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Computational Communication Science: A Methodological Catalyzer for a Maturing Discipline

MARTIN HILBERT
GEORGE BARNETT
University of California, Davis, USA

JOSHUA BLUMENSTOCK
University of California, Berkeley, USA

NOSHIR CONTRACTOR
Northwestern University, USA

JANA DIESNER
University of Illinois at Urbana-Champaign, USA

SETH FREY
University of California, Davis, USA

SANDRA GONZÁLEZ-BAILÓN
University of Pennsylvania, USA

Martin Hilbert: hilbert@ucdavis.edu
George Barnett: gabarnett@ucdavis.edu
Joshua Blumenstock: jblumenstock@berkeley.edu
Noshir Contractor: nosh@northwestern.edu
Jana Diesner: jdiesner@illinois.edu
Seth Frey: sfrey@ucdavis.edu
Sandra González-Bailón: sgonzalezbailon@asc.upenn.edu
PJ Lamberson: lamberson@ucla.edu
Jennifer Pan: jp1@stanford.edu
Tai-Quan (Winson) Peng: winsonpeng@gmail.com
Cuihua (Cindy) Shen: cuishen@ucdavis.edu
Paul E. Smaldino: paul.smaldino@gmail.com
Wouter van Atteveldt: wouter@vanatteveldt.com
Annie Waldherr: waldherr@uni-muenster.de
Jingwen Zhang: jwzzhang@ucdavis.edu
Jonathan J. H. Zhu: j.zhu@cityu.edu.hk
Date submitted: 2018–10–09

PJ LAMBERSO
University of California, Los Angeles, USA

JENNIFER PAN
Stanford University, USA

TAI-QUAN PENG
Michigan State University, USA

CUIHUA (CINDY) SHEN
University of California, Davis, USA

PAUL E. SMALDINO
University of California, Merced, USA

WOUTER VAN ATTEVELDT[1]
Vrije University Amsterdam, Netherlands

ANNIE WALDHERR
University of Münster, Germany

JINGWEN ZHANG
University of California, Davis, USA

JONATHAN J. H. ZHU
City University of Hong Kong, Hong Kong

This article reviews the opportunities and challenges for computational research methods in the field of communication. Among the social sciences, communication stands out as a discipline with a relatively low-profile institutionalized focus on the in-house development of methods. Computational tools are changing this, and they are catalyzing a new set of methods directly suited to tackling foundational research questions in communication. We systematically review how computational methods affect the three fundamental pillars of the scientific method: observational approaches (i.e., digital trace data), theoretical

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approaches (i.e., computer simulations), and experimental research (i.e., virtual labs and field experiments). We stress that data are a catalyzer but not a requirement for computational science. We explore how observational, theoretical, and experimental approaches can be combined and cross-fertilize one another. We conclude that taking advantage of computational methods will require a systematic effort in our discipline to develop and adjust these methods.

Keywords: computational science, research methods, big data, simulations, online experiments, methodology

A growing body of communication research examines how digital technologies change society at every scale, from individuals to families and from organizations to international relations. However, communication scholars have been remarkably slow to recognize the impact of digital tools on the research in their own field. Information and communication technologies have transformed the ways that scholars can obtain information, derive empirical insights, and generate theory.

Historically, the field of communication has put less emphasis on methodological development than other social sciences, such as political science, sociology, psychology, and economics. Among the 63 divisions, sections, and caucuses of the National Communication Association, and throughout its over 100-year history, the word *method* never appears as a stand-alone topic of interest. This does not mean that the field of communication has not been concerned with methods; it has (e.g., Berger, 2015; Frey, Botan, & Kreps, 1999; Krippendorff, 2004; Lindlof & Taylor, 2011; Monge & Cappella, 1980; Monge & Contractor, 2003; Woelfel & Fink, 1980). However, the "lack of methods for the study of [communication] process and adoption of approaches from other fields" (Poole, 2007, p. 181) has long been identified as a challenge to understanding the particularities of our field. This article describes how computational tools are catalyzing a new set of methods uniquely suited to tackling communication research questions, which are increasingly less constrained by historically adopted methodological straitjackets.

Methods are, of course, not the goal of the scientific enterprise, but they play the key role of selective perception to our research cognition (Greenwald, 2012). New methods relax old constraints on the types of questions we are able to ask. This allows researchers to discover new aspects and to develop richer theories of the mechanisms that underlie human and social communication. In the same way that technologies such as the telescope and the workflow of calculus catapulted physics into new stages of scientific maturity, we argue that digital trace data and algorithmic workflows are launching the field of communication to a new level. The impact of this work goes beyond academic exercises. There is a real-world urgency to advance this agenda. Computational communication sciences can provide much needed guidance for a world in which the five most valuable companies also lead in computational communication. Fostering computational communication science proactively shapes a communicative landscape that is currently influenced mainly by commercial and computer science considerations.

This article systematically explores our definition of computational communication science as an application of computational science to questions of human and social communication. As such, it is a natural subfield of computational social science (Cioffi-Revilla, 2014; Contractor, 2019; Lazer et al., 2009). Our definition echoes the transformations already highlighted over the past three decades in other disciplines, including computational physics (Koonin, 1986), computational biology (Waterman, 1995), and computational sociology (Hummon & Fararo, 1995). Our definition encompasses observational, theoretical, and experimental aspects of the scientific enterprise.

In agreement with the concept of the so-called fourth research paradigm (Bell, Hey, & Szalay, 2009; Hey, Tansley, & Tolle, 2009), the initial catalyzer of paradigmatic change in communication is the unprecedented availability of data—also known as big data (Lazer et al., 2009; Watts, 2007). Indeed, communication as a discipline finds itself in the eye of the data revolution, because most publicly available digital footprints left behind by online behavior derive from some form of communication (Cappella, 2017; Shah, Cappella, & Neuman, 2015). Communication traces are often even more readily available than records such as economic transactions collected by banks or human mobility data collected by phone operators, which are driving research in other social science disciplines. Given its abundance and accessibility, the first contact with students of modern data science is often through communication data. Therefore, our first component focuses on observational research that uses empirical digital trace data of communication. Because of its volume, this type of data lends itself to analysis with machine learning techniques.

The second component of our definition focuses on theoretical research. Given the current opportunities and the ensuing omnipresence of digital data from social interactions, theoretical work with computational means is often neglected when considering computational approaches to the social sciences. We understand data science to be a subcategory of computational science. Experience from decades of research in computational physics (Beringer et al., 2012) and computational biology (Venter et al., 2001; Waterman, 1995) indicates that data usually act as the catalyst for computational science. But this research also shows that crunching empirical numbers is not enough and that theoretical explorations of galaxies (Springel et al., 2005), life's evolution (Adami, 1997), human brains (Markram et al., 2011), and ecosystems (Purves et al., 2013) require theoretical models, which can also be fostered by computational means. Some groups have long equated theoretical computation simulations with computational social science (e.g., Cioffi-Revilla, 2014; Conte et al., 2012). Theoretical computer simulations naturally lend themselves to research in the field of communication, because they often elucidate emergent social phenomena, of which communication is a major ingredient.

Third, computational methods revolutionize experimental research. Computational methods provide new opportunities for surveys and field experiments and new platforms for virtual experiments (apps as labs), which allow researchers to efficiently scale from the individual to the group level. Computational communication experiments have been playing a pioneering role in computational social science (Salganik, 2017; Salganik, Dodds, & Watts, 2006).

In sum, we define computational communication science as the endeavor to understand human communication by developing and applying digital tools that often involve a high degree of automation in observational, theoretical, and experimental research. The threefold nature of our definition provides the basic structure of this article. In an additional section, we discuss the combination of the three approaches with an example of computational text analysis. The discussion showcases how observational digital trace data—combined with automated machine learning, computer simulations, and crowdsourced field experiments—are already giving life to computational communication science in practice.

Observational Research: Digital Footprints

The empirical analysis of digitally collected data is the most apparent application of computational methods in communication, as evidenced by several summary articles (e.g., boyd & Crawford, 2012; Lazer et al., 2009; Mahrt & Scharkow, 2013; Shah et al., 2015) and special issues (e.g., Burgess, Bruns, & Hjorth, 2013; Gil de Zúñiga & Diehl, 2017; Parks, 2014). Digital records of interpersonal and group communications are making obsolete many data challenges that traditionally hampered communication research, which, from a 20th-century perspective, were "not readily accessible to observers unless one carries a tape recorder around all day (a cumbersome and hardly practical endeavor)" (Fisher & Drecksel, 1983, p. 68). This leads to exciting theoretical insights but also presents new challenges (Foucault-Welles & González-Bailón, 2018; González-Bailón, 2017). The following paragraphs summarize the most salient opportunities and challenges associated with the analysis of digital trace data.

Opportunities

Revisiting Long-Standing Theories

In contrast to the much-cited claim that the data deluge implies the end of theory (Anderson, 2008), it has, in fact, allowed us to elaborate existing theory. For example, the influential two-step flow theory of Katz and Lazarsfeld (1955) has recently been revisited using Twitter data, making it possible to materialize some of the original goals of the authors: "Ideally, we should have liked to trace out all of the interpersonal networks in the community to see how they link up with each other" (Katz & Lazarsfeld, 1955, p. 309). Recent studies have effectively done that and identify an intricate mix of one-step, two-step, and other multidirectional networked step flows (Barnett et al., 2017; Choi, 2014; Feng, 2016; Hilbert, Vásquez, Halpern, Valenzuela, & Arriagada, 2016). Hilbert et al. (2016) conclude: "Six decades into the discussion of step flow models the work on the issue just seems to begin" (p. 457).

Another example of how the data deluge extends existing theory relates to the long-established result that people who have stronger social connections live longer (e.g., Berkman & Syme, 1979). Comparing 12 million Facebook users to a control group of nonusers, Hobbs, Burke, Christakis, and Fowler (2016) found that the theory applies to the acceptance of friendships, not to their initiation. Generations of studies on this topic failed to identify this link because the directionality of network connections was unclear in less powerful traditional data sources.

Accelerating and Generalizing Observational Findings

Recent research analyzing written correspondence, e-mails, hyperlinks, call logs, censorship, and propaganda records provides consistent evidence that much of human communication exhibits heavy tails, seasonality, and burstiness (Barabási, 2005, 2010; Barnett, Park, & Chung, 2016; King, Pan, & Roberts, 2013, 2017; Oliveira & Barabási, 2005; Rybski et al., 2012; Wu, Zhou, Xiao, Kurths, & Schellnhuber, 2010).

When analyzed as temporal patterns, communication dynamics can be described as a mixture of Poisson and non-Poisson processes under the more general class of renewal processes (Barabási, 2005, 2010). These findings suggest that communication processes across a wide range of media can be modeled with a single and well-understood family of underlying probability distributions. Computational techniques have already added nuance to the description of these patterns. For example, research with social media data shows that these probability distributions describe only the communication behavior of about 70% of users (Darmon, 2015), which begs the question of how the remaining 30% affect the overall dynamics—and why they differ in their behavior (Zhu & Peng, 2009).

Informing Policy Makers and Practitioners

The irruption of digital data has been welcomed by policy makers across the board but mostly in developing countries, where traditional data resources are scarce (Jerven, 2013). Most developing countries, for example, have high rates of mobile cellular penetration (Blondel, Decuyper, & Krings, 2015), which means that call logs and other forms of passive trails (necessary for service providers to operate) can be used to track the behavior of populations—and that information can be used to, for example, prevent epidemics. Researchers have shown that mobile phone (Blumenstock, Cadamuro, & On, 2015) and satellite data (Jean et al., 2016) can be used to construct accurate estimates of the geographic distribution of wealth, which can better equip policy makers to measure and target poverty and vulnerability. Using simple metadata from communication records, such as call duration and call frequency, a battery of sociodemographic variables about the users can be reconstructed with a prediction accuracy of 80%–85% (Blumenstock, Gillick, & Eagle, 2010; Frias-Martinez & Virseda, 2013; Soto, Frias-Martinez, Virseda, & Frias-Martinez, 2011). Computational analysis has also been used to improve disaster management (Bengtsson et al., 2011), contain disease outbreak (Wesolowski et al., 2015), and monitor diverse policy matters (Hilbert et al., 2018a).

Challenges

Identifying Biases in the Data

Digital footprints left behind by technology users are rarely representative; rather, they are ad hoc observations. Still, in the words of Google's chief economist Hal Varian, with big data, "everything's significant" (Taylor, Schroeder, & Meyer , 2014, p. 6). The meaning of statistical inference changes due to the sheer amount of data, but the implications for representativeness are often misunderstood (boyd & Crawford, 2012). That samples are large enough to render traditional measures of statistical significance irrelevant does not mean that sampling problems are absent. However large a data set, it might still be a biased representation of a larger universe, which means that conclusions drawn from that data set cannot be generalized to the entire population. For example, Frias-Martinez and Virseda (2013) worked with large-scale mobile phone data from a Latin American country with penetration rates of 60%–80%. As shown in Figure 1, these data matched social stratification metrics drawn from the population census quite well. However, Blumenstock and Eagle (2012) worked with mobile phone data from Rwanda during 2005–2009, when penetration rates were between 2% and 20%. In this case, the digital footprint is not representative of the total population, given the existence of a digital divide. Such biases can be systemic. It is expected that the digital divide will continue to skew real-world representativeness, given the persistent bandwidth divide, which strongly correlates with income levels (Hilbert, 2014, 2016a).

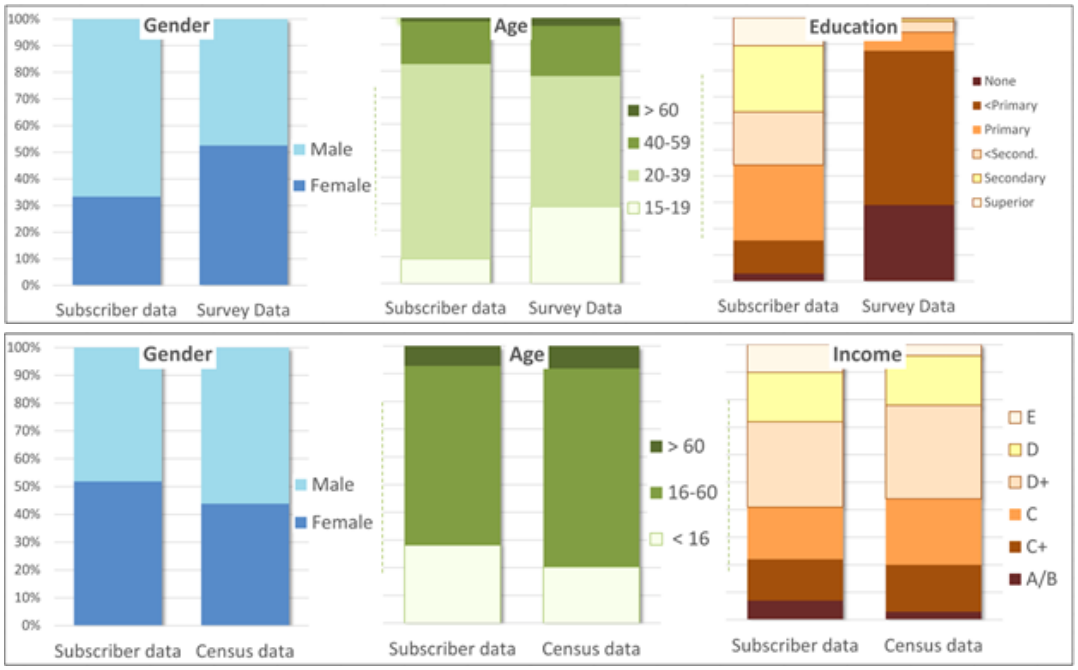

Figure 1. Bias in digital footprints revealed in a comparison of mobile phone subscribers and population data. The upper panel displays data for Rwanda in 2005–2009; the lower panel displays data for a Latin American country in 2009–2010. Related to studies by Hilbert (2016b), Blumenstock and Eagle (2012), and Frias-Martinez and Virseda (2013).

The pervasive challenge of sampling bias in digital trace data is especially notorious for the collection of data from social media sources. This type of data collection involves various sampling issues, including the potential impossibility of constructing sampling frames and of distinguishing bots from humans, platform effects, and variability of data sent through application programming interfaces (APIs; González-Bailón, Wang, Rivero, Borge-Holthoefer, & Moreno, 2014; Hargittai, 2015; Ruths & Pfeffer, 2014). Public APIs typically do not offer "fire hose" access to data but rather what could be called sprinkled "garden hose" access (e.g., specific time frames or unbalanced subgroups). Reconstructing samples for the purpose of reproducibility is often infeasible. Sometimes researchers only have access to positive search results, such as through an API keyword query, which makes it difficult to assess the recall of the used query and hence the validity of the extracted data.

Consistency Across Levels of Analysis

The refined temporal and spatial granularity of observational data allows researchers to conceptualize and operationalize communication phenomena inconsistently at different levels of aggregation (e.g., individual, interpersonal, organizational, and societal). This granularity offers greater analytical versatility, but it can also lead to a higher risk from the ecological fallacy (Robinson, 1950). Researchers need to (re)explicate whether a proposed model is level-free and applicable at different levels of analysis or level-constrained and tenable only at a certain level of analysis. For example, a key variable in past research on bursts and heavy tails is the time difference between two consecutive communicative behaviors, labeled "inter-event" time. Individuals vary widely in their behavior: the scale-free global patterns refer only to aggregated dynamics and demonstrate great heterogeneity in the distribution of inter-event time (Zhu & Peng, 2009). The upside is that the digital trace data often provide detailed spatiotemporal data from multiple levels, which, in theory, should allow researchers to explore different levels of social emergence.

Theoretical Research: Computer Simulations

Within the computational research paradigm, theoretical work is done with the help of computer simulations. For example, in computational biology, computer models of artificial life are at the core of explorations of the theoretically possible (Adami, 1997). Computer models of social dynamics have long been associated with computational social research (e.g., Cioffi-Revilla, 2014; Conte et al., 2012; Epstein & Axtell, 1996). Recent applications show the wide applicability of these theoretical experiments for communication research, including the exploration of online privacy (Tubaro, Casilli, & Sarabi, 2013), issue-attention cycles in news coverage (Waldherr, 2014), mass media and polarization (Flache & Macy, 2011; Mckeown & Sheehy, 2006), the diffusion of innovation (Smaldino et al., 2017; Tutzauer, Kwon, & Elbirt, 2011), opinion formation and the digital divide (Lim, Lee, Zo, & Ciganek, 2014), emotions in online forums (Chmiel et al., 2011), social influence and contagion (Piedrahita, Borge-Holthoefer, Moreno, & González-Bailón, 2017; Centola & Macy, 2007), the spiral of silence (Sohn & Geidner, 2016), and the dynamics of selective media exposure and attitudinal consequences (Song & Boomgaarden, 2017).

Opportunities

Building Complex Models for a Complex World

Formal mathematical models have long allowed researchers to shed light on the theoretical dynamics behind social communication (Smaldino, 2017), ranging from the diffusion of innovations (Bass, 1969; Lamberson, 2011, 2016; Vishwanath & Barnett, 2011) to the strategic use of deception in communication (Searcy & Nowicki, 2005; Smaldino, Flamson, & McElreath, 2018; Sobel & Crawford, 1982). Although all formal models are necessarily simplifications that abstract reality, reducing social complexity to a relatively simple set of solvable equations may be infeasible or reductive past the point of usefulness. As computing power has increased, instantiating formal models on the basis of numerically solvable code instead of analytical equations has vastly increased the number of tractable variables (Gilbert & Troitzsch, 2005; Weaver, 1948; see Figure 2).

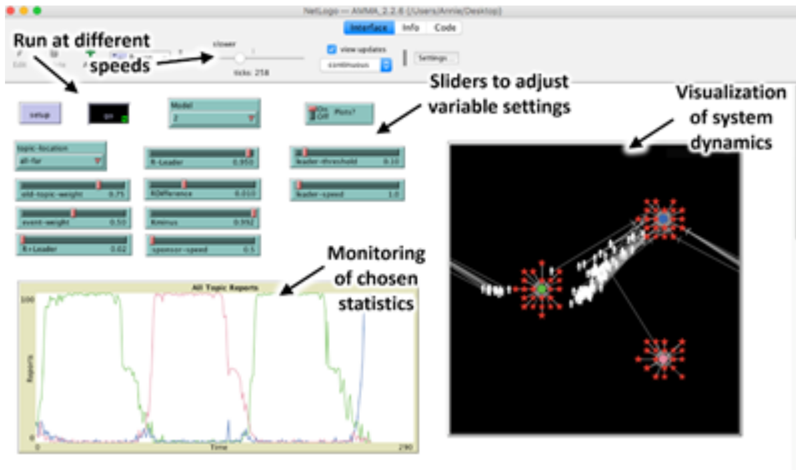

Figure 2. Screenshot of an agent-based model interface in NetLogo to analyze journalists choosing events to report. Circles represent topics, stars represent events, and links signify topic attribution and reports. Related to a study by Waldherr (2014).

Modeling Individual Actors

Many of the first social science simulation models were inspired by models designed to solve computer science and engineering problems; the main building blocks of those models were differential equations and macrolevel factors (Gilbert & Troitzsch, 2005). The increase in computational power allowed those early approaches to become increasingly sophisticated in the mechanisms assumed at the individual level, which encouraged a conceptual transition "from factors to actors" (Macy & Willer, 2002, p. 143). The simulation of individual actors allows the inclusion of diversity and heterogeneity in models, as each actor is a multidimensional variable itself. These more recent models are referred to as agent-based models or multiagent models (Epstein & Axtell, 1996; Wilensky & Rand, 2015), and their strength lies in their ability to provide insights into the emergence of aggregated patterns that arise out of nonlinear dynamics triggered by micro-interactions (Centola & Macy, 2007; Schelling, 2006; Song & Boomgaarden, 2017). This allows researchers to bridge the long-standing distinction between micro and macro approaches to the field of communication, such as the blurring distinction between interpersonal and mass communication (Cappella, 2017). For an example of an agent-based model application, see Figure 2.

Exploring What-If Scenarios and Thought Experiments

Computer simulations allow for the creation of conjectural laboratories where researchers can examine hypothetical situations, identify key regions in the parameter space suitable for empirical experimental manipulation, test experimental treatments that are practically infeasible, and explore the space of theoretical possibilities before undergoing time- and resource-intensive laboratory work (Epstein, 1999; Smaldino, 2017; Smaldino, Calanchini, & Pickett, 2015). One unavoidable limitation of data research (big or small) is that empirical evidence allows us to study only situations that have actually occurred. Predictions based on such data are only useful if the past and the future follow a similar logic (Hilbert, 2015;

Madsen, Flyverbom, Hilbert, & Ruppert, 2016). Observational approaches alone cannot help us understand unprecedented scenarios. Computer simulations, on the other hand, allow for the exploration of what-if scenarios and the wider possibility space within which observed dynamics emerge. In this sense, simulated data are important complements to empirical data and the theoretical implications that can be drawn from their analysis.

Informing Policy Makers and Practitioners

Computational modeling has a long history of informing business and public policy decision making (e.g., Barabba et al., 2002; Homer & Hirsch, 2006; Sterman et al., 2012). What have been called "management flight simulators" allow decision makers to test the effects of potential policies before facing the consequences of implementing them in reality (Sterman, 1992). The development and application of such tools in the field of communication is starting to take off. For example, our increasing understanding of how social networks and social influence shape health outcomes (Shoham et al., 2012) has informed agent-based modeling to test policies for affecting those outcomes (Zhang, Tong, et al., 2015). Likewise, computational models of diffusion have been applied to identify the best "seeds" for spreading messages and behaviors (Banerjee, Chandrasekhar, Duflo, & Jackson, 2013). The science of teams and collective decision making has also benefited from insights collected from simulation models (Lungeanu, Carter, DeChurch, & Contractor, 2018).

Challenges

Joining Data and Theory

While empirical research with digital trace data is often criticized (sometimes unfairly) as purely inductive, descriptive, and lacking theory (boyd & Crawford, 2012; Mahrt & Scharkow, 2013), theoretical research with simulation models has been criticized for focusing on theory and putting too little effort into empirical validation. This computational approach is often seen as being primarily occupied with hypothetical questions (Waldherr & Wijermans, 2013). Both data-driven and theory-driven approaches, however, are clearly complementary rather than competitive. Empirical data offer aid in calibrating the initial conditions of a model and in determining whether the resulting patterns correspond with observed regularities. Efforts are under way to bring together these two strands of computational social science (e.g., Chmiel et al., 2011; Tsvetkova & Macy, 2015; Zhang, Brackbill, Yang, & Centola, 2015), but much more work is needed.

Joining Models and Theory

Today, the vast majority of theories of human communication consists of the scientific strategy to "verbally . . . deduce hypotheses by examining the logical interrelationships among the verbal statements offered by the theory" (Monge & Contractor, 2003, pp. 100–101). Verbal theory is powerful for allowing new interpretations of important phenomena, but it can sometimes be too vague and lead to confusion. This should be especially important in the field of communication, which is notoriously based on the most diverse theoretical traditions (Craig, 1999). Distinguishing and ultimately arbitrating among them can benefit greatly from making the models and their implications precise through formalization. Smaldino (2017) writes:

> [Verbal models] are often a good way to begin an inquiry when the available evidence suggests only some broad type of relationship that might be further refined. The danger with most verbal models is that there are many ways to specify the parts and relationships of a system that are consistent with such a model. Scientific inquiry stalls when data is used to simply support rather than refine a verbal model. Because many different data sets are consistent with a vague verbal model, researchers using such techniques risk lapsing into positing theories that are, by and large, unfalsifiable. (pp. 315–316)

Scholars can build most productively off one another's contributions when they all interpret the contributions in the same way. Because computational models must be specified down to the finest details, they are a key tool for ensuring intersubjectivity, or the stability of interpretation across individuals. For example, using agent-based models to explain social dynamics requires defining a set of simple rules for heterogeneous actors to interact in a given virtual environment "and thereby generate—or 'grow'—the macroscopic regularity from the bottom up" (Epstein, 2008, p. 7). Translating verbal theories into formal theories by writing code and agent rules forces researchers to be more precise with the theory than with approaches based solely on verbal theories, which have traditionally prevailed in communication.

Experimental Research: Virtual Experiments

Computational tools can be helpful for a large variety of experimental designs (Salganik, 2017). Here we focus specifically on virtual experiments, since questions of fundamental interest to communication drove their pioneering designs (Salganik et al., 2006) and are still core to some of the most influential studies (Kramer, Guillory, & Hancock, 2014). Virtual experiments allow for causal inference while improving replicability and illuminating previously unobservable social behavior at the micro, meso, and macro scales.

Two common kinds of virtual experiments are virtual online laboratories and virtual field experiments. Virtual lab experiments use a digital interface to simulate physical laboratory settings in carefully designed online environments (apps as labs), assigning a treatment to different groups and subgroups (as illustrated in Figure 3). In one early exponent of this research approach, a virtual lab was built to show that the ultimate popularity of various products can depend more on early random variation than on the products' intrinsic quality (Salganik et al., 2006; Salganik & Watts, 2008). Methodologically, several researchers have established best practices for building and deploying virtual labs (Mason & Watts, 2010). Increasingly, research is also moving from Web to mobile applications (Zhang, Calabrese, Ding, Liu, & Zhang, 2017).

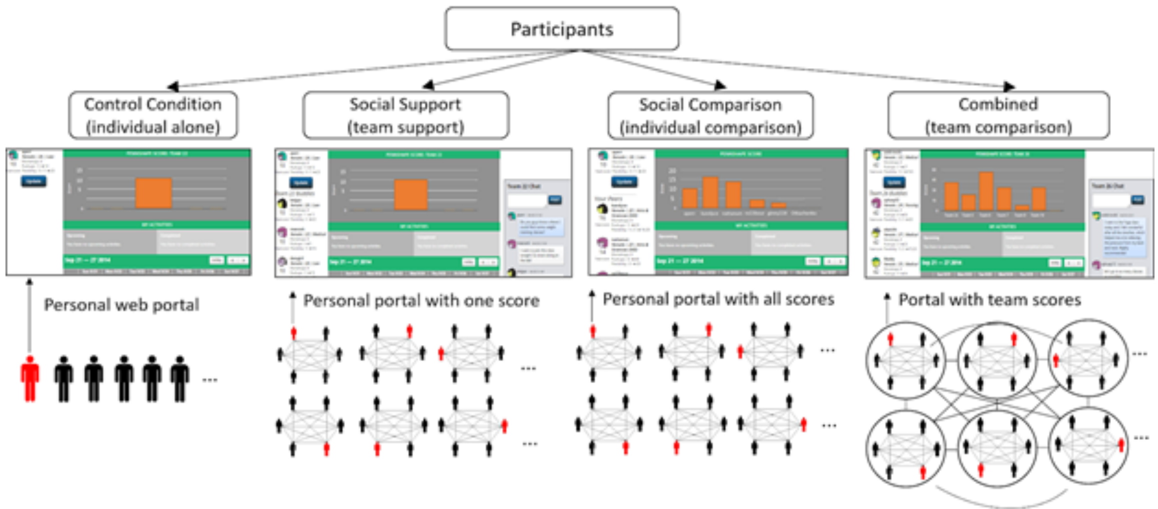

Figure 3. Schematic representation of random assignment to four experimental conditions. Subjects were randomly assigned to different versions of a personalized fitness website that varied the underlying communication networks and social influence incentives. Related to a study by Zhang et al. (2016).

Online field experiments leverage existing digital platforms to study the motivations and behaviors of individuals, organizations, and governments (Castronova et al., 2009; Muise & Pan, 2018; Shen & Williams, 2011). Virtual field experiments are often large in scale. For example, through a virtual field experiment on Facebook, Taylor, Bakshy, and Aral (2013) studied social influence where online content is distributed differentially based on social ties. King, Pan, and Roberts (2014) conducted an online field experiment across 100 social media platforms in China to reverse-engineer censorship decisions across a range of discussion topics and levels of critical content. And Chen, Pan, and Xu (2017) submitted information requests to all county government websites in China, randomly varying the content of the requests to determine what factors increase authoritarian responsiveness. The online setting allowed for unprecedented reach in the design of this experiment (summarized in Figure 4).

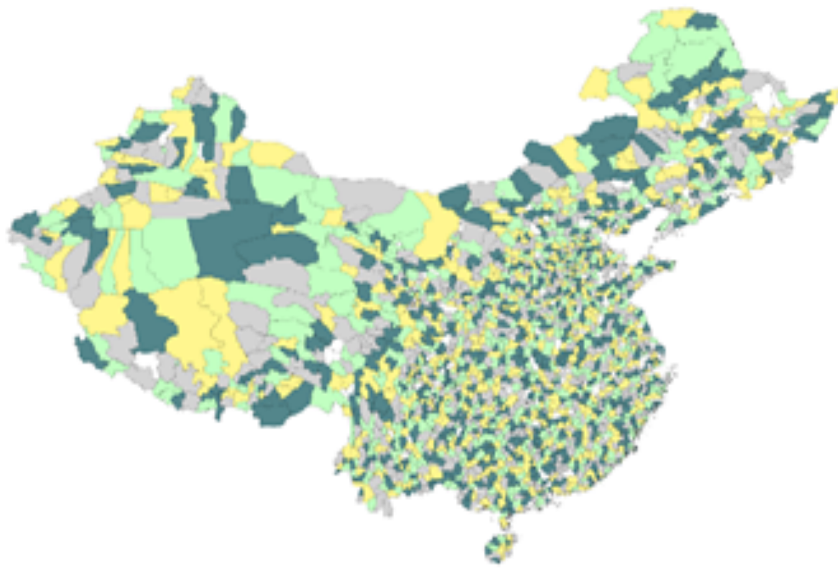

Figure 4. Treatment assignment to all counties in China in a four-condition virtual field experiment. Each color corresponds to a treatment condition. Related to a study by Chen, Pan, and Xu (2017).

Opportunities

Making Scaling Efficient

Virtual experiments improve efficiency at scale. Recruiting efforts in off-line labs that would normally take months can be reduced to days with online crowdsourcing, which often includes more diverse and representative samples. Physical laboratories rarely permit group sizes larger than 12 simultaneous participants, whereas virtual laboratories succeed in recruiting more than 1,200 simultaneously interacting participants (Mao, Mason, Suri, & Watts, 2016). Virtual field experiments can now scale up to the tens of millions (Bakshy, Eckles, Yan, & Rosenn, 2012; Kramer et al., 2014). Services such as Amazon's Mechanical Turk and Volunteer Science and software such as OTree, TurkServer, and NodeGame.js make virtual labs more accessible to researchers without programming experience (Balietti, 2016; Chen, Schonger, & Wickens, 2016; Keegan et al., 2014; Parkes et al., 2012).

Improving External Validity

External validity—the extent to which the results of a study can be generalized to other situations and to other people—is a key constraint facing off-line lab experiments. Virtual labs allow researchers to vary the design of network structures to match external conditions, while virtual field experiments naturally take place on existing social networks and among groups. This methodological feature is difficult, if not impossible, to implement in off-line lab settings.

Understanding Group-Level Behavior

The method of bringing groups of people into the lab was originally developed to test theories of communication (Bavelas, 1950; Christie, Luce, & Macy, 1952; Leavitt, 1951; Luce, 1950). The designs were slow and unwieldy and their results so hard to interpret that, within a few years, researchers made an explicit call to return to experimental designs over simple pairs of individuals (Glanzer & Glaser, 1959). Today, those earlier designs are making a comeback. Simply put, virtual experiments make it possible to obtain data from sufficiently large samples of networked groups, not merely from individuals. For example, virtual experiments have revealed how network topology influences information flows (Centola, 2010; Mason, Jones, & Goldstone, 2008; Salganik et al., 2006; Salganik & Watts, 2008), the evolution of communication over chains of individuals (Bikhchandani, Hirshleifer, & Welch, 1998; Kalish, Griffiths, & Lewandowsky, 2007; Martin, Hutchison, Slessor, Urquhart, Cunningham, & Smith, 2014; Moussaïd, Brighton, & Gaissmaier, 2015), collective intelligence (Lorenz, Rauhut, Schweitzer, & Helbing, 2011; Mao, et al., 2016; Woolley, Chabris, Pentland, Hashmi, & Malone, 2010), collective outcomes (Kearns, Suri, & Montfort, 2006), practical outcomes such as physical activity and health (Zhang et al., 2016), and emotions (Kramer, Guillory, & Hancock, 2014) as well as political choices such as partisanship and voter mobilization (Aral & Walker, 2014; Bakshy et al., 2012; Bond et al., 2012; Coppock & Guess, 2016; Jones, Bond, Bakshy, Eckles, & Fowler,, 2017; Taylor et al., 2013).

Illuminating Previously Unobservable Phenomena

Several researchers have taken advantage of virtual labs to produce time-series data, even in real time (Gureckis et al., 2015; Huff & Tingley, 2015; Salganik et al., 2006). At the same time, virtual field experiments provide a wider variety of data, be it through the combination of different sources or more fine-grained variables. Several novel measures have been developed that encapsulate both time-series dynamics and cross-sectional variety. For instance, see the fine-grained pattern in Figure 4 (Chen et al., 2017) or the causal evidence of temporal virtual field experiments in King et al. (2014).

Challenges

Facing the Replication Crisis

Studies have found that 70% of experimental scientists fail to reproduce at least one other scientist's experiment and 50% fail to reproduce one of their own experiments (Baker, 2016). Two of three psychological experiments cannot be reproduced successfully (Collaboration, 2015). In terms of cost and reach, experimental platforms and the provision of research code have dramatically facilitated the task of replication (Crump, McDonnell, & Gureckis, 2013; Klein et al., 2014), holding the promise that researchers can replicate studies with the click of a button. However, using virtual laboratories also entails a reduction in environmental control, which can threaten internal validity—the extent to which a causal conclusion based on a study is warranted. With virtual experiments, it can be difficult to determine or verify who is participating in the experiment, their level of engagement, heterogeneous cultural backgrounds, common interpretations of the same questions or terms, or even whether the participants are human or artificial. Diversity among subjects can be useful but requires additional methodological safeguards. Additional difficulties may be present for experiments that require simultaneous online coordination as the scope and scale of the experiment expand, which increases the possibility that confounding variables and sample inconsistencies influence outcomes of interest or that the outcomes are not fully captured by the measurement technique.

Violating Assumptions of Causal Inference

Virtual or not, experiments need to control for the adopted statistical assumptions. To generate an unbiased estimate of the causal quantity of interest, the stable unit treatment value assumption must hold. For example, spillover occurs if the treatment administered to some unit is received by another unit for whom the treatment was not intended. Spillover is a particular concern for virtual experiments with social networks, where units receiving treatment may be connected. Various new methods address this issue. For example, cluster-based randomizations are cluster units based on their connections, and treatment conditions are randomly assigned to the cluster level (Aronow & Middleton, 2013; Eckles, Karrer, & Ugander, 2016; Ugander, Karrer, Backstrom, & Kleinberg, 2013). For virtual field experiments conducted on social networks, a growing literature focuses on causal inference and estimation in settings with spillovers (Aronow, 2012; Aronow & Samii, 2017; Athey et al., 2016; Bond et al., 2012; Bowers, Fredrickson, & Panagopoulos, 2012; Christakis & Fowler, 2007; Eckles et al., 2016; Goldenberg, Zheng, Fienberg, & Airoldi, 2010; Rosenbaum, 2007; Tchetgen & VanderWeele, 2012; Toulis & Kao, 2013; Ugander et al., 2013). However, these controls are not yet mainstream and will require additional methodological expansions.

Defining a New Ethical Frontier

Virtual field experiments involve interventions in the real world, and when they are implemented on a massive scale, they have the potential to sway elections and other political, economic, and social outcomes, even when individual-level effects are very small. Many social media firms with the power to run some of the largest-scale experiments do not have ethical practices comparable to academic research—for example, internal review boards, experimental preregistration, creation of replication code and data sets. In 2014, Facebook faced a public relations nightmare when a large-scale experiment was interpreted to imply that Facebook was intentionally manipulating its users' emotions (Kramer, Guillory, & Hancock, 2014). The backlash may have motivated Facebook to create an ethical review process for research at the company as well as an internal court structure for ethical decisions (Jackman & Kanerva, 2016; Seetharaman & Horowitz, 2019). Facebook's first attempts to move past these problems and share with the academic community exposed it to a data laundering scandal, as user data from millions of Americans got into the hands of political operatives from several elections and may be swaying the outcomes of democratic elections (Cadwalladr & Graham-Harrison, 2018). Researchers and review boards alike must carefully weigh benefits and risks when evaluating innovative research designs (Salganik, 2017).

Application: Analyzing Text

This section describes how the complementary computational tools from observational, theoretical, and experimental research have been employed to shed light on one specific field of communication research: analyzing text.

Computer-based content analysis, along with semantic network analysis of textual data, is one of the oldest and most widely adopted computational methods in the field of communication (Stone, Dunphy, Smith, & Ogilvie, 1966) and "places the field of communication at the center of this evolving domain [of computational communication science]" (Shah et al., 2015). Measuring the content of messages is central to studying communication and has informed and cross-fertilized a whole range of disciplines (Krippendorff, 2004). Various natural language processing methods have been developed, including the common keyword extraction combined with frequency and co-occurrence analyses (e.g., Arendt & Karadas, 2017; Danowski, 1993; Diesner, 2015; Doerfel & Barnett, 1999; Miller, 1997; van Atteveldt, 2008) and supervised machine learning to categorize documents according to topics (e.g., Scharkow, 2013) or sentiments (e.g., Ceron, Curini, Iacus, & Porro, 2013). Combining text analysis with network methods has led to advances in understanding semantic networks (Yang & González-Bailón, 2016). More recently, unsupervised topic modeling has been adopted by communication scholars to identify latent topic clusters in text corpora (e.g., Guo, Vargo, Pan, Ding, & Ishwar, 2016; Maier et al., 2018).

Observational Research With More, Complementary, and Cheaper Data

First, in line with our discussion about digital trace data, today researchers can collect data from new platforms such as social media but also from traditional media outlets such as newspapers, whose archives are increasingly digitized—in, for example, the Internet Archive, Google Books, the Cline Center for Democracy archive, and country-specific archives such as the Dutch Royal Library, which dates back to the 17th century. These newly available resources expand the scope of automatic text analysis applications, allowing sophisticated models to be tested on both real-time and historical data. For example, Figure 5 shows the results of visualizing a structural topic model (Roberts et al., 2014) of the inaugural addresses of U.S. presidents, displaying the words used over time organized per topic, allowing for a quick visual exploration of the shifting focus.

Second, at the same time that input corpora are growing, they are also becoming more diverse, such as through computer vision and image recognition. The omnipresent importance of nonverbal communication and images in the field of communication and the large international coverage of image data provide plenty of new opportunities to boost our understanding of human communication, such as for understanding political campaigns (Peng, 2018). The use of deep learning neural networks (LeCun, Bengio, & Hinton, 2015) combined with the possibility to reuse existing pretrained modules (transfer learning) make it possible to create a classification model with relatively few training examples. For example, Casas and Webb Williams (2017) show that classifiers trained on fewer than 10,000 Twitter images succeed at identifying protest events and certain emotions in Twitter images with acceptable accuracy.

Finally, computational techniques allow text miners to alleviate the expensive and labor-intensive task of manually coding (labeling) texts. Coding can be necessary to allow supervised machine learning to link statistical input features (e.g., n-grams and word frequencies, color patterns) to meaningful target outputs (e.g., topic, psychological or moral feature, tone). This type of coding is expensive in terms of manual labor, and it becomes more so when models have to be retrained (or at least revalidated) for new tasks (a process also known as domain adaptation). Computational methods offer two opportunities to alleviate this task.

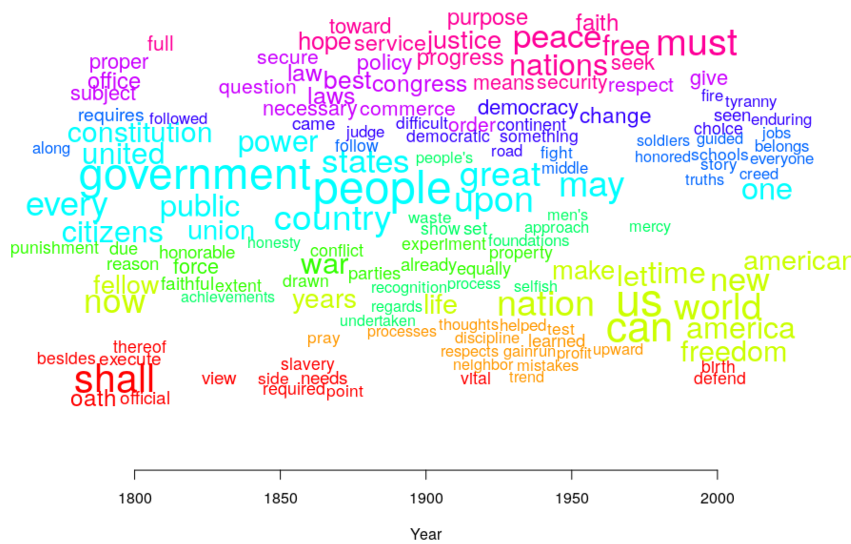

Figure 5. Temporal word cloud of topics in the inaugural addresses of U.S. presidents. The vertical axis and colors show the topic of a word association; the horizontal axis shows modal year of a word occurrence; the word sizes represent their frequency. Adapted from van Atteveldt (2016).

First, the labeling task is lightened because the digital footprint itself often already comes with useful labels, such as online reviews with ratings or expressed sentiment (Pang & Lee, 2008). Moreover, the same crowdsourcing tools for recruiting experiment participants can be used to cheaply and quickly recruit coders. Many complicated coding tasks can be divided into small subtasks that can each be solved without formal coding training. For example, van Atteveldt, Van der Velden, and Fokkens (2017b) report a reliability of kappa > 0.8 for classifying sentiment value and target compared to expert coding with three crowd coders per sentence. Moreover, with crowd coding, it is affordable to get multiple measurements, giving spread as well as point estimates (Benoit, Conway, Lauderdale, Laver, & Mikhaylov, 2016). Tapping into the intuition of the "average" crowd coder might prove advantageous for estimating the meaning of text for the "average" news receiver or communication user (Weber et al., 2018).

Theoretical Research to Build More Complex Models

Analogous to the way complex computer simulations allow bringing together empirical, mathematical, and computational techniques, modern natural language processing combines various lexical, semantic, syntactic, and sometimes pragmatic features to model patterns in texts (Bender, 2013; Jurafsky & Martin, 2008). Starting with empirical analysis, scholars have built a pipeline of methods that can be used with complex models, including full syntactic parsing of empirical input and theoretical modeling of the intended meaning of ambiguous terms (Vossen et al., 2016). For example, van Atteveldt, Sheafer, Shenhav, and Fogel-Dror (2017a) show how the output of preprocessing techniques (rather than raw texts) can be used to analyze conflict coverage, automatically identifying used sources, aggressors, and victims from the syntactic dependency structure.

Computational methods also offer opportunities in modeling other theoretical constructs. Word embeddings capture the meaning of words in preassembled vectors of factor loadings (word2vec), famously finding that if subtracting the vector for Spain from that of Madrid and adding the vector for France, one arrives very close to the vector for Paris, or that "king − man + woman = queen" (Mikolov, Sutskever, Chen, Corrado, & Dean, 2013). This approach shows that semantics can be derived from syntactics. Once one neural net learns some kind of knowledge of this form, these concepts can be copied, pasted, and reused through transfer learning. This theoretical knowledge (stored in the form of vectors in a high-dimensional space) allows researchers to accumulatively create more complex models of meaningful concepts.

Experimental Research With Ethical Challenges

Natural language processing faces the same ethical considerations as other virtual field experiments. Increasingly fractured media consumption patterns require ever more comprehensive and invasive monitoring approaches (Bennett & Iyengar, 2008), and this raises privacy issues. As shown by Kobayashi and Boase (2012), browser plug-ins or mobile phone apps make it possible to gather such data in an ethical way. But even after data gathering issues have been resolved, the subsequent analyses can have unethical consequences, such as discriminatory side effects of content analysis. Machine learning algorithms trained on human texts also quietly learn the stereotypes and prejudices contained in human expressions (Caliskan-Islam, Bryson, & Narayanan, 2016). On a positive note, in a study in which large amounts of text were gathered, it was found that when researchers take special methodological attention, they can dramatically reduce discrimination based on predefined categories (such as race, gender, and religion) while only marginally reducing the accuracy of the machine learning outcome (Bonchi, Hajian, & Castillo, 2016). Algorithms can be much less biased than humans when processing text. However, such desired results have to be constructed actively and are not the default result of mainstream machine learning techniques.

Discussion

Communication as a field is in a privileged position to exploit the computational revolution in the social sciences. Computational approaches offer opportunities to balance observational and experimental research with theoretical models formalized through simulations. Overall, several themes emerge from our review.

Richer, But More Reliable and Verifiable?

Computational methods can yield richer results, but it is not clear that they lead to more reliable and verifiable results. Computational methods allow for the testing of long-standing theories by providing access to previously unobservable patterns, which in turn produce more complex models. At the same time, however, new measurement challenges have emerged, such as biased samples, lack of internal validity, and difficulties in data access. These are serious issues that affect the current replicability crisis. We find two trends in opposite directions. On the one hand, producers of artificial intelligence have started to share their technologies (open AI). For example, techniques like word2vec can be run publicly on Google's TensorFlow interface. However, this is rather like offering an empty brain. On the other hand, companies like Google, Amazon, Facebook, and IBM do not share the artificial brains they have trained over decades to attain fine-tuned knowledge. The data input is not shared. The same is true for scientific research done with unverifiable proprietary data sets (e.g., Bakshy, Messing, & Adamic, 2015). Such restrictions prevent collaboration, validation, and replication (Diesner & Chin, 2016). While computational methods hold the potential to solve some reliability issues (due to larger sample sizes, more realistic experimental settings, and shared code and method workflows), these achievements might be offset by new challenges (systematically biased samples, uncontrollable environments, and proprietary data and algorithms).

New Tools, But New Theories?

Several examples illustrate how new computational tools help amplify, expand, or confirm existing theories by adding empirical evidence and/or models. The methods are useful to test for aspects of theories and to settle contradicting aspects of them. Digital trace data have helped evolve the long-standing two-step flow finding, and they have helped verify that an array of communication dynamics are part of the statistical class of renewal processes. Theoretical computer simulations have helped fine-tune how social networks shape health outcomes, and virtual experiments have expanded existing models of censorship. Besides these important expansions, verifications, calibrations, and corrections, we have not yet seen a full-fledged newly created theoretical framework that can be attributed to contributions made by computational communication science. The need for new theory could be partially motivated by unprecedented communication phenomena. For example, algorithms and bots have started to dominate the personalization of messages (Bakshy et al., 2015), have become a powerful tool for persuasion (Cappella, Yang, & Lee, 2015; Hilbert, Ahmed, Cho, Liu, & Luu, 2018c; Matz, Kosinski, Nave, & Stillwell, 2017), and leave measurable evidence of influence, such as through biased discrimination (Caliskan-Islam et al., 2016; O'Neil, 2017). Bots have already started to influence the communication landscape to a degree that notable different dynamics emerge in some communication spaces, such as collaborative spaces (Müller-Birn, Dobusch, & Herbsleb, 2013), online games (De Paoli, 2017), and elections (Lazer et al., 2018). Until now, computational methods have added evidence to these phenomena, and the digital nature of these dynamics lends itself to the use of computational communication science, but we are not aware of a large-scale theoretical framework that can be mainly attributed to computational approaches. The expectation for such looming breakthroughs stems from the paradigm-shifting role of new methods in theoretical development (Greenwald, 2012).

Practically Relevant, But Ethical?

Our review finds ample evidence that computational approaches can make important contributions to inform practitioners. Real-world settings that provide the sources for digital footprints and virtual field experiments naturally link academic studies to the agendas of public and private actors promoting change. At the same time, some research operates with blurred ethical boundaries. Private and public sector agents can use and abuse computational tools and ignore the conventional ethical guidance followed in most academic research. Content providers constantly A/B test different versions of websites or apps, and intelligence agencies have publicly confessed to illegally using tools of computational social science, knowingly compromising the privacy of citizens. Institutional review boards and researchers are struggling to channel the power of these new tools for social good in research, while a parallel discussion leads to proposals for the creation of an "FDA of algorithms" in North America (Tutt, 2017) and laws such as the "right to explanation" in Europe (i.e., the European Union General Data Protection Regulation, enacted 2016, taking effect 2018).

Scalable Research, But Scalable Researcher Supply?

We find many examples that illustrate how computational science approaches scale research: Big data reaches unprecedented scales by definition; the modular nature of code allows the reuse of parts of computer simulations, adapting models to diverse contexts; and virtual experiments are performed on scales that no brick-and-mortar lab could match. At the same time, it is clear that a new set of skills is required for scholars migrating toward computational research. Typically, social science students are not trained with the required skills to become computational social scientists. This is especially problematic for the field of communication for at least three key reasons—all of which come down to its interdisciplinary nature.

First, the field of communication has roots in both the social sciences and humanities. Curricula are already overloaded with courses that span rhetoric, critical, and journalistic studies; the psychology experimental paradigm and sociological surveys; and statistics, econometrics, and social network analysis. Adding an entire new set of courses seems naïve and impractical. As a result, a large part of computational social science is carried out by students with traditional STEM training (including physics, computer science, and biology). However, those students are missing years of training in social science theory and research questions.

Second, communication as an organized academic discipline is relatively young compared with the other social sciences, and it is sometimes perceived to be less quantitative or rigorous than these other fields. Consequently, computationally inclined scholars may be predisposed toward joining one of the other social science disciplines over communication.

Third, the field of communication has substantial areas of overlap with all the other social sciences, and many potential young scholars could equally find a home in related fields. While many leading communication scholars reside in these other departments and yet maintain a strong connection with the communication community, institutional pressures nudge these researchers toward conferences and journals associated with their home department. Extra effort is needed in the discipline to both train and recruit talent in a highly competitive market. It may require pooling resources among academic departments and programs. In the meantime, most students and scholars gain the required skills in diverse summer schools and workshops, which is a temporary relief but not a sustainable solution.

In sum, the evolution of the field of communication into a computational science comes with the promise to foster the development of in-house, tailor-made methods for the field, but this will not come without a systematic effort to incorporate these methods into the core research agenda. Communication scholars are in a uniquely strategic position to lead the development of the computational approaches that promise to offer novel and exciting insights into the nature of human interactions and the effects of communication for the benefit of the social sciences at large.

Online Appendix of References

An online appendix is available at:

https://osf.io/efuyh/?view_only=3687108daca04fb3b4fa52c6ecc6f451. The appendix contains the complete list of all 215 references cited in this review article. We hope that this extensive list will enable scholars to explore the quickly growing realm of research.

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