Noguchi, Y. (2015). Recruiting better talent with brain games and big data. *All Tech Considered: Tech, Culture, and Communication*. Retrieved from http://www.npr.org/sections/alltechconsidered/2015/02/25/388698620/recruiting-better-talent-with-brain-games-and-big-data

Peck, D. (2013, December). They're watching you at work. *The Atlantic, 312*(5), 72–84.

Shaw, J. (2014, April). Why "big data" is a big deal. *Harvard Magazine, 3*, 30–35.

Van de Ven, A. H. (2015). Welcome to the academy of management discoveries (AMD). *Academy of Management Discoveries, 1*(1), 1–4.

Little Teams, Big Data: Big Data Provides New Opportunities for Teams *Theory*

Dorothy R. Carter
University of Georgia

Raquel Asencio
Georgia Institute of Technology

Amy Wax
California State University, Long Beach

Leslie A. DeChurch
Georgia Institute of Technology

Noshir S. Contractor
Northwestern University

Over the past 25 years, industrial and organizational (I-O) psychologists have made great strides forward in the area of teams research. They have developed and tested meso-level theories that explain and predict the behavior of individuals in teams and teams operating within and across organizations. The continued contributions of I-O psychologists to theory and research on teams require us to address the challenges—several of which

Dorothy R. Carter, Department of Psychology, University of Georgia; Raquel Asencio, School of Psychology, Georgia Institute of Technology; Amy Wax, Department of Psychology, California State University, Long Beach; Leslie A. DeChurch, School of Psychology, Georgia Institute of Technology; Noshir S. Contractor, Kellogg School of Management, Department of Communication Studies, and Department of Industrial Engineering and Management Studies, Northwestern University.

This research was funded in part by the Army Research Office under contract W911NF-14-10686. The views, opinions, and/or findings contained in this report are those of the authors and should not be construed as an official Department of the Army position, policy, or decision, unless so designated by other documents. This material is based on work supported by the National Science Foundation under Grant Nos. SES-SBE 1219469 and ACI-CSE 1244737.

Correspondence concerning this article should be addressed to Dorothy R. Carter, Department of Psychology, University of Georgia, 125 Baldwin Street, Athens, GA 30602. E-mail: dorothyrpc@gmail.com

were well described in the focal article (Guzzo, Fink, King, Tonidandel, & Landis, 2015)—and embrace the opportunities that are being ushered in by big and broad data streams (Hendler, 2013). We suggest that a principal unique value add of the I-O psychologist to the basic scientific endeavor of understanding small teams comes in the form of *theory*—theories that explain why, when, how, and to what end individuals form relationships needed for teams to function in unison toward the accomplishment of collective goals. Some have argued that the big data revolution means "the end of theory," suggesting petabyte data render theoretical models obsolete (Anderson, 2008). On the contrary, we submit that big-data enabled social science holds the promise of rapid progress in social science theory, particularly in the area of teams.

As the focal article notes, big data about teams abounds, ranging from traces left as teams form and perform in online communities (Turek, Wierzbicki, Nielek, Hupa, & Datta, 2010) to big data from computer simulations (Sullivan, Lungeanu, DeChurch, & Contractor, 2015) to big data from wearable sensors (Kozlowski, Chao, Chang, & Fernandez, in press; Pentland, 2000). Simultaneously, the "little team" is now capturing the attention of scholars in a wide range of fields and disciplines who are bringing big data to bear on the very same phenomena that I-O psychologists have been theorizing about and studying for decades. Climate scientists are engaging teams research as they build cyberinfrastructure tools to integrate data, tools, and methods from the disparate fields that study the land, sea, and air (Jacobs, 2012). Biomedical scientists are engaging teams research as part of a new field dubbed "The Science of Team Science" (Cooke & Hilton, 2015) in order to design organizational work systems such as those that led to the discovery of the Higgs boson (Aad et al., 2012) or the sequencing of the human genome (Venter et al., 2001). Computer scientists are engaging teams research to understand forms of human collaboration enabled by the digital revolution such as peer production (Kittur et al., 2013; Wilkinson, 2008) and collective intelligence (Smith, 1994). Like the big data revolution in general, the engagement of these communities in the science of teams presents I-O psychologists studying teams with both challenges and opportunities.

The reality is that big data has brought the study of "little teams" to a crossroads. We wish to extend the discussion of big data to consider the opportunities to better accomplish the thing that we, as I-O psychologists, perhaps are the best positioned to do in the area of teams research: *build and refine theory*. We explore four key opportunities that arise when I-O psychologists pair their ability to develop, operationalize, and investigate social science theory with big data.

First, data-intensive research will enable social scientists to test predictions that derive from major theories "at scale." For example, the team input–process–outcome (I–P–O) model was introduced to explain how certain inputs (e.g., team composition) could lead to team outcomes (Hackman, 1987; McGrath, 1984; Steiner, 1972). This model holds that team processes are the mediating link between inputs and subsequent outcomes. To date, hundreds of studies have tested team I–P–O relationships using samples ranging from 1 to 1,000 teams. Virtual organizational science has relied on this foundational thinking about teams (cf. Jarvenpaa, Shaw, & Staples, 2004; Lurey & Raisinghani, 2001; Martins, Gilson, & Maynard, 2004). Newer models of team performance such as the input–mediator–output–input model (IMOI; Ilgen, Hollenbeck, Johnson, & Jundt, 2005) suggest that the factors linking team inputs and outputs are often constructs other than behavioral processes, such as trust, cohesion, or shared cognition, which emerge over time and manifest at the team level. The way these constructs develop and shift over time is nonlinear and involves feedback loops whereby mediators and outputs at one moment become inputs at another (Ilgen et al., 2005).

However, team I–P–O and IMOI research has barely scratched the surface of testing propositions about the influence of team context and environmental pacers on team internal functioning. Scant attention has been paid to exposing how processes unfold over time. To some degree, prior team theory and empirical research was limited by atomistic data—data centered on individuals or teams as entities. Measures of so-called "social behavior" and "team process" have more closely resembled "individuals' perceptions" than coevolving behavioral repertoires. In contrast, big data is particularly useful for studying team dynamics given that these data are inherently *relational* and afford the investigation of more precisely specified relational theories (Macy, DellaPosta, & Shi, 2015). Mapping the emergence and impact of patterned team-level constructs over time (e.g., using implicit measures of relational constructs captured in real-time) is one way for research to delineate the IMOI cycles through which teams function. We offer this as an illustration of a key advancement that can be made possible by applying large-scale, data-intensive, computational social science (CSS; Lazer et al., 2009) approaches to teams theory.

Second, data-intensive research may well expose new boundary conditions appropriate for incorporation into existing theories of teams. Over the past 2 decades, the social sciences have increasingly utilized meta-analysis as a technique for theory testing. Meta-analysis combines all available estimates of an effect size from published and unpublished studies in order to identify the boundary conditions, or moderators, of a given relationship (Hunter & Schmidt, 2004). In the past, this approach has proven particularly useful in the area of teams (e.g., Bell, 2007; Mesmer-Magnus & DeChurch, 2009), given that access to large samples of teams data is typically untenable. A major limitation of relying on meta-analysis to understand teams, however, is that we are stitching together small data to construct big data, often with little knowledge of sources of variation between samples. CSS approaches, unfettered by small sample constraints, afford teams researchers a new way to chart the boundaries of their theories.

Third, data-intensive research invites new combinations of constructs, and the entry of altogether new constructs, into our theory space. For example, advancements in neuroimaging and sensor data are opening up the possibility that we can incorporate new constructs such as the "fluidity of team membership" (i.e., how and with whom collaboration occurs), "virtual proximity" (i.e., how reachable individuals are throughout the day), and "dominance" (i.e., a "protagonistic characteristic" influence over others in order to balance participation and derive consensus; Kim, McFee, Olguin, Waber, & Pentland, 2012).

Fourth, there are bound to be entirely new phenomena identified through the use of big data. Thus, new theories about collaboration are needed to focus our attention on new or at least increasingly prevalent phenomena. An example of such a phenomenon is a virtual community (i.e., MediaMOO, Wikipedia) in which users come together voluntarily to connect and collaborate (Keegan, Gergle, & Contractor, 2012). With nothing more than a basic infrastructure in place, it is the users who develop the environment (Bruckman, & Resnick, 1995; Bryant, Forte, & Bruckman, 2005).

To recap, big data combined with computational social science methods (Lazer et al., 2009) will define the future of teams research. The increasingly available digital streams afford an unprecedented and unparalleled opportunity for teams research. However, continuing to contribute to research on teams will require I-O psychologists to address the inherent challenges of big data and embrace the opportunities ushered in by big and broad data streams. Furthermore, the impact of data-intensive research in teams research can, perhaps, be seen most clearly when we consider the implications for teams theory.

References

Aad, G., Abajyan, T., Abbott, B., Abdallah, J., Abdel Khalek, S., Abdelalim, A. A., . . . Zwalinski, L. (2012). Observation of a new particle in the search for the standard model Higgs boson with the ATLAS detector at the LHC. *Physics Letters B, 716*(1), 1–29.

Anderson, C. (2008). The end of theory: The data deluge makes the scientific method obsolete. *Wired Magazine*. Retrieved from http://archive.wired.com/science/discoveries/magazine/16-07/pb_theory

Bell, S. T. (2007). Deep-level composition variables as predictors of team performance: A meta-analysis. *Journal of Applied Psychology, 92*(3), 595–615.

Bruckman, A., & Resnick, M. (1995). The MediaMOO project constructionism and professional community. *Convergence, 1*(1), 94–109.

Bryant, S. L., Forte, A., & Bruckman, A. (2005). Becoming Wikipedian: Transformation of participation in a collaborative online encyclopedia. *Proceedings of the 2005 International ACM SIGGROUP Conference on Supporting Group Work*, 1–10. Retrieved from http://dl.acm.org/citation.cfm?id=1099203

Cooke, N. J., & Hilton, , M. L. Hilton (Eds.). (2015). *Enhancing the effectiveness of team science*. Washington, DC: National Academies Press.
Guzzo, R. A., Fink, A. A., King, E., Tonidandel, S., & Landis, R. S. (2015). Big data recommendations for industrial–organizational psychology. *Industrial and Organizational Psychology: Perspectives on Science and Practice, 8*(4), 491–508.
Hackman, J. R. (1987). The design of work teams. In J. Lorsch (Ed.), *Handbook of organizational behavior* (pp. 315–342). New York, NY: Prentice-Hall.
Hendler, J. (2013). Broad data: Exploring the emerging web of data. *Big Data, 1*(1), 18–20.
Hunter, J. E., & Schmidt, F. L. (2004). *Methods of meta-analysis: Correcting error and bias in research findings*. Newbury Park, CA: Sage.
Ilgen, D. R., Hollenbeck, J. R., Johnson, M., & Jundt, D. (2005). Teams in organizations: From input-process-output models to IMOI models. *Annual Review of Psychology, 56*, 517–543.
Jacobs, C. (2012, April). A vision for, and progress towards EarthCube. *EGU General Assembly Conference Abstracts, 14*, 1227.
Jarvenpaa, S. L., Shaw, T. R., & Staples, D. S. (2004). Toward contextualized theories of trust: The role of trust in global virtual teams. *Information Systems Research, 15*(3), 250–267.
Keegan, B., Gergle, D., & Contractor, N. (2012, February). Do editors or articles drive collaboration? Multilevel statistical network analysis of Wikipedia co-authorship. *Proceedings of the ACM 2012 Conference on Computer Supported Cooperative Work*, 427–436. Retrieved from http://dl.acm.org/citation.cfm?id=2145204
Kim, T., McFee, E., Olguin, D., Waber, B., & Pentland, A. (2012). Sociometric badges: Using sensor technology to capture new forms of collaboration. *Journal of Organizational Behavior, 33*, 412–427.
Kittur, A., Nickerson, J. V., Bernstein, M., Gerber, E., Shaw, A., Zimmerman, J., . . . Horton, J. (2013, February). The future of crowd work. *Proceedings of the 2013 Conference on Computer Supported Cooperative Work*, 1301–1318. Retrieved from http://dl.acm.org/citation.cfm?id=2441776
Kozlowski, S. W. J., Chao, G. T., Chang, C. D., & Fernandez, R. (in press). Using big data to enhance the science of team effectiveness. In S. Tonidandel, E. King, & J. Cortina (Eds.), *Big data at work: The data science revolution and organizational psychology*. New York, NY: Routledge.
Lazer, D., Pentland, A. S., Adamic, L., Aral, S., Barabasi, A. L., Brewer, D., . . . Van Alstyne, M. (2009). Life in the network: The coming age of computational social science. *Science, 323*(5915), 721–723.
Lurey, J. S., & Raisinghani, M. S. (2001). An empirical study of best practices in virtual teams. *Information and Management, 38*(8), 523–544.
Macy, M., DellaPosta, D., & Shi, Y. (2015). Why do liberals drink lattes? *American Journal of Sociology, 120*(5), 1473–1511.
Martins, L. L., Gilson, L. L., & Maynard, M. T. (2004). Virtual teams: What do we know and where do we go from here? *Journal of Management, 30*, 805–835.
McGrath, J. E. (1984). *Groups: Interaction and performance*. Englewood Cliffs, NJ: Prentice-Hall.
Mesmer-Magnus, J. R., & DeChurch, L. A. (2009). Information sharing and team performance: A meta-analysis. *Journal of Applied Psychology, 94*(2), 535–546.
Pentland, A. (2000). Looking at people: Sensing for ubiquitous and wearable computing. *IEEE Transactions on Pattern Analysis and Machine Intelligence (TPAMI), 22*, 107–119.

Smith, J. B. (1994). *Collective intelligence in computer-based collaboration*. Hillsdale, NJ: Erlbaum.

Steiner, I. D. (1972). *Group process and productivity*. New York, NY: Academic Press.

Sullivan, S. D., Lungeanu, A., DeChurch, L. A., & Contractor, N. S. (2015). Space, time, and the development of shared leadership networks in multiteam systems. *Network Science, 3*(01), 124–155.

Turek, P., Wierzbicki, A., Nielek, R., Hupa, A., & Datta, A. (2010). Learning about the quality of teamwork from Wikiteams. *Social Computing (SocialCom), 2010 IEEE Second International Conference*, 17–24. Retrieved from http://ieeexplore.ieee.org/xpl/mostRecentIssue.jsp?punumber=5590331

Venter, J. C., Adams, M. D., Myers, E. W., Li, P. W., Mural, R. J., Sutton, G. G., . . . Zhu, X. (2001). The sequences of the human genome. *Science, 16*(291), 1304–1351.

Wilkinson, D. M. (2008). Strong regularities in online peer production. *Proceedings of the 9th ACM Conference on Electronic Commerce*, 302–309.

I-Os in the Vanguard of Big Data Analytics and Privacy

Adam J. Ducey
IBM, Hazelwood, Missouri

Nigel Guenole
IBM Smarter Workforce Institute, London, United Kingdom

Sara P. Weiner
IBM Smarter Workforce, Tucson, Arizona

Hailey A. Herleman
IBM Smarter Workforce, Frisco, Texas

Robert E. Gibby
IBM, Cincinnati, Ohio

Tanya Delany
IBM, Milan, Italy

In this response to Guzzo, Fink, King, Tonidandel, and Landis (2015), we suggest industrial–organizational (I-O) psychologists join business analysts, data scientists, statisticians, mathematicians, and economists in creating the vanguard of expertise as we acclimate to the reality of analytics in the world

Adam J. Ducey, IBM, Hazelwood, Missouri; Nigel Guenole, IBM Smarter Workforce Institute, London, United Kingdom; Sara P. Weiner, IBM Smarter Workforce, Tucson, Arizona; Hailey A. Herleman, IBM Smarter Workforce, Frisco, Texas; Robert E. Gibby, IBM, Cincinnati, Ohio; Tanya Delany, IBM, Milan, Italy.

The opinions expressed in this article are those of the authors and do not necessarily reflect the views of IBM's positions, strategies, or opinions.

Correspondence concerning this article should be addressed to Adam J. Ducey, IBM, 325 James S. McDonnell Boulevard, Hazelwood, MO 63042. E-mail: aducey@us.ibm.com