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The rise of people analytics and the future of organizational research

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ABSTRACT

Organizations are transforming as they adopt new technologies and use new sources of data, changing the experiences of employees and pushing organizational researchers to respond. As employees perform their daily activities, they generate vast digital data. These data, when combined with established methods and new analytic techniques, create unprecedented opportunities for studying human behavior at work and have fueled the rise of people analytics as a new institutional field of practice. In this chapter, I describe the emerging field of people analytics and new organizational phenomena that accompany the use of data and algorithms. These practices are affecting how individuals, groups, and organizations function, ranging from decision-making processes and work procedures, to communication and collaboration, to attempts to monitor and control employees. In each of these domains, I describe recent research and propose new research directions. Many of these domains intersect with the emerging field of Computational Social Science, in which disciplinary scholars are applying computational methods to an expanding array of digitized data, pursuing interests that extend far into the organizational domain. Organizational scholars are well-positioned to bridge organizational and disciplinary advances to stay at the forefront of research on the future of work.

The way many people work has been permanently disrupted. On top of ongoing digital transformations and ever-changing technologies, the COVID-19 pandemic called into question every aspect of employment, from where people do their work, to how people collaborate, to which companies and jobs will survive. Amidst this uncertainty, two patterns are evident. First, these forces have accelerated our reliance on technology to do our work (Leonardi & Neeley, 2022). Second, organizational leaders increasingly use data, often generated by work-related technologies, to quantify and influence many aspects of employee life, from how workers are hired, monitored, and rewarded to how they perform their daily tasks (Kellogg et al., 2020; Kresge, 2020; Tambe et al., 2019). People analytics groups are at the center of these activities (Ferrar & Green, 2021).

The term people analytics broadly refers to using a data-driven approach to address employee-related decisions and practices.[1] I define people analytics as both the *organizational function* within which data collection, analyses, and translation occur as well as a *set of practices* that draw on employee data to inform and aid decision-making processes and employee activity throughout the organization. The rise of this function within organizations mirrors the analytical advances occurring in fields such as consumer behavior (Erevelles et al., 2016), financial forecasting (Martin & Nagel, 2022), health care (Davenport & Kalakota, 2019), and the social sciences (Lazer et al., 2020). Just as data in other areas can provide breakthroughs, employee data can help to answer pressing managerial questions: Who are the best candidates to hire or promote? Are employees maintaining their sense of well-being? Are they collaborating effectively and being productive, even when working remotely? Who is likely to leave? People analytics teams are using tools of behavioral research to answer these questions, scaling up technology-enabled surveys, experiments, and related methods (Salganik, 2019). Alongside the data actively gathered with these traditional methods, employees passively generate digital trace data—the recorded traces of behavior produced when people use electronic devices or platforms—whether on a manufacturing floor, in a delivery truck, around a corporate conference room, or on a laptop while working from home (Edelmann et al., 2020; Kresge, 2020). As data sources expand and algorithms improve, the implications for individual and organizational functioning are potentially profound.

Fortunately, the data collected and used within organizations can also be repurposed for organizational research, opening new ways to measure behavior and study people at work (Salganik, 2019). The rise of people analytics in organizations is associated with new

[1] "People analytics" is used interchangeably with talent analytics, workforce analytics, and HR analytics, among other terms. Ferrar and Green define people analytics as "the analysis of employee and workforce data to reveal insights and provide recommendations to improve business outcomes" (2021, p. 5)

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research opportunities in many areas, from individual behavior and team functioning to larger organizational processes. In some domains, researchers are using new data sources to devise novel tests of existing theories. In other domains, the research questions themselves are novel, induced by scholars studying innovative organizational practices. Across these domains, I describe emerging research and propose new avenues to explore.

The first section begins by recognizing the expanding use of algorithms to guide many types of employee decisions. I describe research testing when decision-makers are likely to incorporate algorithmic input into their decisions and the mechanisms related to these choices (Mahmud et al., 2022). I identify sources of algorithmic bias, along with research that attempts to understand and address this problem (e.g., Ajunwa, 2021; Cowgill & Tucker, 2020). I then describe research that goes beyond discrete decisions to explore algorithms that pervade employees' daily experiences, a phenomenon that is likely to expand as artificial intelligence is embedded in routine work processes. Most of this research on algorithms is conceived at the individual level of analysis, involving individual decision-makers and individual employees who are affected by algorithmic output.

Moving beyond a focus on algorithms and individuals, I address social activities involving communication and collaboration. I describe network research that combines and analyzes digital data in innovative ways (e.g., Rajkumar et al., 2022; Yang et al., 2022). As organizations use network methods internally to analyze their own employees' interactions, I propose new avenues for research to understand how these practices affect employees. Even as collaboration in organizations becomes more networked and fluid (Mortensen & Haas, 2018), teams continue to be a focus of research. I describe and propose new strands of research on teams, including the quest to quantify and improve collective intelligence (Gupta et al., 2019; Riedl et al., 2021) and the growing practice of using algorithms to match people to teams (e.g., Gómez-Zará et al., 2022).

Next, I address research on meetings, which are an excellent forum for studying team processes. Given their prominence in organizational life and the extensive digital records of meeting activity now available (e.g., DeFilippis et al., 2022), meeting dynamics are a ripe area for new research. Meetings can be a rich source of data, from micro audio and video interactions within a single event to macro patterns of meetings across an entire organization, contributing to an emerging research domain dubbed the science of meetings (Mroz et al., 2018; Rogelberg et al., 2010).

Research on conversation analytics is breathing new life into the domain of interpersonal communication. Social interaction has always been at the heart of organizational functioning. Only recently, however, have researchers begun to study verbal interaction by applying advanced analytics to large samples of unstructured conversation data (Yeomans et al., forthcoming). Moving from conversations in dyads or small groups to communication in larger collectives, I discuss how culture scholars have turned to language to operationalize norms and shared patterns of behavior, for example using natural language processing on the text of emails to measure socialization among new employees (Srivastava et al., 2018).

A common thread linking these research topics is the digital trace data underlying recent advances in understanding individual behavior, interpersonal interaction, and organizational functioning. These data have many advantages for research. They are typically rendered and stored automatically by the systems and platforms employees use to accomplish work, requiring no effort on the part of the employee. They can be collected continuously with low marginal costs even at an extremely large scale, providing a comprehensive view of the organization (Gal et al., 2017; Kresge, 2020). Yet, for organizations that gather and analyze employee data, a conundrum inevitably arises. The more granular the data, the higher the potential for invading the privacy of the employees who generate it, especially given the wide range of approaches companies are taking with their employee data. A growing number of organizations monitor employee behavior and productivity by tracking digital activity, especially of those who work remotely (Davis, 2022). Some companies are embracing digital surveillance systems (Zuboff, 2019). I describe recent research that aims to advance our understanding of privacy, employee monitoring, and transparency (Patil & Bernstein, 2022). Given the tensions between the sensitivity and perceived usefulness of employee data, we need more research on the full range of consequences associated with employee monitoring.

The topics I cover are not meant to be exhaustive, but rather represent areas of research associated with prevalent people analytics practices in organizations. Researchers are using new data sources to test existing theories, but the biggest opportunities may be to study new research questions arising from the novel ways organizations are incorporating their internal data and algorithms into every corner of organizational life. These new phenomena can provide a stimulus for theoretical as well as empirical advances. The interplay between researchers analyzing digital data to study organizational phenomena in parallel with organizations conducting related analyses for their own internal purposes will, I propose, increasingly characterize organizational research. I frame this development as part of larger changes to the research ecosystem, which present new opportunities and challenges for conducting organizational research.

Lastly, I connect these trends to the field of computational social science, which Lazer et al. (2020, p. 1060) defined as "the development and application of computational methods to complex, typically large-scale, human (sometimes simulated) behavioral data." Work in computational social science is typically cross-disciplinary, just as people analytics projects are often conducted by team members with diverse skills. In both cases, it is common for computer and data scientists to collaborate with substantive disciplinary or business experts. New sources of digital data that are ever higher in volume, velocity, and variety (Kresge, 2020)—the signatures of so-called big data—create complementarities that drive these collaborations. Some emerging research in computational social science is directly relevant to organizational phenomena in the substance of the research questions or the applicability of methods and analyses. Two examples are the application of natural language processing techniques from computational linguistics to organizational use cases (Chatman & Choi, 2022) and advances in network methods in physics that can be adapted to organizational networks (Song et al., 2012).

Organization scholars are in a strong position to bridge disciplinary research and organizational problems in a way that integrates data and analytic skills with contextual knowledge and theory. The expanding applications of artificial intelligence in different fields and firms may add to such brokerage opportunities (Tambe et al., 2019). The varying methods employed by people analytics groups can also be a testbed for studying mechanisms and boundary conditions of core disciplinary domains such as decision-making processes, biases, communication, culture, and fundamental tradeoffs between employee autonomy and managerial control. Given these emerging possibilities, my purpose is to sketch out a roadmap for scholars to explore as data continues to change organizations, along with the ways we study them. By mapping this terrain, this chapter can help researchers situate their work and see new paths and connections for their own research agendas (Chatman & Flynn, 2005; Polzer et al., 2009).

The opportunity for organizational researchers

In organizations, a wide range of problems can be informed with targeted analyses of employee data. A common starting point for people analytics teams is to analyze hiring and turnover data, before expanding to promotions, compensation, and other elements of the employee life cycle (Tambe et al., 2019). These processes have a decision-making component at their core (e.g., whom to interview, hire, or promote) and typically gravitate toward the use of predictive models, or algorithms (Agrawal et al., 2018, 2022; Kahneman et al., 2021). Many research questions arise as companies add algorithms to their decision-making procedures, generating a surge of recent research on this topic.

Data-driven decision-making processes

One aim of algorithms is to increase the efficiency of decision processes, especially in large organizations. The potential advantages go beyond efficiency, as organizations use algorithms to try to make fairer, more consistent, and higher quality decisions (Kahneman et al., 2021). Achieving these goals is elusive, however, given the challenges of effectively deploying unbiased algorithms in practice. This phenomenon of incorporating algorithms into employee-related decisions is a veritable gold mine of new research questions involving cognitive, motivational, and social processes within organizations.

Adopting algorithmic input in decision-making: from algorithmic aversion to appreciation

How do everyday employees involved in decision-making processes incorporate algorithmic input and data into their decisions? Few organizations have been willing to automate employee-related decisions entirely, meaning human decision makers continue to make or approve decisions. It is far from established, however, that people are good at incorporating algorithmic input to systematically improve decisions (Kahneman et al., 2021).

There is an emerging body of research on the long-standing question of how decision-makers use algorithms (Dawes, 1979; Little, 1970), including when people accept or even seek out the input of algorithms, when they modify or discard it, and what mechanisms and moderators explain how and under what conditions this happens. Studies of algorithm aversion support the hypothesis that people tend to prefer human forecasts over algorithmic forecasts, partly because people lose confidence in algorithms more quickly after witnessing forecasting mistakes (Dietvorst et al., 2015). Research in educational settings provides further evidence of algorithm aversion among teachers, including both experienced and novice teachers (Kaufmann, 2021). Such aversion is partly ameliorated when people have some discretion to modify the algorithmic forecasts (Dietvorst et al., 2018). There is also evidence that people become less averse to using algorithmic forecasts in making decisions as they gain experience while receiving feedback on both their own and algorithmic forecasts (Filiz et al., 2021). Furthermore, Berger et al. (2021) found that aversion can be offset by demonstrating an algorithm's ability to learn from past mistakes.

These algorithm aversion findings are countered, however, by recent work on algorithmic appreciation amongst lay people versus domain experts, demonstrating that lay people, when making a variety of estimates and forecasts, prefer to rely on algorithmic advice over the recommendations of other people (Logg et al., 2019). This pattern held, though not as strongly, when people had to choose between their own estimate and an algorithmic one. Experts in the decision domain did not show appreciation for algorithms, but this seemed to reflect aversion to advice of any type, rather than algorithmic advice in particular. Notably, experts' reticence to use algorithmic input hurt decision accuracy. Even those who used algorithmic advice, however, only adjusted their judgments a little relative to the quality of advice they received. From a different angle, research in the field of marketing shows evidence of over-dependence on algorithms by consumers who rely on recommender systems, even when the recommendations are inferior and pose potential harm to consumer well-being (Banker & Khetani, 2019).

These studies, taken together, illustrate the range of reactions decision-makers have when asked to incorporate algorithmic input into their judgments, and highlight all that remains unknown. One provocative question is the role of perception – or how people judge the authenticity of technological agents, especially along moral or value-laden dimensions – in contexts where humans have traditionally performed the tasks or decisions in question, on people's receptivity to using an algorithm (Jago, 2019). More generally, existing research suggests that features of the algorithm itself, the individual decision maker, the task at hand, and the context may all contribute to aversion toward or appreciation of algorithms (Mahmud et al., 2022).

From algorithmic complements to substitutes

Tendencies toward algorithm aversion or appreciation can be conceptualized as part of a larger question of whether algorithms are a complement or substitute for a traditionally human-centered decision-making process. This is relevant both in everyday practice and in terms of how those in the decision-making context frame algorithmic input (Agrawal et al., 2022). Decision-makers are often motivated to retain control of decisions and can feel threatened if they perceive an algorithm (and the people responsible for the algorithm) as a potential substitute for their judgment and decision-making skill (Kwan, 2017; Staw et al., 1981). Allen and Choudhury (2022) studied one resolution to this puzzle by hypothesizing that algorithms would be most likely to augment human performance for people who had sufficient ability to use algorithmic recommendations and who would not be susceptible to algorithm aversion. They reasoned that domain-specific expertise was related to both mechanisms, such that people with low expertise lacked the ability to incorporate algorithms into their performance, whereas people with high expertise would be averse to favoring the algorithm over their own knowledge. Those with moderate domain expertise would be expected to have both the ability and the openness to use the algorithm's recommendations. To test this hypothesis in a field setting, they studied IT workers who were resolving help tickets with the aid of an algorithm trained to suggest solutions based on previous tickets. As hypothesized, when algorithmic suggestions were provided, they found an inverted U-shaped relationship between years of experience and successful ticket resolution, a pattern that did not occur when workers did the task manually (Allen & Choudhury, 2022; Choudhury et al., 2020).

Studies indicate that framing algorithmic input as a complement (or a support, supplement, or augmentation) to human judgment is likely to be more palatable to decision-makers than if it is framed as a substitute or an automated decision (Grønsund & Aanestad, 2020; Leyer & Schneider, 2021; Raisch & Krakowski, 2021). When those who are asked to use algorithmic input are also involved in the earlier stages of creating the algorithm, or even deciding to use an algorithm in the first place, they could be more likely to accept and use its input. Like any device that affects decisions, algorithms are woven into the political and power dynamics of organizational processes, with advocates and skeptics wrestling for control of not only the outcomes of decisions, but also the role of algorithms in reaching those decisions (Kellogg et al., 2020; March & Simon, 1958; Vaughan, 1997; Jackson, 2021). Kellogg et al. (2020) described algorithms in the workplace as a "new contested terrain of control" involving everyone in the organizational hierarchy, as decision-makers throughout the organization are increasingly confronted with valid algorithmic input that they overlook or override at their own risk.

The influence of algorithms may change as decision-makers gain experience and comfort with them (Filiz et al., 2021). If algorithms are initially conceptualized as a complement to human decision-makers, at what point do they begin to substitute, even in small ways, for the information processing and critical thinking that should accompany an effective decision process? When such micro-substitutions occur, what are the cognitive and motivational mechanisms through which they operate and what effect do they have on decision outcomes? In some cases, decision-makers may even lose their aversion and over-rely on algorithms, a phenomenon that has been studied in the consumer context but not an employee-related context, where the stakes are presumably higher (Banker & Khetani, 2019).

Decision-makers are unlikely to abruptly switch from their prior information sources and procedures to relying exclusively on an algorithmic recommendation (Logg et al., 2019). Rather, they are more likely to combine algorithmic recommendations with their traditional or baseline criteria and information, at least some pieces of which may be components of the algorithm itself. For example, in a common hiring decision scenario, recruiting teams traditionally use criteria such as GPA and years of work experience as inputs into their decisions. If they were to add an algorithmic recommendation to their process, and that underlying algorithm includes weights for GPA and years of work experience, should the decision-maker no longer give any consideration to these two criteria other than using the algorithmic recommendation? One school of thought is that humans should only override an algorithmic recommendation when they have information that is new, or otherwise different from, the information ingested by the algorithm (Kahneman et al., 2021). Inconsistent or erroneous use of algorithms could result in "double-counting" of some factors at the expense of others. People in organizations have different levels of data fluency and are likely to vary in how they interpret algorithmic models. If decision-makers use the algorithm as a prompt to stimulate deeper analysis, rather than simply a nudge toward a particular outcome, this could improve decision quality. There is much we do not know about how individuals or groups make complex decisions with the aid, or hindrance, of algorithmic input (Kahneman et al., 2021).

Ensembles of algorithms

An alternative to finding a single best algorithm is to use input from multiple algorithms, seeking out models based on different assumptions and even different data (Page, 2018). With this approach, multiple algorithms can be conceived as complements to one another. The virtues of ensembles of models align with the advantages of drawing on diverse groups for solving problems (Phillips, 2014) and hybrid decisions where humans and algorithms combine their distinct advantages (Hong et al., 2021). This approach raises several follow-up research questions. Would decision makers be more receptive to algorithmic input if they were presented with the results of two or more algorithms, requiring them to use judgment to adjudicate among them? Does input from multiple algorithms promote deeper analytical thinking and better decisions, or does it cause decision-makers to cast doubt on all algorithms and rely instead on their intuitions? What role does the data fluency of decision-makers play? Those who are driven more by motivated positioning than by logical and cooperative problem solving (De Dreu, 2007) may focus on the algorithm that supports their preferred outcome. Studying the cognitive and motivational mechanisms of how input from ensembles of algorithms is used could reveal new insights into decision-making processes and new interventions to improve them.

Embedding algorithms in larger organizational decision processes

The way algorithms are framed and used is not a static, one-shot phenomenon. Using algorithmic input in an organizational decision-making process goes beyond simply presenting a decision-maker with a quantitative recommendation at the exact juncture when the person is about to make the decision. Many employee-related decisions, such as hiring and promotions, are made through multi-stage, multi-faceted procedures that involve individual judgment at some stages and group deliberation at other stages, with many opportunities for noise, influence, and communication to enter into the process along the way (Bazerman & Moore, 2012; Sunstein & Hastie, 2015). What are the consequences of inserting algorithmic input at different stages of a decision-making process? Is it better to insert algorithmic recommendations early in the decision process with the goal of anchoring decision-makers during subsequent information processing? Or should people first share and process relevant information and come to an independent point of view before seeing what an algorithm recommends? Research on so-called "human-in-the-loop" processes could test different sequences of when human judgment enters a decision process (De-Arteaga et al., 2020).

Our current understanding of whether to use algorithms in decision-making, how specifically to do so, and how algorithms map onto existing broader socio-political struggles within organizations – or even create new ones – is lacking. For example, if algorithms represent a potential threat to decision-makers, several research questions arise about how organizational members use data to construct algorithms. Who is involved in the model-generating process (e.g., data scientists versus business managers), and how does this affect the selection of data and models? If different models optimize different goals, how are choices made about these trade-offs? In a 20-month ethnography, Jackson (2022) studied how decision-makers in a technology firm debated and decided among several hiring platforms offered by vendors. The criteria they used differed based on whether the platform in question focused on racial minority candidates compared to platforms on which most candidates were White. This study reveals how deeply intertwined the use of algorithms in employee decisions is with existing organizational structures, processes, and biases.

Algorithmic biases

Decision-making biases are both prevalent and consequential. As a result, they have been the subject of research for decades. Both individual (Bazerman & Moore, 2012) and group biases (Sunstein & Hastie, 2015) are numerous and well-documented. Algorithmic biases have now joined this inglorious taxonomy (O'Neil, 2016). Proponents argue that models can be used for good if they are used to apply decision criteria with consistency and fairness (Kahneman et al., 2021). Unfortunately, biased algorithms have the potential to do even more damage than human biases, depending on the scale, pervasiveness, and discretion with which they are deployed. The question of how to achieve the benefits of using algorithmic models without exacerbating existing problems or even creating new ones is paramount. When algorithms are biased, their virtue of consistency becomes a profound liability. In organizational contexts involving employee data, we need to study how biases are exacerbated, reduced, or changed by incorporating algorithms into human decision processes, as well as investigate underlying assumptions about how algorithms work.

Biased data

Organizational algorithms are generated from datasets collected both actively and passively. Both types of data can contain biases that would affect the resulting algorithms in potentially significant ways. When historical data are modeled, systematic analyses often reveal biases in the data; the resulting models, if unchecked, produce biased predictions (Ajunwa, 2021; O'Neil, 2016). Several questions arise: What do these models reveal about the quality and fairness of past decisions? How do organizational members respond when confronted with the information that past decisions were systematically biased? When these models reveal bias in past decisions, how can they be adapted to avoid bias in future decisions?

Obermeyer et al. (2019) offer an example from health care where they audited an algorithm that produced racially biased outcomes and reformulated the algorithm to remove this bias. Fixing and using the improved algorithm was presumably better than reverting to the old decision procedures that created the biased historical decisions in the first place, which the initial algorithm revealed. A similar example in the people analytics domain was Amazon's biased hiring algorithm (Bergstrom & West, 2021). It is imperative to extend research on this topic from health care, the judicial system, and other contexts to employee-related use cases that affect employee welfare. Fortunately, behavioral and data scientists have made progress in learning how to audit algorithms for bias and, when found, how to correct detected biases (Corbett-Davies & Goel, 2018; Du et al., 2021; Mehrabi et al., 2021; Obermeyer et al., 2019). This remains an important domain for ongoing research.

Compounded bias: Concerns at the human-algorithm interface

When algorithms are inserted into a human-centered decision process, or when human judgment is inserted into an algorithm-centered process, the potential for bias abounds. Companies may think they are getting the "best of both worlds" by combining algorithmic predictions with human judgment (Agrawal et al., 2022). However, it is equally likely that they are mixing the ingredients for individuals, groups, and algorithms in ways that contribute to biased outcomes – independently or in novel combinations. For example, if an individual decision-maker is provided with algorithmic predictions, and then follows these predictions in some instances but not others, what are the criteria or rules that guide these choices? Even if the algorithm itself is not biased, how do organizations account for and measure biases and inconsistencies that occur at the user level? As these questions suggest, the use of algorithms should be scrutinized not only in terms of the construction and recommendations of the algorithm, but also the way that algorithmic input is combined with human judgment during decision-making processes. Research on human-algorithm ensembles offers a promising direction (Choudhary et al., 2021; De-Arteaga et al., 2020; Hong et al., 2021).

These issues are compounded when there are multiple models from which employees can choose. Given the multitude of modeling techniques available to data scientists, the process through which modelers choose a particular model raises questions that go beyond the accuracy of a particular type of technique. For example, various modeling techniques can rest on different assumptions, or incorporate data sources in different ways, all of which can affect the model output in material ways. Page (2018) proposed that modelers take advantage of this variety to explicitly choose multiple models in order to stoke debate among decision makers. Left to their own devices, how do those creating models reconcile different modeling approaches, and how does this change as more stakeholders have a voice in which models to use? A useful path would be to study how decision-makers utilize ensembles of models in practice.

Algorithmic transparency

One potential path for offsetting the risk of biases is to make algorithms more transparent (Daneshjou et al., 2021; Kleinberg et al., 2019; Walmsley, 2021). In the organizational realm, how do people analytics teams operationalize transparency, and how *should* they do so? Decision-makers who understand how an algorithm works and who trust those who created the algorithm might be more receptive to using algorithmic recommendations. For managers, being able to explain to an employee why they did not get a promotion, for example, can make the difference between retaining or losing that employee (Newman et al., 2020). When algorithms are incorporated into these decisions, transparency and interpretability are crucial for helping managers provide valid explanations. Transparency pertains to both the technical details of the data and algorithms, but also organizational questions about the intended purpose of the algorithm, the rationale for why it is being used, who has control over its current and future use, and related issues (Jarrahi et al., 2021). Transparency can be complicated, however. One concern is with tradeoffs between model accuracy and model interpretability (Slack et al., 2021). A related concern is that sharing granular details of machine learning algorithms could both befuddle managers and limit model builders, posing a puzzle of how transparent to be, with whom, how often, and with how much detail (Bernstein, 2017).

Data-driven work processes

The use of algorithms in the workplace extends far beyond their use in discrete and episodic decision-making contexts. Workers are being quantified as never before as the ongoing digital revolution converts every action and interaction into a trail of data. These data can be fed into algorithms, which can then produce predictions, categorizations, and suggestions to change behavior (Iansiti & Lakhani, 2020). Whether through subtle nudges or overt instructions, whether this is done with full transparency or in a shroud of secrecy and opacity, and whether these activities are primarily intended for the good of the workers or the shareholders, the practice of people analytics introduces a wide range of possibilities for deploying algorithms, with an equally wide range of potential consequences (Gal et al., 2020; Huselid, 2018; Wood, 2021). A surge of recent research has begun to document, conceptualize, and understand how data and algorithms are influencing day-to-day activities of workers and those who manage them.

Embedding algorithms in the flow of work

Much of this research focuses on freelance gig workers performing so-called platform work, which is to a large extent algorithmically managed. For example, Rahman (2021) studied how freelance workers responded to an evaluation algorithm that was not transparent, such that workers could not discern the criteria on which they were being evaluated. One reason freelance platforms make their algorithms opaque is to limit the ability for workers to game the algorithm and artificially inflate their scores. Yet this opacity also makes it hard for workers to legitimately improve their evaluations. Worker responses to this dilemma ranged from experimental behavior aimed at surfacing the algorithm's criteria and improving performance, to an approach of limiting their activity to preserve their existing score. Workers perceived the algorithmic evaluation system as a form of control, but one that frustrated their efforts to improve because it was opaque and unpredictable (Rahman, 2021).

Lix and Valentine, 2020 studied algorithmic ranking systems and found that their study's freelancers were highly engaged by the algorithm and even came to trust it. A few mechanisms helped to understand this pattern, especially when juxtaposed to others' reactions to the algorithm as opaque and coercive, similar to the description by Rahman (2021). Algorithmic rankings were more positively received when they reduced uncertainty, increased perceptions of procedural justice by virtue of their consistency and documentation, and generated a sense of a shared experience among freelancers (Lix & Valentine, 2020). These inductively derived mechanisms suggest pathways through which algorithmic evaluations can be designed to foster more positive experiences and outcomes for those whose work is influenced by them.

Cameron (2022) studied workers in the ride-hailing industry whose work is guided by interaction with an app that is driven by algorithms and that largely substitutes for managers and colleagues. Though one might predict that these workers would rapidly disengage from the app and their work, many instead reacted by reframing their work as a game that they could control and win. Cameron (2022) observed some workers who became engaged in a relational game by focusing on satisfying customers, with the aim of receiving high customer ratings. Other workers engaged in an efficiency game in which they sought to maximize the amount of money they made per unit of time, often by minimizing effort beyond the necessary requirements of the job. In both cases, workers forged a sense of meaning around the work which helped them stay engaged, even with minimal or no interaction with managers (Cameron, 2022). In many contexts, the interaction between service workers and the customers they serve is orchestrated and, in effect, supervised by the platforms that introduce and match them. The algorithms that drive these platform dynamics influence the power dynamics between parties, creating new opportunities and constraints for controlling transactions (Cameron & Rahman, 2022; Maffie, 2022; Vallas & Schor, 2020).

Just as algorithms have been inserted into work processes, nudges have also become embedded in the architecture of choices that employees make (Beshears & Kosowsky, 2020). From choices about retirement savings to those about when to exercise, people change their behavior as a function of their decision environment (Beshears et al., 2021). As algorithmic input is increasingly incorporated into decision environments, researchers could study whether nudges help decision makers appropriately consider algorithmic recommendations.

Automated work processes: social robots and more

New technologies that communicate with employees are driving changes in the workplace that need to be understood more clearly through research. The automation of work processes, introduction of robots to perform work tasks, and the use of chatbots to provide information and answer questions are some examples. Robots are already a part of work processes in some organizations. Amazon, for example, has robots that assess the performance of delivery drivers and give them evaluative feedback (Soper, 2021; Tschang & Almirall, 2021). Beane (2019) conducted an ethnographic study to reveal how surgical trainees, when learning robotic surgery, were limited by traditional practices, and instead benefited from learning in a more isolated, more specialized, and less supervised way.

Yam et al. (2022) conducted two laboratory experiments featuring so-called social robots, which are "designed to autonomously interact with people across a variety of different application domains in natural and intuitive ways" (Vollmer et al., 2018, p. 1), including in education (Breazeal et al., 2016; Breazeal et al., 2016) and health care (Bigman et al., 2021). They tested the hypothesis that adding human-like feature to robot supervisors would cause people to be more receptive to their feedback. This hypothesis was not supported. Instead, anthropomorphized robots, compared to more mechanistic robots, caused feedback recipients to attribute more agency to the robot, which in turn led them to perceive negative feedback as abusive and to retaliate against the robot (Yam et al., 2022). This is an intriguing extension of research showing how people respond to technologies that are anthropomorphized (Waytz et al., 2014).

Communication, collaboration, and culture

Perhaps the greatest potential of digital data lies in the ability to measure interaction and connectivity between people. Organizations are increasingly using communications meta-data to reveal patterns of interaction among employees via email, chat, meetings, and related modes (Cardon, Ma, & Fleischmann, 2021; Impink, Prat, & Sadun, 2021). These data typically consist of who communicated with whom, with associated timestamps and other relevant parameters, revealing the structure of communication patterns, though not the content. Mayo and Woolley (2021), for example, used meta-data from emails among banking sales group employees to measure their levels of coordinated attention. They found that “bursty” communication, operationalized as emails that were temporally clustered, was positively associated with a group's ability to use resources effectively.

Communication over digital media also generates unstructured data in the form of text, audio, and video streams. These data contain the content of interaction, allowing more to be inferred about social relations compared to meta-data alone. Researchers can use techniques such as natural language processing (Kulkarni & Cauvery, 2021) and vocal cue analysis (Pentland, 2008) to parse emails and meeting transcripts to analyze sentiment and other relational dimensions. Communication data of all types are most useful when joined to complementary data sources from HR information systems, survey responses, or sales and operational data. Together, these data have the potential to unlock new insights into how people and organizations function.

These data are useful for studying interaction at multiple levels of analysis, depending on the phenomenon under study and the researcher's interests. A foundation of social life is the dyadic relation (Blau, 1964), which is even more multidimensional when digital connections are layered alongside other forms of connectivity. The same types of data that can characterize dyadic relations can also be used to measure interaction in groups. Teams are a foundational work unit in many organizations, and researchers have a long-standing interest in studying group processes and communication (Homans, 1950). Capturing and coding behavior within groups has been notoriously challenging and time-consuming, though highly valuable for understanding actual group processes (Weingart, 1997). Computer-mediated group discussion, and the digital data that can be captured and stored with the click of a Zoom button, allow the data-gathering phase of research to occur more efficiently, even at large scale.

Dyadic features can also be used to construct network properties among individuals in any size collective, from teams (Balkundi & Harrison, 2006; Shah et al., 2021) to departments (Kleinbaum et al., 2013). Even the networks of very large organizations can be mapped using digital traces from enterprise tools that are used throughout the company. Jacobs and Watts (2021), for example, used anonymized email data from individuals in 65 publicly traded firms to measure firms' internal network properties, documenting wide heterogeneity across companies and strong associations between network dimensions and organizational size.

Digital communications data in organizations can address a wide range of research questions. Next, I focus on some prominent and emerging research themes to serve as examples of the possibilities afforded by these data.

Networks

Network researchers are in a particularly good position to create new insights from digital data. Any digital traces that signify connections between pairs of people can be used to construct network graphs. Long-standing research questions about network dynamics should receive renewed attention to test whether new connectivity measures, in a world where the opportunities for people to interact across time and space have never been greater, reveal patterns like those found with traditional methods. In a recent test of Granovetter's (1973) strength of weak ties theory, Rajkumar et al. (2022) aimed to replicate and extend these ideas using LinkedIn data from over twenty million people over a 5-year window. The core tenets of the theory were supported based on experiments involving two billion new ties and 600,000 new jobs. Moreover, the results were nuanced in ways that elaborated the original ideas, with different types of ties having varying effects that were moderated by industry, for example. In addition to testing classic theories, digital network data are also useful for understanding new challenges, for example those presented by pandemic-inspired remote work arrangements. Another study of network ties, this one within a single organization before and after the onset of COVID-19, found that workers' collaboration networks became more siloed and stable, with fewer ties across different groups (Yang et al., 2022). This study capitalized on digital meta-data from emails, meetings, instant messages, and video and audio calls from over 61,000 employees over six months.

Even as industry and academic researchers collaborate to push the cutting edge of network scholarship, firms are introducing network concepts to their employees. Organizational network analysis has become popular for gaining a line of sight, beyond an organization chart, into which employees are collaborating and which are at risk of becoming isolated (Novak et al., 2011). A growing number of companies give employees information about their own connectivity and position in their organizational network, introducing new research questions about how providing such information changes the behavior of the recipient. To support this practice, firms are conducting their own network analyses internally, using both passive digital data along with more traditional survey methods. A growing cadre of vendors including Microsoft Viva, Polinode, and Cognitive Talent Solutions offer software platforms and services to help companies gather and analyze employee network data, accelerating this practice further. Just as researchers make many judgments when transforming raw data into operational variables, so too are analytics teams in organizations engaging in feature engineering to create network metrics that best fit their purposes. These trends introduce many research questions, such as which metrics are helpful to leaders or employees, how recipients change their behavior in light of receiving these metrics or learning that their digital data are being used for these purposes. More generally, what is considered a "good" network position by employees? If everyone tries to become more central, does this have diminishing returns for the collective? What is an optimal network structure that allows employees to utilize others' expertise, knowledge, and availability in an efficient way that optimizes collective outcomes?

Teams

Historically, research on networks and teams had little overlap. That has changed as scholars have gained insights into the internal networks of team members along with the consequences of how teams are embedded within larger organizational networks (Balkundi & Harrison, 2006; Reagans & McEvily, 2003; Wu et al., 2021). This interplay between teams and networks reflects the organizational reality that collaboration in modern organizations is increasingly fluid and adaptive (Mortensen & Haas, 2018). Yet, teams are still a distinct phenomenon. Managers formally assign employees to teams and organize work and rewards accordingly, and many employees psychologically identify with their teams, imbuing team memberships with meaning and a sense of belonging (Marks et al., 2001). Given the abundance of digital data on teams, researchers have an opportunity to shine new light on long-standing questions.

One example of research on the fundamental importance of teams is provided by Wuchty et al. (2007) who, by analyzing digitized records of millions of papers and patents, convincingly established that teams outperform individuals in the production of scientific knowledge. Marshalling even more data, Wu et al. (2019) further showed that smaller teams produced more disruptive scientific ideas compared to larger teams.

Another recent direction for team research is in the emerging domain of collective intelligence, the idea that some teams are systematically more effective than others across a variety of tasks (Woolley et al., 2010). In contrast to most team studies, which tend to focus on a single type of task, the concept of collective intelligence highlights the need to consider how teams adapt their processes to changing tasks. Several researchers have begun testing hypotheses and exploring possibilities related to these questions (Riedl et al., 2021). Get et al., 2019 explored how collaborative process metrics can be used to measure and improve collective intelligence, raising the possibility of using automated mechanisms to do this in real-time. This work has the potential to illuminate and test causal mechanisms that drive collective performance and to help real groups in practice, creating a pathway for technology and artificial intelligence to improve team functioning. It will be important to understand how technology-enabled interventions affect the psychological states of team members in conjunction with team effectiveness (Marks et al., 2001), especially for team members who had to adapt their work processes when the pandemic forced them to work remotely (Whillans et al., 2021).

Organizations are using algorithms to assign people to jobs, projects, and teams, creating a new arena for research on team composition and team recommendation systems (Gómez-Zará et al., 2022; Twyman et al., 2022). Skills typically serve as important criteria for matching, necessitating valid techniques for identifying relevant skill dimensions and evaluating employees on these dimensions (Kresge, 2020). Platforms such as Upwork and Catalant match workers with work projects, using matching techniques that share similarities with recommendation algorithms for movies, products, songs, or other people (e.g., LinkedIn, Twitter, or Facebook). Researchers should explore how these algorithms are constructed, how well they work, and how people respond to being assigned to a team through an algorithm (Gómez-Zará et al., 2020).

The science of meetings

Meetings are a rich source of data for studying team interaction, as they provide a structured, observable venue for collaboration. Despite their widespread use in organizations, meetings have been relatively understudied by researchers, making them a promising area of investigation in their own right. The proliferation of online meeting platforms in recent years, such as Zoom, has made it easier to record and analyze meetings, subject to participant consent. Researchers have begun to examine the various parameters that can impact the effectiveness of meetings, including the purpose, medium, length, and size, along with in-meeting communication patterns and participant behavior. This research has given rise to the emerging domain of the science of meetings (Mroz et al., 2018; Rogelberg et al., 2010; Schwartzman, 1986), which aims to understand and improve the effectiveness of these ubiquitous organizational events.

For micro researchers, internal meeting dynamics offer a wealth of granular data to measure many dimensions, including the visual and audio streams that comprise group interaction during the meeting, transcripts of the content of what participants say, along with the potential to survey participants about their perceptions of the meeting. For macro scholars, organizational meetings can also be studied by zooming out to understand larger patterns of activity. Departments may differ in how they utilize meetings to accomplish their work, including how may attendees are invited, how long meetings last, when they occur, how many are scheduled, and how formally they are structured. Meeting attendance can also be used to study ties between people, given that co-attending a meeting, especially a small one, can be used to infer some amount of meaningful interaction. In this way, meetings can be used to construct an understanding of the organizational network.

Whether zooming in to the dynamics of distinct meetings or zooming out to measure aggregate levels of meeting activity, meetings are a potent source of information about how individuals, groups, and organizations function. Given the calendar platforms that most organizations use to schedule and organize meetings, a wealth of meta-data is potentially available to measure many of these parameters. Polzer et al., 2022 used firm-level meta-data from over 200,000 organizations to test whether increasing volumes of meetings and email were associated with diminishing and even negative returns on firm revenue. They found evidence of the deleterious effects of collaboration overload for meetings and email separately and in combination. DeFillipis et al. (2022) used digital meta-data from over three million individual knowledge workers in 16 major metropolitan areas to document the effect of COVID-19 lockdowns on collaboration patterns. In the post-lockdown period, people engaged in more and bigger meetings, but they were shorter than pre-lockdown meetings. People's workdays also increased, based on the time from their first to last email or meeting each day. These studies demonstrate the scale at which digital work activity can be examined across firms and even countries.

Conversation analytics

A complement to studies of teams and meetings is the emerging domain of conversation analytics. Though scholars have long studied conversations and communication in all its forms, the rise of automated conversational abilities and the increase in communication data, along with new tools to analyze conversation, have combined to invigorate this field. Recent advances in deploying large language models add fuel to the use of automated communication in organizations, along with an urgency to understand the conversational dynamics and consequences that result. On the applied side, the sales and customer service functions are prominent starting points for many organizations to measure and improve communication patterns and outcomes. Technologies designed to improve sales outcomes have aimed squarely at this segment. One example is Gong, a company that captures and analyzes written and spoken sales conversations and then provides conversation metrics and prescriptions to salespeople, with the goal of helping them improve (Brooks & Spelman, 2021).

Research on conversations is similarly capitalizing on new ways to capture conversational data and new methods for analyzing it (Yeomans et al., forthcoming). For example, Yeomans et al. (2020) developed a machine-learning algorithm to study conversational receptiveness, specifically by extracting signals during conversation that participants were receptive and open to opposing views. To do this, they used a natural language processing model that had been pre-trained to identify markers of receptiveness from natural language. They found that receptiveness, as measured by the algorithm, predicted a variety of positive outcomes of conversations across lab and field studies. Moreover, they were able to develop an intervention, based on the algorithm, that helped participants be seen as more collaborative and persuasive (Yeomans et al., 2020). This paper represents one example of a burgeoning field that has the potential to use very granular communication data to revolutionize the way we study and understand people's social and work lives (Huang et al., 2017).

Organizational culture

Researchers are also using language as a window into organizational culture. Srivastava et al. (2018), for example, analyzed the language in over ten million emails to measure enculturation, or the degree to which new hires' language patterns fit the prevailing language norms in the larger organization. They found that cultural fit, operationalized as language match, was associated with individual attainment and attrition (see also Bhatt et al., 2022; Goldberg et al., 2016; OS). Chatman and Choi, 2022 describe the rise of computational linguistics as a method for measuring culture. In a related vein, Marchetti (2019) examined cultural compatibility between firm acquirers and their acquisition targets by analyzing employee reviews posted on Glassdoor.com using natural language processing techniques. She found that higher compatibility was associated with better stock returns, validating the cultural signal providing by employee reviews. More broadly, these studies demonstrate the value of using digital data to reveal new insights about how culture operates in organizations.

Monitoring, privacy, and transparency

Many aspects of work and management are now subject to algorithmic and technological influence. A corollary is that digital work is susceptible to being monitored and evaluated in automated ways (Vallas & Schor, 2020). The reach of algorithms extends into goal setting, performance management, learning and development, compensation, and other dimensions of employee experience (Parent-Rocheleau & Parker, 2021). When algorithms are introduced into a work process, they inevitably change the design of the work, both in intended and unintended ways (Valentine & Hinds, 2021). The success of algorithmic interventions depends in part on their technical quality, but perhaps even more on the extent to which people in the affected ecosystem understand and trust the algorithms and those who control and oversee them (Glikson & Woolley, 2020). This raises questions about monitoring, transparency, privacy, fairness, and the control that people retain over the process and outcomes of their work activities (Parent-Rocheleau & Parker, 2021). The use of algorithms has profound implications for power dynamics and relationships between managers and workers (Kellogg et al., 2020).

Supervision and control have always been foundational principles of building organizations. Perhaps it should not be surprising, then, that sales of software for monitoring computer activity increased substantially when the COVID-19 pandemic began and employees started working from home (Kantor et al., 2022; Davis, 2022). Monitoring software can track everything from keystrokes to mouse clicks, eye gaze to browser activity, to screenshots that give computer monitor a whole new meaning (Kantor et al., 2022). Patil and Bernstein (2022) studied the use of monitoring technologies in a law enforcement context, finding that employees' responses to being monitored depended on who had access to the data. When employees had access to their own data, they experienced benefits from being able to show others, including their supervisors, their perspective. This reduced the psychological distance between employees and their evaluators, reducing the negative effects of lower autonomy that are typically associated with the use of monitoring technologies (Patil & Bernstein, 2022). This study is an excellent example of how examining new organizational practices can lead to novel empirical and theoretical contributions. Given the nuances and complexities of monitoring employees, we need more research like this on the boundaries of private information amidst the quest to optimize productivity and employee welfare (Cappelli et al., 2020).

During COVID-19, the need for social distancing drove employers to track employee movement. People's physical location and movement can be traced by badge swipe devices, stationary cameras, and apps on people's phones. Many employees do not want their physical location tracked by their employer, however, even for goals couched in terms of employee safety and well-being or for optimizing office utilization (Ajunwa et al., 2017). When collecting such data, questions of de-identification, data aggregation, confidentiality, transparency, and data security should be front and center for the organization. For researchers, to the extent that a company is already collecting, storing, and using employee location data, there is an opportunity to responsibly study these dynamics, including employees' responses to these practices.

There is an entire subfield of individual measurement, which some proponents refer to as the quantified-self movement, where people use technologies to measure their own behavior and productivity with the goal of self-improvement (Hassan et al., 2019). These tools range from software to improve focus while writing or coding to wearable devices that track physiological metrics to monitor stress, track sleep quality, or gauge workout intensity. While these tools are meant to allow individuals to improve their own performance, they raise research questions about the role of the organization in collecting, analyzing, and reporting these types of individual data, to whom the data belong, how the data should be used, and whether the data are biased to favor some groups over others (Ajunwa et al., 2017).

Researchers can also gather ever-growing data external to organizations that is relevant to individual employees and organizational functioning. One major example is labor market data, which are now more fine-grained in terms of supply and demand for certain candidates, jobs, and skills (Deming, 2017; Fuller et al., 2022) . Organizations themselves are gathering and using such data to predict employee turnover, for example, based on local demand for different employee skills. Employees themselves post their skills and experiences on public platforms such as LinkedIn or reviews of their companies on Glassdoor, making these data transparent to the public and amenable to being scraped and analyzed. Employees' social media posts are also a potential source of data, with posts mentioning everything from how they felt about their commute to work to more personal views about their colleagues or themselves (Grijalva et al., 2020). When these data are transparent to the public, they can be analyzed by those working in companies and by external researchers.

Bridging to the disciplines: the rise of computational social science

Organizational Behavior has always been at the intersection of organizations and disciplinary fields, especially psychology and sociology. And like organizations, the disciplines are experiencing changes driven by the explosion of digital data. Social science research is witnessing the emergence of a new field that has taken off in the last decade (Lazer et al., 2020). It is distinguished by the use of new sources of data, typically digital and large-scale, which is streaming from all walks and dimensions of life (Salganik, 2019). These data are giving rise to new computational methods created through the collaborative efforts of scholars from different disciplines to study human behavior. Computational social science is the umbrella term that is commonly used to define this domain.

This nascent field is cross-disciplinary, comprised of social scientists, computer scientists, statisticians, and others forming an intellectual community (Lazer et al., 2020). New data sources also include historical archived data, such as administrative records, that are newly digitized, making them amenable to new analytic techniques at scale in ways that were not feasible before (Edelmann et al., 2020). Data sources related to employees are also being analyzed by scholars in economics, accounting, and other business disciplines. Recent examples include large sample studies of the relationships between turnover and subsequent firm performance (Li et al., 2022) and between CEO-employee pay disparity and firm performance (Rouen, 2020).

Many of the research topics described earlier, such as the effects of infusing algorithms into workplaces, should become mainstream within Organizational Behavior. Such research will be imperative for understanding employee behavior, performance, and well-being. In fact, consistent with the cross-disciplinary ethos of computational social science, researchers in multiple fields outside of organizational behavior are already studying similar topics in fields such as computer-human interaction (Lee et al., 2015), information systems (Jussupow et al., 2020), computer and data science (Rajkumar et al., 2022; Sühr et al., 2021), complex systems (Page, 2010), sociology (Edelmann et al., 2020), and computational linguistics (Bhatt et al., 2022; Pennebaker, 2022). For example, studies of algorithmic decision-making and bias in health care, law, banking, education, or public policy have clear implications for the use of algorithms in hiring, promotions, and related employee domains (e.g., Kaufmann, 2021). The problems in these fields differ in substance and context, but are analogous in problem structures, methods, and research approaches (Hofman et al., 2021). The computational approach to these problems increases the adjacencies and overlaps among seemingly disparate fields (Lazer et al., 2020). Organization scholars are closer than many realize to a wide array of disciplines such as computer science, which in turn are moving closer to the world of organizational practice by virtue of applying similar computational approaches.

There are striking parallels between the rise of People Analytics, within organizations, and the rise of Computational Social Science, within and across many disciplines. This makes the opportunity for organizational scholars all the more prescient, given their position at the intersection of organizations and the disciplines. This parallel does raise the question of why people analytics is gaining traction only recently, when the big data revolution and data-driven approaches have been in wide use for decades in other domains. Employee data is often considered more internally sensitive than operational, customer, or other types of data, raising caution flags about how it is used, and by whom. A more deep-seated reason for the lag in adapting analytical approaches to employee data is the cultural mindset that employee-related decisions should not be made by unfeeling algorithms, and that employees should not be objectified by reducing them to numbers (Belmi & Schroeder, 2020; Pardo-Guerra, 2022; Cremer and Stollberger, 2022). The current trajectory, then, is perhaps as much a function of changes in the cultural norms and perceived legitimacy of applying analytics to employee data, as it is driven by new sources of data, new technologies, or newfound benefits of analytic approaches. The good news is that efforts within organizations to responsibly use employee data are increasingly spearheaded by new people analytics teams that could be natural allies of organizational research. These teams are part of the changing ecosystem of organizational research, which I discuss next.

The changing research ecosystem

The long-standing gap between research and practice has been the subject of debate, critique, and lament for decades (Lawler et al., 1999; Pearce & Huang, 2012; Rynes et al., 2001). The demand for articles and books that translate research for an audience of practitioners has created a booming cottage industry (Pfeffer & Sutton, 2006). This gap may be shrinking, however, as more organizations hire well-trained researchers to put their skills to work inside organizations. Witness the technology companies that have hired scores of social science PhDs to complement their computer and data scientists (Bock, 2015). Some companies have grown their own internal research groups to conduct and publish research (Teevan et al., 2022). More broadly, newly-minted PhDs as well as their more experienced colleagues are being hired to use their research skills for internal organizational purposes either instead of or alongside more generalizable scientific pursuits. This trend has also created new industry career paths for PhDs to do applied research that is directly relevant to specific organizational problems or decisions (Bock, 2015).

On a deeper level, these new career paths are a manifestation of a more profound change. Organizations face challenges that can be addressed by a better, localized understanding of employee behavior. Organizations, especially large ones, have plenty of data, along with abundant opportunities to gather more (Hartmann & Henkel, 2020). One reason organizations hire social science researchers is because they possess the skills needed to do the work of people analytics–using internal data to help solve organizational problems. These skills include substantive disciplinary knowledge such as the theories and literature of psychology, sociology, behavioral economics, or organizational behavior, as well as methodological and analytical expertise for conducting rigorous behavioral research. The gap between research and practice is shifting in part because internal research in organizations is accelerating, with teams of highly-skilled researchers applying advanced analytic techniques to proprietary datasets (Hartmann & Henkel, 2020). In some cases, the frontier of this type of research, including the use of machine learning and artificial intelligence, is being conducted by practitioners who enjoy the advantages of working with abundant data and data scientists.

The gap may be shrinking for other reasons, too. Practitioners trained as researchers can evaluate and use academic research directly, without relying on translation. Moreover, research collaborations between academics and practitioners are more likely to be productive when both parties have similar values, training, language, and goals for achieving rigor and relevance (King & Persily, 2020; Shapiro et al., 2007). As managers and HR professionals acclimate to using employee data for research as they see benefits from their internal research, they may become more open to deeper collaborations with academics. Trends such as the use of design thinking, which essentially parallels the scientific method, may also open the door to more and better collaborations. That said, the fact that workers are generating digital trace data does not mean that it is easy to obtain for research, given the privacy and legal issues surrounding sensitive employee data, nor is it straightforward to infer theoretically relevant relationships from raw digital data. Even with challenging privacy and legal considerations (King & Persily, 2020), however, the changing landscape of the organizational research ecosystem should, in theory, help to bridge the proverbial gap between research and practice (Amabile et al., 2001).

Conclusion

It is an exciting time to study organizations. While this era's disruptions and challenges are daunting for those who work in and lead organizations, there is a silver lining: every attempt to try something new is an opportunity to learn. The global pandemic forced many employees to work from home and accumulating research confirms that many now prefer to do so, at least sometimes. This illustrates how disruptive changes can produce unexpected outcomes, and how data can help firms adapt to new realities. Academic researchers will continue to play an important role in gaining new insights into psychological, sociological, and organizational phenomena. Ideally, these insights will inform and improve organizational functioning. We should explore new directions brought about by the rise of people analytics and computational social science while never losing sight of the people who are the heart of organizational life.

Data Availability

No data was used for the research described in the article.

Declaration of Competing Interest

The author declares that he has no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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