Unconventional Methodology in Organization and Management Research

Edited by

Alan Bryman and David A. Buchanan

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Dedicated to the memory of Alan Bryman, 1947—2017

4 Innovations in unobtrusive methods

Andrew P. Knight

Introduction

Twenty years ago, engineer and computer scientist Rosalind Picard (1997, p.228) imagined a future in which 'a financial analyst might combine his cell phone, pager, online stock reports, analysis software, and personal email agent into one computer that fits in a belt, watch and shirt pocket'. Clearly the future is now. An estimated 1.4 billion people owned a smartphone in 2013—more than one fifth of the global population (Heggestuen, 2013). By 2020, that proportion is expected to rise to approximately 70 per cent (Ericsson, 2015). And smartphones are just the tip of the iceberg, as a proliferation of internet-connected devices expands the linkages among humans, computers, and networks. Consider just a few of the devices released recently. Glasses developed by companies like Google and Snap enable users to capture and share multimedia content in real-time; wristbands like those developed by Fitbit, Apple, and Samsung facilitate fitness tracking, payments, and more.

The ubiquity of connected devices (Swan, 2012)—and the metrics that they unobtrusively capture—has led data to become increasingly central to the global economy. Companies have integrated novel unobtrusive data streams into their business models and operations (e.g. Walker, 2012; Wilson, 2013). These data streams can elucidate consumer preferences and responses to advertising, enhance human resource practices, and improve collaboration networks—to name just a few publicized applications.

Much like new data streams have enriched contemporary businesses, innovative unobtrusive methods hold great promise for researchers who study organizational functioning (Tonidandel et al., 2016). The idea that researchers can benefit from using unobtrusive methods is certainly not new. More than half a century ago, Webb and colleagues (1966) implored researchers in their classic book *Unobtrusive Measures* to use a more diverse set of data streams in their work, noting that, 'Today the dominant mass of social science research is based upon interviews and questionnaires. We lament this overdependence upon a single fallible method' (pp.1–2). Notwithstanding a steady drumbeat of pleas over the years for researchers to use

unobtrusive methods (e.g. Hill et al., 2014; Webb and Weick, 1979), survey methods continue to dominate the literature, especially in organizational behaviour, and researchers still often rely on a single data source (Podsakoff et al., 2012; Scandura and Williams, 2000).

The purpose of this chapter is to describe a new suite of unobtrusive methods, such as the traces that people leave throughout the digital world as they search the Internet, post content on social media, and navigate an increasingly digitally connected physical world. These methods, which did not exist when Webb and colleagues published their book, make it easier and cheaper for researchers to use unobtrusive methods than ever before. As a result, we social science researchers have fewer and fewer excuses for relying on a single source of data, obtrusively acquired, in empirical studies.

I begin by discussing three ways that new unobtrusive methods can enrich organizational research. Then, I explain why now is a propitious time for these methods to become ubiquitous. After discussing these broader issues, I detail five new unobtrusive methods and describe how researchers have used them in recent work. I conclude by offering some caveats and cautions, as well as a few recommendations, for using new unobtrusive methods.

The value of new unobtrusive methods

As with learning any new method or statistical approach, learning a new unobtrusive method will require an investment of time and energy. Why might one make this investment and adopt one of the methods described in this chapter? The unobtrusive methods described below can add value to almost any research programme in several ways.

First, several of these methods sidestep reactance effects—alterations in participants' cognitions, attitudes, or behaviours as a result of their awareness that someone is studying them. Survey methods are particularly vulnerable to reactance effects. Consider, for example, Schwarz's (1999) commentary on how subtle survey elements, such as introductory prompts or terminology, can alter participants' responses. The new unobtrusive methods are not completely immune to reactance effects; participants might alter their behaviour in substantive ways if they know that computer programmes or wearable sensors are recording what they do. However, these methods are not vulnerable to reactance effects in the same way as survey methods. Accordingly, data collected through the methods described in this chapter can help to triangulate on valid effects.

Second, researchers can benefit from using these methods to examine dynamics—how and why phenomena change over time. Several commentators have noted the dearth of research in organizational behaviour that examines and models patterns of change (e.g. Cronin et al., 2011). One reason underlying the lack of research on dynamics is that the dominant approach for data collection—the self-report survey—is not amenable to frequent administration. Because unobtrusive methods do not require a participant to consciously respond to a question, they can be particularly useful for recording a continuous stream of data over time (e.g. Kozlowski et al., 2016). To use an analogy, the measurement approaches frequently used in organizational research today provide static photographs of behaviour; novel unobtrusive methods, in contrast, can provide dynamic movies that enable researchers to analyse phenomena in motion.

Third, novel unobtrusive methods help researchers expand the scale of their investigations. Several of these methods passively record phenomena using technology that is already widely disseminated (e.g. web browser, smartphone). The cost of repurposing technologies that are already in people's hands for research is relatively low and affords the opportunity to expand the scale of an investigation with respect to context and to time. Expanding the scale of research with respect to context—collecting data across larger and more diverse sets of groups, organizations, industries, and cultures—is useful for addressing calls for research that accounts for the role of context (Cappelli and Sherer, 1991; House et al., 1995; Johns, 2006). Expanding the scale of research with respect to time—collecting data across longer time horizons—is useful for addressing fundamental questions of change, such as how organizations grow and develop, or wither and die, over time.

A propitious time for unobtrusive methods

The time is ripe for researchers to reap the benefits of unobtrusive methods. Much has changed in the fifty years since Webb et al. published their influential book. The methods that they proposed in the 1960s were costly, requiring major investments of time and resources in data collection and analysis. Consider how time intensive it would be to manually track the wear on carpet tiles at a museum to understand consumer preferences. The cumbersome nature of unobtrusive methods in the past limited their feasibility.

Several technological developments have made unobtrusive methods more accessible than they were fifty years ago. First, there has been a steady march of miniaturization in computer-driven devices. Around the time Webb and colleagues published their book, Intel co-founder Gordon Moore (1965) predicted that there would be exponential growth in the number of transistors that could be squeezed onto each square inch of an integrated circuit, with the number doubling every year. This prediction—'Moore's Law'—largely came to fruition over the subsequent decade, and a steady march of increasing computing power has continued ever since. One by-product of Moore's Law has been the miniaturization of computing devices. The room-sized computers of the 1950s became the desktop computers of the 1980s and 1990s; the desktop computers of the 1990s became the pocket computers of the 2000s. We have gone from having a single computer for an entire business, to a computer on everyone's desk, to a computer in every pocket and, increasingly, a computer on every wrist. This proliferation of devices provides a means for capturing behaviour in new unobtrusive ways.

A second development, supported by miniaturization, is enhanced precision and affordability of a variety of sensors, contributing to the widespread deployment of sensors throughout society. As an example of this growth in the deployment of sensors, consider the technological trajectory of the Samsung Galaxy S smartphone from its debut in 2010 through the Galaxy S6 model released in 2015 (Fitchard, 2016). Embedded in the original Galaxy S were about a dozen sensors, such as an accelerometer, proximity sensor, and magnetometer. The number of sensors nearly doubled over the next five years, with the Galaxy S6 adding a pedometer, barometer, gyroscope, and heart rate monitor. The inclusion of such sensors in devices carried by millions of people provides researchers with the ability to unobtrusively measure behaviour in new ways. The Galaxy smartphone is just one illustration of the diffusion of sensors throughout society. From networked thermostats to connected office lights, sensors are everywhere, capturing and storing data that could be of use to researchers (Swan, 2012). This trend continues to grow; it has been estimated that a self-driving car will generate 100 gigabytes of data a second (*The Economist*, 2017).

A third development is the ubiquity of networked computers. Over the past two decades the Internet has become interwoven with business and society. Beyond just laptop computers and smartphones, we increasingly live in a world that is the Internet of Things, in which devices communicate regularly not just with us but with other devices. Concordant with interconnectivity is regular logging of activity on computing networks, resulting in a staggering volume of information being stored about the everyday environment that surrounds us. Consider a contemporary office. As workers arrive and swipe magnetic cards to enter elevators and offices, their movements are tracked. Wireless network beacons in the ceiling record pings as their smartphones request access to the network. Networked cameras unobtrusively capture video streams of parking lots, entry ways, and stairwells. The exponential growth in connected devices—and the consequent growing reliance on connectivity to accomplish daily tasks—makes available to researchers a wealth of unobtrusively collected data.

A fourth development is the increasing standardization of protocols and methods for providing data access to third parties. Standardization is essential to manage the scale of data currently collected and stored in organizations. Further, standardization is essential to enable computers to communicate with one another and facilitate the growth in interconnectivity described above. The value of standardization is evident in the proliferation of application programming interfaces (APIs)—pathways for third parties to interact with an application—in many software applications. As one example, the technology company Garmin has an API for its fitness tracking application. Through the API, and with the user's consent, other applications can access and display a user's stream of fitness activities. Standardization of database structures and methods for accessing data, like this one, can also enable researchers to more easily use data.

A fifth development is the increasing availability of computational resources—hardware and software—to process the large datasets created by these technologies. Compared to limited access in the 1960s, researchers today have at their fingers the computational horsepower needed to process and analyse large datasets. Computing power has grown exponentially since the 1960s, increasing roughly by a factor of a trillion. The computing power that many people today carry around in their pockets equals or exceeds the supercomputers used in the 1980s. And in addition to hardware advances, researchers have easy access to algorithms to process large data sets. The R project (R Core Team, 2015) is one example of how the open source software movement, along with the dissemination of tutorials and guidance through online forums and courses, has given researchers the tools needed to make sense of large-scale data streams.

Webb et al. (1966) were ahead of their time. But in the years since their plea for researchers to complement surveys with unobtrusive methods, the technological landscape has changed. Together, the five factors described above reduce the costs of using unobtrusive methods and make now a propitious time for the diffusion of these methods.

New unobtrusive methods

Webb and colleagues described five categories of unobtrusive methods, giving examples of and ideas for how these methods could be used in research. Using their categories as a starting point, I describe a suite of new unobtrusive methods that are amenable for use by researchers today. Table 4.1 gives an overview of these methods. Although these methods are presented within discrete categories, these are in reality not mutually exclusive. A given method can (and often does) fit multiple categories, stemming from the interdependence of the physical and digital worlds today, as well as the fact that data are central to the functioning of most contemporary organizations.

Table 4.1 New unobtrusive measures

type	classic measures (Webb et al., 1966)	new measures	background and example articles
trace data	datasets created using traces left in the physical world through the erosion or accretion of physical material	datasets created using traces left in the digital world by people's navigation of their physical and digital environments	Dai et al. (2014); Kosinski et al. (2015); Park et al. (2015); Wang et al. (2016)
public archival data	datasets compiled using information routinely collected and made public by, generally, government entities	datasets compiled by the government and made widely-available and easily-accessed via the public Internet	Barnes et al. (2015); Bianchi (2016); Harrington and Gelfand (2014)
private archival data	datasets compiled using information routinely collected, but held privately, by entities like for-profit corporations	datasets created using information routinely collected, but held privately, by private entities' information-technology systems	Jackman and Kanerva (2016); Kleinbaum et al. (2013); Pierce et al. (2015); Saavedra et al. (2011); Staats et al. (2016)
simple observation	datasets created by systematically and manually coding people's public and observable behaviour	datasets created by recording attributes of people's affect and behaviour using wearable sensors and devices	Chaffin et al. (2017); Ingram and Morris (2007); Kim et al. (2012); Knight and Baer (2014); Swan (2012)
contrived observation	datasets created by systematically and manually coding video or audio recordings of people's behaviour in structured situations	datasets created by automatically coding, using computers, video or audio recordings of people's behaviour or textual content	Barsade et al. (2015); Kosinski et al. (2016); Li et al. (2015); Woolley et al. (2016)

TRACES: FROM PHYSICAL TO DIGITAL

The physical traces that people leave throughout the world are evidence of their behaviour. In addition to these traces—like wearing down carpet tiles in a museum—people today leave traces throughout the digital world. Digital traces reflect the data streams that result from the logging of people's behaviour—in both the physical and digital worlds—in digital data streams.

To appreciate the potential of digital trace data, imagine some of the moments that can now be unobtrusively captured in a slice of a typical day. Your day might begin with a smartphone buzzing to awaken you. As you move to silence the alarm, the device records what time you begin your day. It is possible that the device has been tracking your sleep, marking when you are in deep sleep and when you are restless, throughout the night. Fast forward to your arrival at your workplace. To enter your building you hold your identification badge, which has an embedded radio frequency identifier (RFID) tag, up to a reader. The networked reader logs your entry and opens the door.

Minutes later, when you sign into your computer, your presence at your desk is recorded and logged. Meanwhile, your smartphone has been pinging wireless beacons in the ceiling, leaving the footprints of your smartphone in the network's logs.

As this illustrates, many behaviours leave traces throughout the digital world, enabling researchers to measure time usage, physical location, and more. Researchers have recently begun to leverage the power of digital trace data to understand a wide range of phenomena. For example, Dai et al. (2014) used digital trace data to study how temporal landmarks prompt individuals to engage in aspirational behaviour. Partnering with a university, the authors gained access to records of how frequently students used the university's fitness centre. Attendance was unobtrusively tracked as students swiped magnetic identification cards to enter the centre. Focusing on a delimited time period, this yielded data on fitness behaviour for nearly 12,000 people for more than 400 days—a dataset with more than 5 million observations. Because the central question of the investigation was how temporal landmarks induce changes in aspirational behaviour, having a continuous record of behaviour over time was essential. Findings showed that individuals do engage in more aspirational goal-directed behaviour when they encounter temporal landmarks such as New Year's Day.

A second example concerns the study of handwashing behaviour in hospitals by Staats et al. (2016). The researchers partnered with a supplier of technology that monitors handwashing behaviour to understand how the implementation of a monitoring system influences caregivers' compliance with handwashing standards. The monitoring system used RFID tags—one worn by caregivers and a second attached to handwashing stations—to record valid opportunities for handwashing (i.e. times when providers should wash their hands because, for example, they are entering a patient's room) and actual handwashing behaviour (i.e. times when providers washed their hands in a way compliant with standards). Staats et al. (2016) examined a rich dataset tracking handwashing behaviour across time in a set of hospitals that had implemented the technology. In total, the multilevel dataset contained records for more than 5,000 caregivers working in 71 units of 42 hospitals for two and a half years. Because handwashing opportunities were timestamped, there were more than 19 million observations in the dataset. Illustrating the value of this data stream, Staats et al. (2016) examined the effect of having the system activated (i.e. compliance would be tracked and monitored by management) and the effect of having the system deactivated (i.e. compliance would be tracked, but not monitored by management). The record of behaviour over time enabled the researchers to answer questions about how workers' behaviour changed in response to a monitoring system; monitoring increased compliance, but continued compliance was dependent on sustained management attention.

Both Dai et al. (2014) and Staats et al. (2016) illustrate the power of using digital trace data to understand organizational phenomena. In particular, these studies show the utility of digital trace data for unpacking phenomena over theoretically meaningful time horizons and at a scale that would be difficult to accomplish using more traditional research methods.

PUBLIC ARCHIVES: FROM CUMBERSOME TO CLICKABLE

Researchers have long benefited from archival data collected by government entities. Webb et al. recognized the value of this type of archival data, highlighting it as an unobtrusive data stream that could complement survey data. One benefit of public archival data is that the government bears the cost of collection and maintenance. But a major hurdle to using such data in the past was the transaction cost of data access. However, the rise of the Internet—and a push for transparency in some societies—has now made many valuable public archival datasets easily accessible. Rather than mailing a request for a dataset and waiting months to receive disks, researchers can now access data easily using government websites. In the United States, for example, researchers can access datasets regularly collected by—to name a few—the Bureau of Labor Statistics, the Census Bureau, and the Social Security Administration. Many agency websites provide links to download databases, along with data dictionaries and guidance.

Bianchi's (2016) investigation of the connection between the state of the economy and individualism provides several examples of using publicly available and easily accessed data via the Internet. First, she used data on the state of the economy, operationalized as the annual unemployment rate, provided by the United States Bureau of Labor Statistics via the Internet. Bianchi (2016) linked unemployment data with several other publicly available datasets, which she used to measure individualism in different ways and over long time horizons. In one study, she used data on baby names between 1948 and 2014 provided by the United States Social Security Administration. Bianchi (2016) operationalized individualism as the use of relatively unusual, compared to more commonplace, baby names. Linking name data with unemployment rates enabled Bianchi to show—using a dataset comprising more than a quarter of a billion observations—that American parents selected unique names for their babies more frequently during economically prosperous years.

In a second study, Bianchi (2016) analysed the lyrical content of American popular music over nearly 35 years. She accessed the lyrics of songs on the Internet and used the Linguistic Inquiry Word Count software (Pennebaker et al., 2007) to measure the proportion of lyric words that were first-person singular (indicating higher individualism) versus first-person plural (indicating lower individualism). First-person singular words are, for example, 'I' and 'Me'; first-person plural words include, for example, 'We' and 'Us'. Bianchi (2016) examined covariation between pronoun usage and the state of the economy over time, finding that in prosperous years song lyrics were more individualistic.

These studies illustrate a key benefit of publicly available archival data (aside from the fact that the government bears the cost of collecting and maintaining the data). Many public archival datasets track the same metric over a large scale (i.e. across a large number of people) and over a long time horizon (e.g. across decades). Each of these properties is useful for understanding how more macro contextual trends might influence behaviour.

PRIVATE ARCHIVES: FROM PERSONNEL TO INFORMATION TECHNOLOGY

Webb et al. distinguished between archival datasets held by the government and archival datasets compiled and maintained by private entities, such as personnel data on turnover or absenteeism within a private corporation. In the years since their book, the nature of private archival data has changed dramatically. Whereas in the past private archival data were limited in scope and in scale, many organizations today collect and store vast amounts of data in their daily operations. Also driven by the developments described above, the locus of work in many organizations has shifted from face to face and physical to virtual and digital. This trend is evident if you consider how researchers work today. Whereas accessing an article in the past required a trip to the library, researchers can now log into their library through a web browser and download an article at their own desk. Whereas editing a manuscript with a colleague in the past required mailing and marking up a physical copy, researchers today can collaborate on a digital file in the cloud. And whereas the journal review process in the past required printing and mailing hard copies, researchers today can upload digital files to Internet-based applications that coordinate the review process. All of these activities are tracked and stored in digital private archives that could be used in research.

For example, Saavedra et al. (2011) partnered with a stock trading firm focused on day trading. Partially due to regulations requiring the firm to capture trading behaviour and traders' communications, the firm's information technology systems offered the potential to examine how patterns of communications might influence the pattern of decision making across traders. The researchers examined the emergence of synchronous trading and the performance implications of making a trade either before or after the synchronous trading of most other people. Further, the researchers also examined how communication patterns among traders relate to the emergence of synchrony. Saavedra et al. (2011) gained access to two data archives, focused on sixty-six employees over roughly a year and a half. The first data source comprised more than a million live trades, captured on a second-by-second basis. The second data source contained 2 million messages sent via an instant messaging system. Because, like trading activity, messages were timestamped, the researchers could examine second-by-second communication and trading behaviour. Their results revealed several fascinating aspects of synchronous behaviour in a real-world setting. This study illustrates how the data that private corporations routinely collect and store through information technology systems can help understand dynamic interpersonal phenomena.

Also illustrating the value of private archival data, Pierce et al. (2015) partnered with a vendor of a point of sale (POS) system used by staff in restaurants to, among other tasks, enter customers' orders and send them to the kitchen, prepare customers' bills, and process customers' payments. The POS system captured a running record of activities that the restaurants used in their operations (e.g. for inventory, marketing). The research centred on how the activation of a theft-monitoring module in the POS influenced employees' behaviour. Using a proprietary algorithm, this module flagged actions by employees that likely constituted theft. The researchers identified a sample of nearly 400 restaurant locations that had, at some point in a two-year window, activated the theft-monitoring module. Importantly, the module could be applied to historical data even if it had not been activated at the time the data were initially captured; so, the authors could examine how the implementation of the monitoring module influenced employees' behaviour and outcomes, such as losses, revenue, and tips. Exemplifying the power of novel unobtrusive methods, the data were multilevel and permitted a fine-grained analysis. The researchers examined revenue and tips at the employee-week level of analysis (i.e. average revenue and tips for each worker on a weekly basis) and also at higher levels of analysis, such as the restaurant level over time. The dataset contained data on the behaviour of more than 22,000 employees, yielding a dataset with more than 400,000 weekly observations. Results showed that how a monitoring system changes workers' behaviour is complex, possibly leading workers to invest additional effort in productive activities to secure higher tips from customers.

Private archival data offers researchers many of the same benefits as public archival data. Working with private entities may also offer the advantage of customizing an unobtrusive method to focus on or capture something of particular interest to a researcher. Both of the examples above show the importance of close collaborations with private entities—collaborations enhanced when researchers study problems of interest to the private entities.

SIMPLE OBSERVATION: FROM PEN AND PAPER TO WEARABLE SENSORS

The kind of simple observation that Webb et al. described—watching and recording notes or measurements of behaviour over time—is costly to implement. Because capturing data in this way requires researchers to spend time directly observing others, the time required to collect data is a multiple of the number of observations and the amount of time subjects are watched. Given these costs, simple observation has been used relatively sparingly in organizational research. The technological developments described above, however, have facilitated a new form of 'observation', in which the observer is not a researcher, but a wearable device comprising sensors. Devices with sensors are ubiquitous, exemplified by the smartphones that more than a billion people now own. In addition to devices designed and manufactured for consumers, engineers and researchers have developed devices specifically for research. For example, one multidisciplinary team has developed a wearable sensor platform to continuously assess team dynamics, such as the development of cohesion over time (e.g. Kozlowski, 2015). A second team (Kim et al., 2012) has developed a device with a set of sensors (e.g. microphones, Bluetooth, infrared) to map social networks.

In one early application of this technology, Ingram and Morris (2007) used a wearable sensor to study interpersonal dynamics during professional 'mixers'—events organized to facilitate relationship formation. The authors were specifically interested in the degree to which mixers fulfil their stated purpose of sparking relationships between previously unfamiliar people. In the study, ninety-two members of an executive MBA program wore devices around their necks during a roughly 90-minute networking event. The devices used infrared sensors to record when two devices were facing one another, as would happen during a face-to-face conversation. The authors operationalized a meaningful conversation between two people as an instance when the infrared sensors of two badges detected one another continuously for one minute. Wearable sensors enabled Ingram and Morris (2007) to address questions that a traditional survey-based approach cannot answer. For example, having a continuous record of interactions enabled the authors to examine the temporal dynamics of homophily. They found that homophily effects are strongest early in a networking event, but that heterophily becomes more common as the event progresses. Addressing such a question using a survey would require participants to document their conversations throughout the evening—a task that would interfere with their networking.

As a second example, Knight and Baer (2014) used a wearable sensor to study how physical space influences group dynamics, proposing that groups produce more creative ideas when working in a non-sedentary space, which induces them to stand, than when working seated around a conference room

table. Standing, they argued, leads to elevated levels of group arousal and lower levels of territorial behaviour—expressions of possessiveness over contributions to the group. Together, activation and territoriality influence the creativity of the group by shaping how much people collaboratively build upon one another's ideas. To measure arousal, participants wore a wrist-based device that measured electrodermal activity. The devices that Knight and Baer (2014) used (see Poh et al., 2010) recorded individuals' physiological arousal eight times per second. This example illustrates two benefits of wearable sensors. First, the use of a wearable device allows researchers to track information that may not be accessible to participants. Second, a sensor can provide continuous measurement over time.

Wearable devices range in how unobtrusive they are—something that is in the eye of the beholder. The devices described above are on the more obtrusive side of the continuum, given that they were specifically deployed for the purposes of the investigation. In thinking about how obtrusive a given device is, it is important to consider the degree to which wearing the device is a routine for research participants. The more that wearing the device is a part of daily life—such as an activity tracker that one regularly wears or a smartphone carried in a pocket—the less obtrusive the research is likely to be.

CONTRIVED OBSERVATION: FROM MANUAL TO COMPUTER-ASSISTED CODING OF RECORDINGS

Webb et al. described a second kind of observation—involving the use of video and audio recordings—which they referred to as contrived observation. The use of recording devices can reduce the costs of data collection, since multiple devices can be used to collect data over time and across situations. However, the use of recording devices introduces the additional challenge of making sense of what has been recorded. Traditionally, researchers have employed teams of trained coders to transform recorded material into standardized measures of constructs. Accordingly, the costs of observation shift; rather than observing behaviour in real-time, researchers must observe behaviour on recordings. Several recent innovations, however, have enabled researchers to more efficiently make sense of data in the form of audio and video recordings. Through the application of machine learning, computer scientists and researchers have developed algorithms that can score audio, video, and text data automatically. Although improvements in microphones and video cameras have enhanced the precision of the raw inputs, software—developments in machine learning—is the underlying engine of these new methods.

The study of the dynamics of emotional contagion by Barsade et al. (2015) provides one illustration of the use of computer-assisted coding. The researchers sought to test predictions regarding how the emotional expressions of in-group and out-group members might differentially influence people. The authors postulated that congruent contagion—in which one person's expressions mirror another person's—would occur from exposure to an in-group member, but counter contagion—when one person's expressions are opposite another person's—would occur from exposure to an out-group member. This study used computer-facilitated coding of research participants' facial expressions to precisely track the timing of individuals' facial expressions in response to an experimentally manipulated stimulus. Using software called *Noldus FaceReader 5*, the authors captured participants' emotional expressions in real-time using a camera mounted on top of the computer that the participants used to view video-based stimuli. *FaceReader* detects changes in several hundred points on the face. Using this facial mapping, the software classifies individuals' facial expressions into a set of standard emotions, such as happiness, sadness, surprise, fear, and disgust. This study illustrates how new technology can ease the burden of converting video recordings into usable data to answer theoretically grounded research questions.

The study of competition, group composition, and collective intelligence by Woolley et al. (2016) offers a second example of this new form of contrived observation. The researchers' laboratory study examined how competition among group members influences collective intelligence in different ways, depending on the group's gender composition. The researchers used group members' conversations to measure competition, operationalized as the frequency with which members interrupted one another. Each group member wore a headset with a microphone, which recorded each person's contributions to the group. Illustrating the utility of computer-assisted coding, the authors used algorithms to transform the digitized audio stream into a time series dataset with a binary indicator of whether a given group member was speaking at a given point in time. This time series dataset was then used to construct measures of speaking patterns within the group, including times when one person interrupted another's speech. This study shows the value of using computer algorithms to efficiently process audio recordings of interpersonal interactions.

Similar computer-assisted approaches are also increasingly used to reduce the costs of coding textual data, and processing data from digital traces of behaviour, shown in the aforementioned Bianchi (2016) study. As an additional example, Kosinski et al. (2015, 2016) illustrate how algorithms can help code data captured through new unobtrusive methods. To date, their work has focused principally on the use of textual digital trace data and traces left on websites like Facebook. In one study, Kosinski et al. (2013) showed that personal characteristics—demographic attributes, political orientation, and sexual orientation—can be inferred from an individual's behavioural ratings of content on Facebook (i.e. 'likes'). Similarly, Park et al. (2015) used computer-assisted coding of the text of individuals' social media posts to

measure personality according to The Big 5 taxonomy. The authors demonstrated the reliability and validity of the computer-coded approach, connecting this language-based measure to scores produced through a traditional survey-based approach. This stream of work highlights how computer-assisted coding can streamline methods that were onerous and time-consuming in the past.

Caveats, cautions, and recommendations for using new unobtrusive methods

New unobtrusive methods clearly present many opportunities for researchers. Yet, because of the novelty of these methods, several caveats are necessary. Before embarking on using a new unobtrusive method, researchers should consider issues of requisite expertise, measurement validity, and research ethics.

ACQUIRING REQUISITE EXPERTISE

Researchers using a new unobtrusive method must carefully consider whether they possess the knowledge, skills, and expertise needed to use the method effectively and efficiently. Several approaches, involving sensors and computer-assisted coding, for example, require specialized expertise. To use these methods effectively a researcher would benefit from having deep knowledge of specifically how the technology interacts with the human body, or with external signals of interpersonal behaviour. For example, understanding how a Bluetooth sensor measures interpersonal interactions (i.e. through the strength of the signal connecting two devices) can help in understanding why interactions may seem under- or over-detected in different environments. For some methods, the necessary expertise transcends the technology itself. Because these methods often capture considerable volumes of data over time, benefiting from a new unobtrusive method likely requires a set of skills that are not as critical when using smaller-scale datasets. With large-scale datasets, tasks like database maintenance and data manipulation are impossible if a researcher is not a skilled computer programmer. Programming skills are essential for efficiency and to minimize error.

Given the depth of expertise required for some of these methods, researchers interested in using a new unobtrusive method would benefit from collaborations with domain experts. Multidisciplinary teams can help organizational researchers (and technologists) climb the steep learning curve of a new method. Indeed, a number of the exemplar papers described above resulted from the work of multidisciplinary teams of social scientists, computer scientists, and engineers.

ADDRESSING MEASUREMENT VALIDITY

Because these methods are relatively new, it is imperative that researchers adopt a healthy scepticism regarding measurement validity; reviewers certainly will. Scholars (e.g. Daft, 1995) have noted that lack of evidence for measurement validity—even for established measures—is a common reason that papers are rejected by management journals. When a measure is new and without a track record of use, demonstrating validity is paramount. To provide confidence in the validity of a new unobtrusive measure, researchers should follow the same process used to validate any measure (e.g. Edwards, 2003). At a high level, it is important to connect clearly the conceptual definition of the construct with the operationalization of that construct. To do so, it helps to map the causal model that connects a latent construct with a concrete indicator (Borsboom et al., 2004; Edwards and Bagozzi, 2000). Further, and especially for new measures, evidence of convergent and divergent validity can build confidence that the measure assesses what it is intended to assess. Existing measures, such as surveys, can be useful in this process. However, one must remain open to the idea that an unobtrusive measure may show a weak link with an obtrusive one. This does not necessarily mean that the new measure is flawed; indeed, it could be that the new measure reveals the flaws or idiosyncrasies of established approaches. Social network researchers, for example, have shown that there are differences between email-based network measures and survey-based network measures. These differences do not necessarily invalidate an email-based method. It is incumbent on the researcher, however, to explain why email is the right measure given the interpersonal interactions being studied.

Validating a new measure is especially important when using new technologies. Illustrating the importance of in-depth and systematic validation of a new unobtrusive method, Chaffin et al. (2017) examined the measurement properties of one type of wearable device designed to track interpersonal interactions (Kim et al., 2012). Chaffin et al. (2017) used several carefully controlled studies to examine the measurement properties of a subset of the sensors in the device. For example, they attached devices to easels and manipulated the distance separating the easels, comparing the physical distance to the output of the device. Their findings raised concerns about the reliability and validity of the sensors for assessing interpersonal interactions. Given that these tests were conducted under controlled conditions, these problems could be exacerbated in field applications.

Findings such as those generated by Chaffin et al. (2017) underscore the fact that exciting new technologies do not sidestep old standards of measure validation. When considering a new unobtrusive method, it is imperative to question how well the measurement properties of the method have been tested, what might be required to instil confidence in the validity of the measure, and—of course—how closely the measure fits with the phenomenon under examination. If systematic validation of an archival data source is not possible, it is advisable to use several different measures to triangulate on the phenomenon of interest. This is precisely the approach used in several studies described above, such as Bianchi (2016) who used baby names, song lyrics, and more to measure individualism. Any one indicator is insufficient. By packaging them together, however, Bianchi (2016) builds confidence that her conclusions are not due to measurement artefacts.

CONTENDING WITH AMBIGUOUS ETHICAL STANDARDS

A third issue requiring special consideration when using a new unobtrusive method is research ethics. Researchers should, of course, always consider the ethics of their design and measurement approaches. New methods require special attention, however. Compared to established methods for which researchers and Institutional Review Boards (IRBs) have decades of experience, formal policies, and established norms, new methods break new ethical ground. For unobtrusive methods, this is often with respect to issues of informed consent and privacy. Many of the methods described above—and especially the use of digital trace and archival data—are riddled with ethical grey areas.

Consider a recent examination of contagion using data from Facebook (Kramer et al., 2014). The authors partnered with Facebook specifically to study how exposure to posts with different affective tones influences users' behaviour. The design involved manipulating the prevalence with which a subset of Facebook users viewed relatively positive or relatively negative information. Although the users did not provide informed consent for this research study, they had agreed to Facebook's terms of use, which allow Facebook to shape information feeds. This kind of manipulation of content (and design) is ubiquitous in web and mobile applications. Does the fact that Facebook regularly manipulates content eliminate the need for researchers to seek informed consent? In this case, the authors' IRB determined that because the researchers were working with Facebook, the study did not fall under its purview.

Nevertheless, the study generated considerable controversy and led several commentators to argue that it violated research ethics. The editor of the *Proceedings of the National Academy of Sciences* issued a formal expression of concern, 'that the collection of the data by Facebook may have involved practices that were not fully consistent with the principles of obtaining informed consent and allowing participants to opt out' (Verma, 2014, p.10779). A primary source of ambiguity is the fact that for-profit corporations are not subject to federal research ethics standards because they do not receive federal funding. Clearly this presents researchers using new unobtrusive methods—and, in particular, those using private archival data—with an unmapped ethical landscape. Sparked by reactions to the study, Facebook's

Jackman and Kanerva (2016) recently called for greater attention by for-profit entities to ethical standards for research, detailing the steps that Facebook has taken. As this example illustrates, it behoves the researcher using new unobtrusive methods to seek counsel and guidance from multiple perspectives, thoughtfully vetting any project with respect to issues of consent and privacy.

Conclusion

Did you download this chapter from a digital repository? If so, you have left a trace in the digital landscape—one that some enterprising researcher might use. The world has changed dramatically in the decades since Webb and colleagues' plea for researchers to complement survey and interview methods with unobtrusive methods. Unobtrusive methods are now more accessible and cheaper to use than they were even just 20 years ago. Using digital trace data, large-scale archival data, wearable sensors, and computer-assisted coding, researchers can gain new insights into organizational phenomena.

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