Basic Premises of the Functional Perspective of Leadership

Leadership is defined as any process or practice that a leader undertakes to direct, motivate, or encourage his/her employees to achieve organizational objectives (4, 11). The leadership role is embedded in the wider organizational hierarchy that also defines who holds the authority to lead and who should follow (cf. 32). The functional perspective emphasizes leadership as an influence process in which a leader needs to fulfill specific functions to attain the broader goals; this is achieved via the enactment of concrete processes and practices (4, 6, 33). Following Lord (6, p. 115), the functional perspective also assumes that leadership is defined by the joint perception of followers, hence emphasizes employee's buy-in as co-pivotal for leadership effectiveness.

This perspective is reasonable to adopt because it disentangles the broad concept of leadership into its smallest and tangible constituent parts (6). Hence a functional perspective enables researchers to be precise on the avenues of how and to what extent algorithms automate leadership (cf. 11, p. 30 for advocating such an approach). Also, the functional leadership perspective assumes that leadership needs to be legitimated by employees, i.e. employees have to be willing to be led. Facing a growing permeation of workplaces with technology, employees' willingness to be led under these novel circumstances is thus crucial for effective technology deployment (see 34). Lord (6) classifies twelve leadership functions and categorizes these along two dimensions: targeted towards *task performance* or *group maintenance*. The first dimension includes functions such as developing plans, coordinating behaviors, removing barriers, and providing resources or facilitating evaluation, analysis, and integration, for instance. The second dimension comprises the stimulation of high task motivation, the fulfillment of employees' non-task needs, reduction or prevention of conflicts, or the development of a positive emotional atmosphere (6, p. 117). Morgeson and colleagues (4, p. 10) adopt a similar perspective as they cluster 15 functions into the dimensions *preparation of work* (e.g., how teams, workflows, and processes are organized) and *execution of the work* (e.g., task or contextual performance). In this vein, leadership functions targeted to the preparation of work include team composition, and development, setting goals, and expectancies, or the installation of feedback channels. Examples of the latter dimension comprise performance monitoring, provision of resources, problem-solving, or the challenge of work results.

2.3. “Gallic Villages” of Leadership Automation – What is Left for Humans?

Echoing the most recent book of De Cremer (11, see also 24), algorithms appear superior in enacting those leadership functions, where they can capitalize on rule-adherence and mathematical if-then logic, based on reliably processing vast amounts of data, faster than humans and without errors (e.g., 7). For instance, Ravid and colleagues (21) provide a comprehensive review of the broad knowledge of how algorithms automatize performance monitoring. Appelbaum and colleagues (27, p. 38) do the same for how algorithms automate learning and development leadership functions or to assess work productivity and Duggan and colleagues (35) review how algorithms autonomously lead gig-economy employees.

Yet, we have identified three areas of leadership functions, where humans will be superior in executing leadership functions, at least for a considerable time to come (see Figure 1) These are (1) *jumping back and forth between functional leadership targets*, (2) *leading in the unexpected, and (3) leading with compassion*. We call them “Gallic villages” of leadership and argue that leadership cannot and will not be fully automated.

2.3.1. Jumping back and forth between functional leadership targets. Leadership in everyday practice means that leaders have to navigate through a broad amalgam of topics, which often does not allow a sequential enactment of leadership functions (36). For instance, performance monitoring is an ongoing function and its effectiveness is highly dependent on how such monitoring processes (with or without the aid of algorithms) are embedded in a wider set of workplace norms and organizational culture (e.g., 37, 38). Hence, this requires leaders to simultaneously tango more informal leadership functions and, if needed, to make adaptions either in the way how formal monitoring processes are designed or how sense-making of the resulting data is enacted. Additionally, the continuous jumping of leaders between preparation- and execution-of-work-oriented leadership functions gets further fueled by the advent of algorithms. We surmise that this is due to the nature of algorithms and their machine-learning capabilities. Once applied, they continuously refine and develop functionalities that translate organizational complexity into zeros and ones. Put it differently, they contribute to decompose formerly complex and interdependent workflows for the sake of data processability and analyzability. Thus, leadership needs to make sure that the decomposed work packages (no matter whether performed by humans or algorithms) re-integrate and mesh smoothly to secure overall work performance. Recalling the nature of how AI-/ML-algorithms function, humans remain superior in performing the so needed jumping back and forth between various leadership functions or deliberately balancing various functions simultaneously.

2.3.2. Leading in the unexpected. Apart from that many organizations operate in VUCA-market environments (cf. 39), the likelihood for irregularities in workflows, the management of unforeseen or unexpected events, or the fast adaption to changing circumstances become the new parameters of leadership success (40). This stresses the importance of considering the context for leadership effectiveness (see also 41, 42). Algorithms, however, are “unable” to consider the leadership context because they are programmed to find the best-generalized solution and if more data is provided to develop a better one, based on logical and mathematical operating procedures (7, p. 248 call algorithms supercarriers of rationality). Hence algorithmic leadership is focused on specific problems where an optimal solution is searched for; in this area, smart machines are most likely to eventually outperform humans. Prescriptive capabilities, for instance, can improve trade-off decisions due to their large, and “objective” information base and by assigning success probabilities of available outcomes. Yet this very feature at the same time undermines algorithms from drawing on “contextualized judgements”. As a consequence, the algorithmic solution might be the optimal in terms of technical correctness but it still might not be adequate in terms of its fit with HR philosophy or company values. For instance, the often-cited hiring-/firing-by-algorithm examples might be effective in processing vast amounts of job applications and creating shortlists. However, if one were to disregard the HR philosophy or diversity values in this specific case, the workforce would likely consist of “old, white men over 60” (cf. 43).

2.3.3. Leading with compassion. Finally, at present, algorithms are not empathetic and thus are also not able to show compassion. Compassion is understood as consisting of three components (1) noticing another person's suffering, (2) empathically feeling another person's pain, and (3) acting in a manner to ease the suffering” (44, p. 94). We propose that in a context where some of the leadership functions are automated this particular human skill will be in great demand. First, a technology-intensive workplace is found to augment the psychological load of employees. Hence, pain – both in the form of fatigue and thus more physical pain but also in the form of heightened stress levels, and thus psychological pain is likely to be present in such a workplace (45). Second, automation even beyond the automation of leadership is demanding some amount of employee standardized behaviors and hence a certain "dehumanization" of work is one of the likely consequences (18). Human leaders can counteract by not only sensing and emphasizing this situation but also by offering sympathy and psychological support (46). Finally, some of these technologies are rendering employees invariably more vulnerable, particularly when consequences such as "fired by the algorithm" are credible scenarios. Here too, leaders need to interfere based on their ability to understand the specific context where such decisions happen, by understanding employees' position, and by being able to decide when compassion is the better option than following an automatism dictated by the machine. Leading with compassion will therefore include mediating between generalized algorithmic decisions and the specific subjective contextual factors, to protect and defend the human value in an automation driven organization (34).

3. Emerging Trust Implications for Leadership

As we have argued, algorithms' foresighted and prescriptive functionalities have the potential to automate leadership functions in manifold and hitherto unforeseen ways. However, as of now, we have argued three "gallic villages" of leadership to be immune to algorithmic automation. Hence two-boss situations will be the norm. Drawing on what we just outlined we expect that three areas of possible trust concern emerge/need to be highlighted: The triangle relationship between employee, algorithms, and human leaders (1) *blurs responsibilities*, (2) *might create conflicting decisions of human leaders and algorithms*, and (3) *employee voice might not be heard*. To gain a nuanced understanding of all three trust-related areas, we describe in the following triangle scenarios, illustrate them with examples from business practice, and raise emerging trust implications. For each scenario, we introduce Charly as an exemplary employee and Juliette as his leader "of flesh and blood" who have to interact with algorithms to complete their tasks.

3.1. The Blurring of Responsibilities Between Human Leaders and Algorithms.

3.1.1. Scenario. In this triangular relationship, Charly may be instructed by Juliette to accomplish a certain task and that task cannot be accomplished without Charly interacting with algorithms (note that otherwise, the relationship would not be a triad). During this interaction, the algorithm naturally requires Charly to intervene, to post-process, or to react to the results of that algorithm's functioning. One day, an error occurs in the completion of work for which Charly is held responsible by Juliette. Charly, however, feels betrayed since Juliette instructed him to follow the algorithm's recommendations. Furthermore, he feels treated unfairly, since he neither decided to deploy algorithms into workflows nor possesses relevant knowledge to critically assess or predict functioning errors of algorithms.

3.1.2. Example from business practice. This scenario materializes in the work of content moderators and fake checkers at Facebook and Twitter (47). Their task is to manually evaluate the content of posts or tweets for fake news or racist content within seconds. To carry out this task they have to rely on algorithmic shortlisting, which is thought to solve issues of language ambiguity (48, 49). Such accounts of ambiguity are recently fueled since language adapts at growing speed to local parlances, teenage slangs, or simply because words can have a completely different meaning depending on the context or zeitgeist (e.g., "that's shit" vs. "crazy shit"). Yet, ambiguity can be problematic for the algorithm too, and as a consequence, not all posts and tweets are shortlisted. However, Facebook and Twitter pay their employees based on success rates of false-negative assessments and, hence, clearly attribute "errors" slipped through their fingers" to the human and not the algorithmic agent. Thus while responsibilities are not attributable, an imbalance towards handling this lack of attributability in favor of the machine arises (50).

3.1.3. Emerging trust implications. In general, any two-leader- and, of course, triad-situation is linked to some amount of responsibility diffusion. Here we understand responsibility as taking ownership of actions and behaviors and, in the context of leadership, to take over responsibility for others (51). Hence, responsibility is also centered around moral obligations naturally linked to humans and, thus is also an integral part of the leader-employee trust relationship. Both employee and human leaders are likely to expect each other to be bound by shared values and to show integrity (52, 53). Any "shirking" of such expectation is likely to put a strain on trust. Also, if employees feel that they are always "on the short end of the equation", i.e. the algorithm might be liable but not responsible and responsibility always lies with the employee – employees' beliefs in the human leaders' benevolence might falter.

Specifically, human leaders might be perceived to fail to meet employees' subjective expectations of how treatment in the workplace should look like according to their psychological contract (Robinson, 1996). Employees perceive the leader's behavior when not living up to responsibility as a violation of their right to be protected, supported, and cared for by their leader (51). Such a lack of authenticity, in turn, might further fuel negative trust beliefs. Based on both the breach of the psychological contract (14) and the lack of a genuine attitude, employees likely assume that human leaders lack benevolence towards them.

By limiting human leadership to the mere formal execution of the leadership function and thus not actively tackling the diffusion of responsibility, the human leader is perceived to lack moral responsibility (51) and to be disintermediated from leadership (34). Especially since moral responsibility cannot be assumed by algorithms as their non-living nature impedes general responsibility or accountability attributions (51, 54), it is the responsibility of the human leader to protect employees' rights and save their face instead of blaming them. Hence, if leaders do not address issues of responsibility diffusion, their felt integrity is likely to suffer. Echoing Kellogg and colleagues (34), the "disintermediation" of leaders from leadership prevents employees from appealing to human leaders (55), which is likely perceived as inhumane or even imprisoning (56). With regards to the trust relationship, these perceptions might be attributed to either a leader's unwillingness to actively address issues of responsibility diffusion or from hazardous hiding behind formal rules and processes, at the cost of employees. As a consequence, employees' trusting beliefs, but also benevolence and integrity expectations are likely to take damage.

3.2. Contradictions Between Human Leaders and Algorithms.

3.2.1. Scenario. From such a "two-leader-situation", it is likely that contradictions between algorithms' and human enactment of leadership functions emerge. Put simply, an algorithm might incentivize the adherence to prespecified performance KPIs to achieve promotion or bonus, whereas Juliette might encourage Charly to share his knowledge with peers or invest in a learning culture from errors, that conflict with strict adherence to the algorithms KPI directive. So for Charly, a problem of leadership credibility arises. Due to the uniqueness of the decision situation, Charly's experience would be a poor guide in solving this problem and both available solutions will put a strain on the leader-employee relationship. Given the amalgam of organizational power structures, dependencies, and interpersonal bonds, it is very likely Charly decides to follow Juliette's advice even though he would find the algorithm more credible.

3.2.2. Example from business practice. This scenario materializes in the plane crash of Garuda Indonesian Flight 159 in 1997. Due to dense fog during the landing approach, the pilot had to solve conflicting directives from the human air traffic controller and the approach chart map. Due to personal experience and an overview of all air traffic in that region, the air traffic control instructed the approach to the airport from the south, hence turn left for landing. Due to noise and the poor audio quality, the pilot was not sure if he got the advice right and consulted the approach chart map (i.e., the algorithm) proposing the contrary. Trapped in conflicting directives from both, the algorithm and the air traffic controller, the pilot finally decided to follow the human advice; but because valuable time was lost and topography changed from flat to mountainous the human instruction turned out to be "false". Hence, this example illustrates the significance of credibility problems and strain arising from this triad relationship.

3.2.3. Emerging trust implications. The few and experimental results show that humans are more inclined to follow algorithms in conflicting or contradicting situations (57). Furthermore, these results show that the more difficult and risky a situation gets, the greater the probability that employees will opt for the algorithm, at the cost of the human directive (58). It is noteworthy, however, that these insights were generated under lab conditions, with no experience with either the human or the algorithm and in the absence of any social bonds. Hence if employees "rightly" follow the algorithmic directive, we would not expect any problematic trust issues to arise (59). However, we identified two conditions from business practice, that might make trust challenges occur. First, if employees' trust is not a free choice, and second if employees have (negative) experiences with algorithms.

First, and adhering to the "trust as a poisoned chalice" argument of Skinner and colleagues (60), it might be that employees' decision to follow the human leader depends on the social structures of the organization, i.e., social bonds, fear of negative social consequences or the compliance with social protocols and hierarchies. In this case, employees would trust leaders reluctantly. Such felt, but unwanted trust from the side of the leader might also undermine the trust relationship between both parties, particularly when a human leader's decision was mistaken (60) as his/her "fault" decision might be perceived as weighing particularly heavy.

Secondly, it might that employees already have experience in interacting with algorithms as well as on their possible insufficiencies. In this case, employees' trust in leaders would be a result of heuristics (61), of prior experience, or the grown tendency to trust people more than algorithms, simply because "there you know what you have and how they tick" (59). In this case, a leader's mistaken decision also impacts the trust relationship, but the extent of this remains unclear, to date. One might surmise, that the mistaken decision might lower employees trusting beliefs, because then, perceived vulnerabilities and helplessness becomes even greater, in that he/she no longer knows whom he/she can follow.

3.3. Employee Voice Might not be Heard.

3.3.1. Scenario. Ultimately, Charly might also be confronted with Juliette and the algorithm "having the same opinion", evoking feelings that the two have conspired against Charly while ignoring his concerns and interests (i.e., employee voice). For instance, a predictive algorithm autonomously evaluates Charley's performances based on historic performance data and comes to the result that Charly is not to be promoted or that his bonus is withheld. Juliette might support the algorithmic forecast and puts it into effect without consulting Charley who is trying to explain why the performance data might be wrong.

3.3.2. Example from business practice. Zooming into the gig-economy business practice, Uber's ride-assigning algorithm frequently penalizes drivers with low-rated customer feedback via deactivating their presence on the smartphone application for certain time-intervals. Thereby the driver gets sanctions for unwanted behaviors. Even though Uber pursues a zero-tolerance policy on low customer ratings (whether or not they are reasonably justified), each case is still reviewed by a human leader. However, in most cases, the Uber leaders agree with the algorithm's choice, without reaching out to the drivers themselves to justify the decision or provide driver-feedback channels. Even valid proof against substance misuse (e.g., blood tests or camera footage) or better knowledge of customer rating biases often do not lead to a quicker reactivation of a driver's account through human leaders (62).

3.3.3. Emerging trust implications. This "two-leader-situation" outlines how a leader's perceived trustworthiness suffers from his/her "blind reliance" on algorithms. There are several reasons why leaders might often prefer not to consider employees' contextual accounts in their decision making. First, the "blind reliance", i.e., a lack of detailed knowledge on algorithmic data processing and analysis, might push them into the position to "overuse" the algorithm, similar to a "gold fever" mentality (7, 63). Secondly, leaders might find themselves entrapped in an "illusion of control", i.e., a tendency to believe more in the superiority of algorithms, the more complex a decision gets (64, 65). Third, giving employees a voice is time-consuming and might lead to embarrassing situations if one or the other party has to admit to a lack of detailed knowledge on the algorithm's functioning. Taken together, and if not seen as a leadership priority, employee voice is likely to be underused.

As a consequence, such overreliance might be perceived as a "fraternization with the algorithm", thus would be evaluated by the employee as a manifestation or signal of a leader's disrespect towards the follower. Besides, Santiago (66) highlights, that fraternization with the algorithm can be perceived as a degradation of the employee. The results of Abbass (67) can be interpreted similarly, as he illustrates that handing only the "left-overs" tasks to employees creates unhuman workplaces in which algorithms receive the "filet pieces" of work.

Besides giving employees a voice is an important antecedent for interpersonal justice perceptions (68). Thus, employees who feel not heard will adjust their integrity and benevolence beliefs regarding their supervisor. Benevolence defined as goodwill towards the employee is similar to compassion a uniquely human attribute, which algorithms can mirror, but never apply due to its analytical and rational nature (69). However, benevolence, compassion, and integrity as trustworthiness antecedents (70, 71) are of special importance for the perceived humanness and trust development in workplaces (72-74). Hence, the lived-out lack of benevolence and compassion shown towards employees leads to loss of agency (51), a perceived violation of the psychological contract (14), feelings of injustice (75), and hence unwillingness to be vulnerable and follow (67, 76).

4. Concluding Remarks

We have argued that algorithms and automated leadership functions alter the trust dynamics between employees and their human leaders. We propose that novel trust challenges are evoked that need to be analyzed in more depth. In our ongoing research, we will employ a diary method to capture these new relationship dynamics, to explore possible trust interruptions, and to observe how trust between human leaders and employees is preserved or altered.

Further research should also analyze trust dynamics from a multilevel approach. Two additional levels are of particular importance. First, trust in algorithms is likely to influence the dynamics of the triad we have identified. For instance, high-level trust in algorithms may undermine the relationship-troubling dynamics sketched in this article in a more pronounced fashion. Second, trust in the employer is also another important contingency as it might buffer conflicts and soften the possible strain evoked by the two-boss situation. In all, while insights on the trust-technology relationship are growing quickly, research on new relationship dynamics between human agents in organizations caused by technological interventions is lagging. This is why we analyzed how algorithms are changing trust relations between human leaders and human followers.

4. References

[1]. Dzieza J. How hard will robots make us work? THE VERGE. 2020.

[2]. Wesche JS, Sonderegger A. When computers take the lead: The automation of leadership. Computers in Human Behavior. 2019;101:197-209.

[3]. Gardner SD, Lepak DP, Bartol KM. Virtual HR: The impact of information technology on the human resource professional. Journal of Vocational Behavior. 2003;63(2):159-79.

[4]. Morgeson FP, DeRue DS, Karam EP. Leadership in teams: A functional approach to understanding leadership structures and processes. Journal of Management. 2010;36(1):5-39.

[5]. Zaleznik A. Managers and leaders: Are they different? Harvard Business Review. 2004;82(1):74.

[6]. Lord RG. Functional leadership behavior: Measurement and relation to social power and leadership perceptions. Administrative Science Quarterly. 1977:114-33.

[7]. Lindebaum D, Vesa M, den Hond F. Insights from "the machine stops" to better understand rational assumptions in algorithmic decision making and its implications for organizations. Academy of Management Review. 2020;45(1):247-63.

[8]. Prassl J. Humans as a service: The promise and perils of work in the gig economy: Oxford University Press; 2018.

[9]. Amelia US LLC. Amelia - The most human AI Retrieved from: https://amelia.com/(last access: November 20th, 2020)2020 [

[10]. Kolbjørnsrud V, Amico R, Thomas RJ. How artificial intelligence will redefine management. Harvard Business Review. 2016;2:1-6.

[11]. De Cremer D. Leadership by algorithm. Who leads and who follows in the AI era? Hampshire (GB): Harriman House 2020.

[12]. Jarrahi MH. Artificial intelligence and the future of work: Human-AI symbiosis in organizational decision making. Business Horizons. 2018;61(4):577-86.

[13]. Creed WED, Miles RE. Trust in organization. A conceptual framework linking organizational forms, managerial philosophies, and the opportunity of costs of controls. 1996. In: Trust in organizations Frontiers of theory and research [Internet]. Thousand Oaks: Sage Publications; [16-38].

[14]. Robinson SL. Trust and breach of the psychological contract. Administrative Science Quarterly. 1996;41(4):574-99.

[15]. Ford RC, Randolph WA. Cross-functional structures: A review and integration of matrix organization and project management. Journal of Management. 1992;18(2):267-94.

[16]. Joyce WF. Matrix organization: A social experiment. Academy of Management Journal. 1986;29(3):536-61.

[17]. Long CP, Sitkin SB. Control–trust dynamics in organizations: Identifying shared perspectives and charting conceptual fault lines. Academy of Management Annals. 2018;12(2):725-51.

[18]. Lee MK. Understanding perception of algorithmic decisions: Fairness, trust, and emotion in response to algorithmic management. Big Data & Society. 2018;5(1):1-16.

[19]. Derrick D, Elson J, editors. Exploring Automated Leadership and Agent Interaction Modalities. Proceedings of the 52nd Hawaii International Conference on System Sciences; 2019.

[20]. Dimitrov A. The digital age leadership: a transhumanistic perspective. Journal of Leadership Studies. 2018;12(3):79-81.

[21]. Ravid DM, Tomczak DL, White JC, Behrend TS. EPM 20/20: A Review, Framework, and Research Agenda for Electronic Performance Monitoring. Journal of Management. 2020;46(1):100-26.

[22]. Lu VN, Wirtz J, Kunz WH, Paluch S, Gruber T, Martins A, et al. Service robots, customers and service employees: what can we learn from the academic literature and where are the gaps? Journal of Service Theory and Practice. 2020.

[23]. Cascio WF, Montealegre R. How technology is changing work and organizations. Annual Review of Organizational Psychology and Organizational Behavior. 2016;3:349-75.

[24]. Schafheitle S, Weibel A, Ebert I, Kasper G, Schank C, Leicht-Deobald U. No stone left unturned? Towards a framework for the impact of datafication technologies on organizational control. Academy of Management Discoveries. 2020;6(3):455-87.

[25]. Nilsson NJ. Principles of artificial intelligence. Burlington: Morgan Kaufmann Publishers; 2014.

[26]. Davenport TH, Kudyba S. Designing and developing analytics-based data products. MIT Sloan Management Review. 2016;58(1):83.

[27]. Appelbaum D, Kogan A, Vasarhelyi M, Yan Z. Impact of business analytics and enterprise systems on managerial accounting. International Journal of Accounting Information Systems. 2017;25:29-44.

[28]. Markoff J. Computer Wins on 'Jeopardy!': Trivial, It's Not. The New York Times 2011.

[29]. Bertsimas D, Kallus N. From predictive to prescriptive analytics. arXiv preprint arXiv:14025481. 2014.

[30]. Lepenioti K, Bousdekis A, Apostolou D, Mentzas G. Prescriptive analytics: Literature review and research challenges. International Journal of Information Management. 2020;50:57-70.

[31]. Lecher C. How Amazon automatically tracks and fires warehouse workers for 'productivity'. THE VERGE. 2019.

[32]. Flamholtz EG, Das TK, Tsui AS. Toward an integrative framework of organizational control. Accounting, Organizations and Society. 1985;10(1):35-50.

[33]. Podsakoff PM, MacKenzie SB, Bommer WH. Transformational leader behaviors and substitutes for leadership as determinants of employee satisfaction, commitment, trust, and organizational citizenship behaviors. Journal of Management. 1996;22(2):259-98.

[34]. Kellogg KC, Valentine MA, Christin A. Algorithms at work: The new contested terrain of control. Academy of Management Annals. 2020;14(1):366-410.

[35]. Duggan J, Sherman U, Carbery R, McDonnell A. Algorithmic management and app-work in the gig economy: A research agenda for employment relations and HRM. Human Resource Management Journal. 2020;30(1):114-32.

[36]. Mintzberg H. The nature of managerial work. New York: Harper & Row; 1973.

[37]. Spitzmüller C, Stanton JM. Examining employee compliance with organizational surveillance and monitoring. Journal of Occupational and Organizational Psychology. 2006;79(2):245-72.

[38]. Alder GS. Employee reactions to electronic performance monitoring: A consequence of organizational culture. The Journal of High Technology Management Research. 2001;12(2):323-42.

[39]. Mohanta B, Nanda P, Patnaik S. Management of VUCA (Volatility, Uncertainty, Complexity and Ambiguity) Using Machine Learning Techniques in Industry 4.0 Paradigm. New Paradigm of Industry 40: Springer; 2020. p. 1-24.

[40]. Rosing K, Frese M, Bausch A. Explaining the heterogeneity of the leadership-innovation relationship: Ambidextrous leadership. The Leadership Quarterly. 2011;22(5):956-74.

[41]. Judge TA, Piccolo RF. Transformational and transactional leadership: A meta-analytic test of their relative validity. Journal of Applied Psychology. 2004;89(5):755-68.

[42]. D'Innocenzo L, Mathieu JE, Kukenberger MR. A meta-analysis of different forms of shared leadership–team performance relations. Journal of Management. 2016;42(7):1964-91.

[43]. Dastin J. Thomson Reuters Technology News [Internet]. Retrieved from: https://www.reuters.com/article/us-amazon-com-jobs-automation-insight/amazon-scraps-secret-ai-recruiting-tool-that-showed-bias-against-women-idUSKCN1MK08G (last access: July 14th, 2020)2018.

[44]. Lilius JM, Worline MC, Dutton JE, Kanov JM, Maitlis S. Understanding compassion capability. Human Relations. 2011;64(7):873-99.

[45]. Parker SK, Grote G. Automation, algorithms, and beyond: Why work design matters more than ever in a digital world. Applied Psychology: An International Review 2019;0(0):1-45.

[46]. Shuck B, Alagaraja M, Immekus J, Cumberland D, Honeycutt-Elliott M. Does Compassion Matter in Leadership? A Two-Stage Sequential Equal Status Mixed Method Exploratory Study of Compassionate Leader Behavior and Connections to Performance in Human Resource Development. Human Resource Development Quarterly. 2019;30(4):537-64.

[47]. Newton C. The trauma floor: The secret lives of Facebook moderators in America. THE VERGE. 2019.

[48]. Bano M, editor Addressing the challenges of requirements ambiguity: A review of empirical literature. IEEE Fifth International Workshop on Empirical Requirements Engineering (EmpiRE); 2015: IEEE.

[49]. Roy D, Reiter E. Connecting language to the world. Artificial Intelligence. 2005;167(1-2):1-12.

[50]. Wagner B. Liable, but Not in Control? Ensuring Meaningful Human Agency in Automated Decision-Making Systems. Policy & Internet. 2019;11(1):104-22.

[51]. Winter DG. A motivational model of leadership: Predicting long-term management success from TAT measures of power motivation and responsibility. The Leadership Quarterly. 1991;2(2):67-80.

[52]. Mayer RC, Davis JH, Schoorman FD. An integrative model of organizational trust. Academy of Management Review. 1995;20(3):709-34.

[53]. Rousseau DM, Sitkin SB, Burt RS, Camerer C. Not so different after all: A cross-discipline view of trust. Academy of Management Review. 1998;23(3):393-404.

[54]. Simmler M, Markwalder N. Guilty robots?–Rethinking the nature of culpability and legal personhood in an age of artificial intelligence. Criminal Law Forum. 2019;30(1):1-31.

[55]. Schwartz D. Embedded in the crowd: Creative freelancers, crowdsourced work, and occupational community. Work and Occupations. 2018;45(3):247-82.

[56]. Weber M. The theory of social and economic organization. New York: Oxford University Press; 1947.

[57]. Lyons JB, Stokes CK. Human–human reliance in the context of automation. Human Factors. 2012;54(1):112-21.

[58]. Dzindolet MT, Pierce LG, Beck HP, Dawe LA. The perceived utility of human and automated aids in a visual detection task. Human Factors. 2002;44(1):79-94.

[59]. Brower HH, Lester SW, Korsgaard MA, Dineen BR. A closer look at trust between managers and subordinates: Understanding the effects of both trusting and being trusted on subordinate outcomes. Journal of Management. 2009;35(2):327-47.

[60]. Skinner D, Dietz G, Weibel A. The dark side of trust: When trust becomes a 'poisoned chalice'. Organization. 2014;21(2):206-24.

[61]. Ayton P, Fischer I. The hot hand fallacy and the gambler's fallacy: Two faces of subjective randomness? Memory & Cognition. 2004;32(8):1369-78.

[62]. Kerr D. Uber drivers are losing their jobs over fake DUI complaints. C|net. 2020.

[63]. Hirschi C. Die Automatisierung der Angst. Wir brauchen mehr Grundwissen in Technologiegeschichte. Frankfurter Allgemeine Zeitung. 2017.

[64]. Thomas SL, Nafus D, Sherman J. Algorithms as fetish: Faith and possibility in algorithmic work. Big Data & Society. 2018;5(1):1-11.

[65]. Leicht-Deobald U, Busch T, Schank C, Weibel A, Schafheitle S, Wildhaber I, et al. The Challenges of Algorithm-Based HR Decision-Making for Personal Integrity. Journal of Business Ethics. 2019.

[66]. Santiago T. AI Bias: How Does AI Influence The Executive Function Of Business Leaders? Muma Business Review. 2019;3(16):181-92.

[67]. Abbass HA. Social Integration of Artificial Intelligence: Functions, Automation Allocation Logic and Human-Autonomy Trust. Cognitive Computation. 2019;11(2):159-71.

[68]. Colquitt JA, Conlon DE, Wesson MJ, Porter CO, Ng KY. Justice at the millennium: a meta-analytic review of 25 years of organizational justice research. Journal of Applied Psychology. 2001;86(3):425-45.

[69]. Rosenblat A. Uberland: How algorithms are rewriting the rules of work. Berkley (CA): University of California Press; 2018.

[70]. McKnight DH, Carter M, Thatcher JB, Clay PF. Trust in a specific technology: An investigation of its components and measures. ACM Transactions on management information systems (TMIS). 2011;2(2):1-25.

[71]. Mishra AK, Mishra KE. The research on trust in leadership: The need for context. Journal of Trust Research. 2013;3(1):59-69.

[72]. Colquitt JA, Scott BA, LePine JA. Trust, trustworthiness, and trust propensity: A meta-analytic test of their unique relationships with risk taking and job performance. Journal of Applied Psychology. 2007;92(4):909-27.

[73]. Kim W, Kim N, Lyons JB, Nam CS. Factors affecting trust in high-vulnerability human-robot interaction contexts: A structural equation modelling approach. Applied Ergonomics. 2020;85:103056.

[74]. Calhoun CS, Bobko P, Gallimore JJ, Lyons JB. Linking precursors of interpersonal trust to human-automation trust: An expanded typology and exploratory experiment. Journal of Trust Research. 2019;9(1):28-46.

[75]. McNall LA, Roch SG. A social exchange model of employee reactions to electronic performance monitoring. Human Performance. 2009;22(3):204-24.

[76]. Bigras É, Léger P-M, Sénécal S. Recommendation Agent Adoption: How Recommendation Presentation Influences Employees' Perceptions, Behaviors, and Decision Quality. Applied Sciences. 2019;9(20):4244.