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Studying the Digital: Directions and Challenges for Digital Methods

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Abstract

The methodological tool chest available to those who study digital technologies ranges from those that are uniquely digital methods to approaches that are well established in the social sciences. This domain of work includes the application of methods to answer questions about the relationship between digital technologies and the social world, as well as the use of digital methods to answer questions about the offline world. New or old, quantitative or qualitative, the methods used to study the digital have strengths and weaknesses unique to this area of research. These issues include questions about the scope of cyberethnography, the validity of trace data, and the analytical division between on- and offline interaction. This review focuses on an overview of different methods, their history, and their strengths and weaknesses as applied to the study of digital technologies, including ethnographic approaches, interviews, surveys, time and media diaries, trace data, and online experiments.

INTRODUCTION

Social interactions increasingly involve the use of digital technologies. Sometimes referred to as information and communication technologies, new media, the virtual, or simply the Internet, these technologies include email, social media, the Web, virtual worlds, virtual reality, cell phones, and a host of emerging ways that people share information and become and remain connected through the use of electronic devices. The study of how these technologies shape and are shaped by the social world has grown from a niche focus to an established area of sociological study (Earl 2015, Wellman 2006). The study of digital technologies is both a specialized area of inquiry within sociology and an area that bridges into other disciplines, including those in the social, information, communication, media, and computer sciences (Loader & Dutton 2012), and into other sociological concentrations, including the study of inequality, education, criminology, organizations, sex and gender, race and ethnicity, and urban and community sociology. Indeed, the question of whether digital technologies should be studied without considering how they are used in concert with offline or real-world activities is one of many theoretical issues that shapes methodological choices for how digital technologies are studied and understood. In the same way, mobile devices and social media are now embedded into everyday life, and areas of sociology that have traditionally not considered their role must ask how these technologies are interacting with the focus of their work. As the emphasis on these technologies increases, so does the need to understand the unique considerations associated with studying and measuring their use.

The methodological tool chest available to those who study digital technologies ranges from methods that are uniquely digital to traditional approaches that are well established in the social sciences. This domain of work includes the application of methods to answer questions about the relationship between digital technologies and the social world, as well as the use of digital methods to answer questions about the offline world. New or old, quantitative or qualitative, the methods used to study the digital have strengths and weaknesses, many of which are unique to this area of research.

This review focuses on an overview of different methods, their history, and their strengths and weaknesses as applied to the study of digital technologies. The review includes ethnographic approaches, participant observation, interviews, surveys, time and media diaries, trace data, and online experiments. It will help the reader address questions such as, Should the ethnography of digital technologies consist only of online observation? How should exposure to digital technologies be measured in a survey? Can trace data or big data replace the need for surveys? And are online experiments as valid and reliable as offline experiments? The goals of this review are to document some of the unique methodological challenges faced by those who study digital technologies and help researchers evaluate the strengths of different approaches to facilitate the selection of a method most suited to their specific research question.

QUALITATIVE APPROACHES

Ethnography

As Internet access in organizations and homes increased in the mid-1990s, the first sociological research in the area was appropriately qualitative in nature. This work came on the heels of scholarship conducted primarily in laboratories and organizations on how the introduction of computer-mediated communication, especially email, would affect work processes (Garton & Wellman 1995). The Internet was a new and unstudied phenomenon with a geographically distributed user base of early adopters. It was both novel and difficult to study. Early sociological inquiry often explored issues of community, identity, and role-playing in text-based discussion systems, virtual worlds, and online games. Early studies were often a reaction to and in competition with more journalistic reports of the virtual community (e.g., Dibbell 1998, Rheingold 1993). Journalists would recount sensational, autobiographical stories of how online bulletin boards intermixed ad executives, hackers, and software pirates in online fantasy worlds, where people risked becoming lost in alternative realities (Sinha 1999). These accounts were often from the perspective of an outsider, who could not relate to those involved, or the perspective of someone who was so immersed that it was difficult to detangle direct observation from the author's imagination of those activities. Although early online scholars also immersed themselves in the settings they studied, they were reflective on their use of traditional ethnographic approaches. They were systematic in their use of field notes, combined personal experience with unobtrusive observation, and most often, they adopted mixed methods, such as in-person interviews (Correll 1995, Markham 1998). Thus, while these sociological pioneers worked to understand whether people's online identities were as legitimate as their offline identities (Turkle 1997), they also struggled to communicate the legitimacy of studying online activities to academic audiences (Markham 1998) and the rigorous and specialized nature of their methods to more lay audiences (Kendall 2002).

It would be a misconception to label early ethnographies of the digital experience as "digital" or "online" ethnography. The focus was generally not limited to online behaviors, but to differentiating between on- and offline realities, identities, and relationships. For example, Kendall (2002) spent three years participating in an online world known as BlueSky while also attending real-world get-togethers and conducting in-person interviews with participants. She studied how participants' offline identities, predominantly as white men, affected their online representations of masculinity and heterosexuality. In doing so, she engaged and contributed to the larger literature on the social construction of gender and racial identities. She also explored the differences between what participants perceived as a space that was analogous to a physical community, a "virtual pub," and the differences inherent to interacting in a "spaceless place" (Kendall 2002, p. 145). This research, as with much early ethnography of online activities, was a natural extension of the ethnographic tradition familiar to most sociologists and anthropologists (e.g., Du Bois 2014 [1899], Gans 1962). As such, the work of Kendall (2002) and many of her contemporaries was recognized for tempering the exuberance of early accounts of online activities (Drew 2005). It was also criticized in relation to that work for having a "cold sociologist's eye," breaking down elements of online interaction through "clinical examination," and for not only meeting those she observed in person, but keeping record of her interactions "in a kind of personal diary format" (Cobb 2003, p. 414).

Today, the ethnography of digital technologies and its methodologies is more widely recognized and widespread. Robinson & Schulz (2009) provide a thorough review of the ethnographic tradition and focus of early online researchers. Several texts, such as works by Boellstorff (2012) and Hine (2015), do an excellent job of guiding both the experienced and novel ethnographer through the online experience. However, there is considerable diversity in the definition and practice of ethnography, both on- and offline, and much has changed in how ethnographies of digital technologies are conducted.

A traditional understanding of ethnographic practice tends to focus on the role of field research, in which the researcher immerses themselves in a social setting. They observe or participate, either overtly or covertly, and by drawing on multiple sources of information from individuals and institutions, attempt to experience and understand the social world as those who are found in the setting do (Madden 2010). Much ethnographic work that is focused on digital technologies does not fit neatly within this traditional definition.

Some scholars favor labels, such as "netnography" (Kozinets 2002), "cyberethnography," or "virtual ethnography" to refer to a unique adaptation of the ethnographic approach to studies of digital technologies. This approach is a reaction to the uniquely distributed nature of online contact and an acknowledgment of the difficulty associated with studying individuals situated across a geographic space. It often implies that ethnographic observations in the context of digital activity can be completed through the wholly online observation of interactions and text (Lane 2016b).

Although many researchers highlight the importance of observations conducted in real time (Boellstorff 2012), the unique characteristics of digital technologies mean that cyberethnography could be based on a review of interactions that took place at an earlier time. When not conducted in real time, cyberethnography more often resembles content analysis and other archival methods. This "trace ethnography" turns preexisting logs of online, text data into thick descriptions (Geiger & Ribes 2011), finding meaning as if in the field at the time. For example, Sharma et al. (2015) conducted an "ethnography of email" to understand the work practices of distributed scientific collaborations. As part of their approach, they kept field notes of weekly "observations" of emails. Emails were coded for themes and combined with metadata, such as sender and receiver, to generate graphical visualizations. Sharma et al. (2015) identified patterns of interaction and inequality. However, such approaches almost always lack the time commitment, immersion, scope, and risk associated with traditional ethnographic field work (Howell 1990).[1] When adopting such an approach, it is appropriate to ask where the analysis of text, video, and pictures—especially when not reviewed in real-time—ceases to be ethnographic and becomes content, discourse, or conversation analysis, which are methods with their own tradition, principles, and expectations (Evans & Aceves 2016). When field notes are replaced by recorded, archived content, is it archival or ethnographic? As in other topical domains, what is truly ethnography and what is something else are open to critique (Atkinson 2015).

Cyberethnography is a response to the distributed nature of digital technologies and is consistent with the shift in the structure of personal community from groups to networks (Rainie & Wellman 2012). Applying rigid spatial boundaries to the study of social interaction has long been problematic for ethnographic and broader sociological approaches to the study of social structure (Wellman 1979). Thus, the shift from the study of colocation to the study of copresence has strong analytic appeal for ethnographic approaches to the study of digital technologies (Beaulieu 2010). Yet, when cyberethnography consists of online observation alone, it fails to acknowledge that a sharp online/offline dichotomy does not represent how most digital technologies are integrated into everyday life. Much online interaction is with contacts formed and maintained offline. They include ties that share homes, schools, workplaces (Boczkowski 2005), neighborhoods (Hampton 2003), and other places (Gray 2009). They are often multiplex in their communication patterns, communicating online (through multiple channels), over the phone, and in-person (Haythornthwaite 2002, Wellman & Hampton 1999). In much the same way, online interactions often move offline (Sessions 2010). By limiting observations to what happens online, cyberethnography often resembles autoethnography and usability studies rather than a study of culture and context.

Lane (2015) provides a particularly good example of how the ethnography of digital technologies benefits from examining interactions that take place on- and offline. In his study of Harlem, Lane spent five years studying the lives of local teenagers. He observed how interactions unfolded, not just in person, on the street, but online, through the use of social media. He observed how initial, momentary, aggressive exchanges that took place between boys and girls on the street led

[1] Digital technologies also introduce new risks for the ethnographer. Social media, search engines, and online archives of video and papers make the ethnographer more visible and accessible to their research subjects. Jackson (2012) recounts how one of his participants found an online announcement for a lecture he was scheduled to give, and called to ask what he was planning to say about them. The one-sided voyeurism (Jackson 2012) of the ethnographer has been replaced by mutual and "pervasive awareness" (Hampton 2016).

to subsequent, repentant contact that unfolded over days and weeks through social media. He documented how the "code of the street" (Anderson 2000) had been augmented by videos of teenage confrontations, posted online and providing a permanent public record of their performance. Such information, accessible to friends, rivals, parents, and the police, shaped the narrative of street encounters, molding reputations and setting up future meetings. Public acts on the sidewalk are intertwined with private and public interactions online, revealing important aspect of teenage relations that Lane could not have gained from looking on- or offline alone. As argued by Lane (2016a, p. 47), "How can a digital network ever be studied only on its own terms? Under what conditions could ethnographic understanding not be enriched or stand to change by getting to know even a single research participant in person?"

Other Qualitative Methods

When applied to the study of digital technologies, the terms "ethnography," "participant observation," "interviews," and "content analysis" should not be used interchangeably. Each approach, alone or in combination, has a unique place and offers value to the study of digital technologies.

Examples of participant observation that was not ethnographic include Hampton & Gupta (2008), who conducted systematic observations of patrons of coffee shops with wireless Internet access. In this research, the question of how the social interaction of wireless Internet users differs from that of nonusers in a semipublic space was explored through a comparison of observations from four different cafés, in two cities, across different times of the day/week. The approach used theoretical sampling across people, contexts, and artifacts. In a similar way, Hampton et al. (2010), in a study of media use in public spaces, used behavioral mapping approaches, combined with supplemental, detailed observations and site surveys. Behavioral mapping involves mapping the use of technologies and the location and variety of behaviors in public spaces. These approaches provide alternative, systematic, and qualitative means to explore variation in media use and record and analyze social behavior.

The traditional, in-person interview continues to provide an important tool in the study of digital media. This approach is particularly important for sensitive topics, in which the researcher needs to establish trust, such as in the study of children and youth (Livingstone 2008), in studies that compare users and nonusers of the Internet (Reisdorf et al. 2016), and in researching other hard-to-reach populations, such as prisoners (Reisdorf & Jewkes 2016) and immigrants (Katz & Gonzalez 2016). In addition, interviews conducted online can remove some of the costs of travel, coordination, and transcription of in-person interviews. It is equally possible to use online interviews for topics related to digital technologies as it is to interview participants about topics that are unrelated to technology use.

There is considerable disagreement about the quality of online interviews. Some scholars suggest that the lack of visual and auditory cues and the asynchronous nature of some technologies make online interviews most appropriate for standardized, structured interviews (Mann & Stewart 2000). Online interviews can inhibit the mutual interaction necessary for in-depth discussions. In a comparison of in-person and instant-messenger-based, semistructured interviews with adolescents, Shapka et al. (2016) found that online interviews produced fewer words, took longer, and required more rapport building, but they did not differ in the level of self-disclosure or the variety of themes that emerged. A comparison of telephone-based interviews with those conducted by email and instant messaging reported similar findings (Dimond et al. 2012). The growth of video technologies reintroduces audio and visual content and may be more similar to in-person interviews (Nehls et al. 2014). However, video and audio quality can dramatically affect trust among participants (Bekkering & Shim 2006), and the use of digital technologies in the interviewing process is ripe for technical problems for both researcher and participant.

Content analysis has always straddled the line between quantitative and qualitative methods (Krippendorff 2004). In addition to the textual analysis of online content and natural-language-processing and machine-learning approaches to textual analysis (Evans & Aceves 2016), researchers have also been analyzing the content of other media to explore technology use. For example, Given et al. (2016) pioneered the analysis of video recordings taken by parents to study children's use of technology in the home. Hampton et al. (2015) compared the content of archival Super 8 films from the 1980s and recent digital videos to study change in public spaces as a result of mobile phone use. Morel et al. (2010) used recorded audio and video conversations from mobile phones to analyze the sequential organization of verbal and nonverbal interactions of mobile phone users. Licoppe & Figeac (2015) expanded this approach and used smartphone videos to follow people throughout their day and analyze their use of technology, everyday interactions, activities, and attention. Hwang & Sampson (2014) used Google Street View (an online system that provides a virtual experience of walking down the street) in a study of neighborhood change, coding photographs of 2,709 Chicago city street block faces from 2007 to 2009. Such methods are part of a growing trend, explored in more detail in a later section, of using digital technologies as a tool to study more traditional, offline sociological problems.

QUANTITATIVE APPROACHES

As the population of Internet users increased, it became increasingly desirable and possible to utilize methods that increased generalizability. This does not imply that qualitative studies of digital media are less appropriate today than they were in the past. The strength of qualitative approaches for focusing on unstudied processes, social context, and exploratory questions made qualitative methods the dominant approach of early digital research. The Internet continues to be composed of populations situated in unique contexts, and the Internet is continuously being remade through the introduction of new technologies. As researchers attempt to understand these contexts and the use of these technologies, qualitative research will continue to be an appropriate choice for many questions. However, as the technology and study of digital media have matured, the appetite for quantitative data has increased. It has become increasingly possible to test theories and hypotheses with findings that are more generalizable than those that can be obtained through qualitative research alone.

One of the biggest challenges faced by quantitative researchers is perhaps the most basic: how to measure online behavior and activity. A variety of approaches are available, including traditional, self-reported survey measures of exposure, time, and media-use diaries, as well as approaches that are unique to the study of digital media, mainly the use of trace data and online experiments.

Survey Measures of Exposure

The difficulties of measuring media exposure are well established (Webster & Wakshlag 1985). Many of the issues that researchers face in measuring exposure to digital technologies are an extension of established issues associated with informant accuracy (Bernard et al. 1984). The best practices for measurement validity from this literature can be applied to the study of digital technologies. However, there are issues of measurement validity that are specific to the study of digital technologies. One such issue is how to obtain a reliable, self-reported measure of Internet use.

Composite measures of exposure. Participants often have difficulty reporting on a basic measure of whether they use the Internet. For example, in nationally representative telephone surveys, the Pew Research Center asks participants if they "use the Internet or email, at least occasionally." In 2015, 80% of respondents ($N = 2{,}004$) answered "yes" to this question (Pew Res. Cent. 2015b). "Email" is included in the question wording because many participants do not recognize that when they check their email they are using the Internet. However, this only scratches the surface of the difficulty participants experience in recalling Internet use. In a subsequent question in the same survey, Pew asked, "Do you access the Internet on a cell phone, tablet, or other mobile handheld device, at least occasionally?" Twenty-five percent of those who answered that they do not use the Internet or email reported using the Internet at least occasionally on a mobile device. Additional questions about specific Internet technologies, such as "Do you use a social network site or a mobile app for social media like Facebook, Twitter or Instagram?" revealed that an additional 6% of those who answered "no" to both previous questions did use social media. The Pew Research Center addresses this issue through the creation of a composite variable that combines these three questions (Pew Res. Cent. 2015a, p. 45), but many of those who use Pew data as a secondary source are unaware of this issue. Most of those who collect their own data on Internet use rely on a single question. In the case of the Pew data, failing to use a composite measure of Internet use would misidentify as nonusers at least 6% of participants from a random sample of the general, adult population. For research questions related to digital inequality, this omission would overstate the proportion of Americans without Internet access by over 40%.

Typologies. For most research questions, a user/nonuser dichotomy is too coarse a distinction to adequately examine the relationship between digital technology use and social outcomes. The range of online platforms and activities is immense and constantly expanding. Although there have been attempts to develop typologies that capture the breadth of ways that people use digital media (Brandtzæg 2010), there is no agreement on the dimensions that should be incorporated into a typology of use. Suggested dimensions have included "social" and "solitary" (Zhao 2006), "entertainment" and "instrumental" (Heim & Brandtzæg 2007), "basic" to "all-around" (Livingstone & Helsper 2007), "intense" to "limited" (Shih & Venkatesh 2004), and many others. Although researchers should let theory guide their choice of dimensions to capture variation in use, a recent review by Blank & Groselj (2014) identifies several common pitfalls and provides a useful starting point.

Blank & Groselj (2014) are critical of previous attempts to create typologies of online use because of their tendency to ignore the multidimensional aspects of Internet use and to conflate discrete dimensions, such as amount and type of use. They argue that variation in individual Internet use consists of three distinct dimensions: amount, variety, and types of use. Amount, a continuous variable, corresponds to frequency of use (e.g., hours per day). Variety or breadth of use is also a continuous variable that refers to specific activities (e.g., using email, watching videos, etc.). Types of use, a series of nominal categories, refers to broad classifications of Internet use; they identify ten: entertainment, commerce, information seeking, socializing, email, blogging, content creation or production, classical mass media (e.g., news, sports, and events), school/work, and vice (e.g., gambling and pornography). Although the dimensions of Blank & Groselj (2014) capture much of the variation found elsewhere in the literature, their dimensions are not exhaustive. Researchers have found valid theoretical reasons to focus on additional dimensions, such as digital skills (van Deursen et al. 2016, Robinson et al. 2015) and variation in adoption of digital platforms (e.g., Facebook, Snapchat, Twitter, etc.) (Hampton et al. 2011).

Dimensions of platform use. Much of the current research on digital technologies focuses not on Internet use in general, but on the use of specific platforms (e.g., Facebook, Snapchat, etc.) or types of digital technology (e.g., social media). This focus on a single platform does not reduce the complexity of capturing valid measures of exposure. For example, a study of Facebook by Hampton et al. (2012) identified more than 20 measures of variation in Facebook use, including frequency of the following:

- Friend requests (sent and received)
- Friend requests accepted (requests to others and requests from others)
- Sharing content of different types (e.g., web links, photos, etc.)
- Commenting on friends' content (receiving and giving)
- "Liked" friends' content (receiving and giving)
- Private messages (sent and received)
- Tagging in photographs (tagging others and being tagged)
- Group participation (joining, joining others to a group, being added by others)
- Hiding friends on the news feed
- Accessing the site (on a computer, mobile device, etc.)
- Friend count

The same study found that users tended to specialize in the types of activities in which they participated. That is, someone who frequently used Facebook for private messaging was not necessarily contributing frequent comments on the content of other users. Different online activities, and Facebook activities in particular, represent different social activities and have been associated with different outcomes related to trust, social capital, social support, and political participation. This is consistent with theories of social affordances (Norman 1990) and research on the properties of technologies that provide opportunities for different social outcomes. Thus, an overall measure of Facebook use is likely to combine participants with very different online practices related to different outcomes. Such findings highlight not only the complexity and importance of developing a clear, theoretically driven operationalization of digital technology use, but the difficulty of measuring exposure on platforms that often have many independent dimensions of use and social activity.

Psychometric scales. Some researchers have attempted to overcome the difficulty of measuring exposure by replacing or combining measures of exposure with psychometric scales of people's attitudes. For example, the Facebook Intensity scale (Ellison et al. 2007) has been widely adopted as a measure of Facebook use (e.g., Burke et al. 2010, Vitak et al. 2010). The Facebook Intensity measure is calculated as the mean score from a combination of Likert-type scales focused on emotional connectedness to the Facebook platform, integration into daily activities, frequency of Facebook use, and number of Facebook friends. This approach has the advantage of reducing the dimensionality of digital media use. However, as is the case with most psychometric scales, the Facebook Intensity scale represents latent variables that are intended to represent an underlying, hypothetical construct. Although these measures can demonstrate a high degree of internal reliability, they often lack formal tests of content, criterion, and construct validity (Appel et al. 2014). The lack of balance in these scales can also introduce acquiescence response bias, which inflates measures of internal reliability and correlations with some outcome variables (Kuru & Pasek 2016). Like single measures of exposure, composite measures may not provide adequate variation in the dimension of theoretical importance to test the relationship between platform use and the outcome of interest.

Time and media diaries. Along with survey measures that attempt to capture frequency and type of use, popular measures of exposure include global time estimates (e.g., Gil de Zúñiga et al. 2012, Hughes et al. 2012). Typically, these questions take a form similar to "How many hours do you spend using email (or using Facebook, a computer, the Internet, etc.) in a typical day (or a typical week)?" or "How many hours did you use the Internet yesterday (or in the past 24 hours)?" Participants are asked to respond on a Likert scale or to report the actual number of hours that they used a specific technology. Many national, representative surveys, including those by Pew Research, the Kaiser Family Foundation, the National Longitudinal Survey of Adolescent Health, and the National Longitudinal Survey of Youth (Vandewater & Lee 2009) have utilized this approach.

Despite the ubiquity of global time estimates, an extensive body of research documents the issues of measurement validity associated with them. Asking participants to report time spent on a construct related to media use, such as "the Internet," assumes that participants have a common understanding of what "the Internet" is. As already demonstrated, a substantive proportion of the general population cannot reliably determine if they use the Internet. These issues likely extend to other constructs, such as social media and video games (Kahn et al. 2014). As suggested by Robinson & Godbey (1997), requesting a global estimate also assumes that participants can reliably search their memory for all episodes of an activity over a given time period and distinguish the activity from other activities that may have occurred simultaneously (e.g., watching television, socializing, eating, etc.). People generally do not keep a ready, cumulative count of time spent on media or other activities, and the recall of many activities is subject to systematic bias. When asked to provide time estimates on multiple activities (technology and other activities), participants often provide estimates that add up to considerably more than the 168 hours available in a given week. There can be considerable loss of reliability when participants are asked to report on longer time periods or on a "typical" day or week. Some have attempted to improve the validity of these measures by asking participants to report on specific time periods (e.g., what they were doing yesterday between 7 AM and noon, noon and 6 PM, and 6 PM and midnight), in the "last week" as opposed to a "typical week," or "yesterday" as opposed to an "average day." Short time periods, such as reporting on "yesterday," tend to be more reliable than "typical" day or week time questions (Michelson 2005), although there are mixed findings as to whether these practices improve predictive validity (Chang & Krosnick 2003).

Time-use diaries provide more detailed and reliable measures of exposure than general time estimates (Michelson 2005, Robinson & Godbey 1997). With time diaries, participants maintain a spreadsheet and self-report individual activities in sequence, typically over a short period of time (e.g., 24 hours), but occasionally over longer periods, such as a full week. Time diaries generally include a record of the start and stop time of each activity, where the participant was and with whom, and possibly a record of any secondary activities. Although reliable, this approach is especially burdensome for participants, which can negatively affect response rates.

A modified time-diary approach, a communication diary that is limited to recording activities that involve the use of media and in-person communication (Baym et al. 2004), can reduce the burden on the respondent. However, the limited focus on communication activities curtails the use of such diaries in research questions that require a comparison to time spent in other social and personal activities. Communication diaries have also been found to understate significantly the frequency of communication. They have a bias toward omitting extremely short communications, such as text messages, and recording outgoing contact over incoming contact (Greenberg et al. 2005, Higgins et al. 1985).

The experience sampling method (ESM) (Csikszentmihalyi & Larson 2014) attempts to strike a middle ground by maintaining the increased validity of the diary approach and reducing the respondent's burden. With ESM, time is sampled through the use of a digital device, such as a pager or mobile phone; participants are interrupted at different periods throughout the day or week and report on the activities they are doing at that moment as well as their psychological state.

ESM has the advantage of reducing the participant's burden and can provide a reliable method to measure the frequency of activities over a large sample of participants and times, but it does not provide a measure of total time or exposure to communication activities. In the digital media literature, ESM has relied heavily on availability sampling and, as a result, suffered from issues of generalizability (Kross et al. 2013).

Time-use diaries have had notable but relatively limited adoption in the study of digital media (e.g., Anderson & Tracey 2001, Robinson & Martin 2010). In part, this is because of failures on the part of some of the largest government-funded time-use studies to adequately measure digital media use. For example, the American Time Use Survey (ATUS) has been conducted by the US Bureau of Labor Statistics since 2003. It consists of more than 145,000 completed diaries, is collected annually, and can be linked to data files from the Current Population Survey. The ATUS reports that between 2011 and 2013, the average American used information technology for 1.5 hours per week, an increase of 0.5 hours per week over the past decade (Robinson & Tracy 2015). These estimates contrast with other studies that find adults spend more than half of their waking hours engaged in media or communication activities, and that time use of information technology has doubled over the past decade (Ofcom 2015).

Unreliable estimates of technology use in the ATUS are a result of a methodological failure to adapt diary procedures to differentiate types of information technology (e.g., using a computer versus using a mobile phone). The unreliable estimates also result from a failure to measure the short, infrequent secondary use of digital media (e.g., multitasking, text messaging, etc.). In addition, they result from a failure to differentiate the use of digital technologies from traditional media (e.g., watching a movie on a digital device is coded as television viewing; video games are coded along with board games), and to acknowledge their role in other daily activities (e.g., socializing, work, shopping, etc.). National time-use studies in the United Kingdom, France, and other countries have started to adapt their methodologies to include prompts for participants to record their media use in conjunction with main activities and to identify secondary media activities that might otherwise be omitted (Fisher et al. 2015). However, in the United States, not only have ATUS data become nearly unusable as a means to understand changes in American daily life as a result of digital media use, but their prominence as a large, annual, federally funded survey makes it difficult for other researchers to obtain funding for competing time-use surveys.

Trace Data

The use of trace data has been one of the most celebrated methodological opportunities to study new technologies. Social scientists have long used data generated by digital media, such as computer logs of email exchanges, to study exposure and interaction (Rice 1990). However, as the volume and variety of trace data have increased, they have received increased attention under the umbrella of big data and computational social science (Lazer et al. 2009). Trace data include a wide range of artifacts. Some of the most common examples include computer logs of email or instant message exchanges (Leskovec & Horvitz 2008), traditional telephone calling logs (Zipf 1949), mobile call data records (Blondel et al. 2015), and social media data from sources such as Twitter (Himelboim et al. 2013) and Facebook (Ellison et al. 2014, Hampton et al. 2012, Lewis et al. 2008). These data are collected passively as a result of an individual's interaction with computer systems. Such data can be incredibly detailed and massive in size, documenting every keystroke, interaction, and mouse click. Once collected, trace data can be used on their own or in combination with survey and experimental data (Boase 2016, Hampton et al. 2012, Wells & Thorson 2017). When they contain geographic identifiers, trace data can augment data from Census datasets (e.g., Massey & Rugh 2014), which tend to have few and inadequate measures of media exposure.

Trace data can provide highly reliable measures of media exposure. They eliminate measurement error from the inaccuracies in self-reported data. Proponents point to the low cost of collecting and analyzing trace data in comparison to survey research and to the possibility of utilizing data on the full population of users engaged with a medium, as opposed to having to rely on a sample (Schober et al. 2016). Trace data can be obtained from a variety of sources, including the following:

- Scraping: using computer scripts to collect sections of a web page and store that information in a database (Wesler et al. 2008)
- API (application programming interface): a programming tool provided by a digital media company to build software that interacts with its system (Morstatter et al. 2013)
- Programs and websites designed to collect trace data (Hansen et al. 2011)
- Custom applications and computer scripts (Fiore et al. 2002, Hampton 2007)
- Online text corpuses from email lists, text messages, discussion forums, and archives (Evans & Aceves 2016, Gad et al. 2015)
- Partnerships with companies that provide digital media (e.g., Facebook, Microsoft, Yahoo) (Burke et al. 2010, Ellison et al. 2014, Hampton et al. 2012)

Once obtained, trace data are often stored in relational databases (e.g., MySQL) that use computer programming and query languages to aggregate and manipulate data (Wesler et al. 2008). Relational databases are unlike most statistical programs used in the social sciences (e.g., SPSS) and require specialized programming knowledge that is generally not taught in traditional methods courses in the social sciences (Rubinson 2014).

Some have argued that trace data replace the need for survey research and probability sampling (Mayer-Schönberger & Cukier 2013, Schober et al. 2016). Proponents argue that trace data are superior to survey data by suggesting that research questions of interest to those who study digital media do not require probability sampling, because digital media content effectively represents the sentiments and behaviors of the broader population and because trace data provide a solution to an increase in nonresponses in survey research (Bollen et al. 2011, Mayer-Schönberger & Cukier 2013, Schober et al. 2016, Tumasjan et al. 2011). While extolling the lower cost of collecting trace data and the elimination of concerns over the reliability of self-reporting data, these arguments often exaggerate the imperfections in other methods and overlook or minimize the disadvantages of using trace data.

Trace data are most clearly applicable to a relatively small set of research questions and have their own issues of measurement validity. Although trace data may map well onto some constructs of interest (for example, using frequency of visits to a platform as a measure of exposure), other constructs are not clearly operationalized through the use of trace data. Personality, opinions, demographics, political affiliation, and mood are often inferred through automated discourse, sentiment, and topic analyses, or through other behavioral trace data (Golbeck et al. 2011). Such analyses often have unknown measurement errors and generally lack criterion validity. For example, can the count of positive and negative words in a corpus of Facebook posts be interpreted as positive and negative emotion (Kramer et al. 2014)? Or do researchers need more information on the context of the content before inferring mood? Proponents of the use of trace data often emphasize "subjectivity of the participants' answers" to surveys (Blondel et al. 2015, p. 2) while overlooking the subjectivity of trace data.

Trace measures also introduce analytical issues that make it difficult to distinguish statistical from substantive differences. As an example, although a statistical difference is present, in a corpus of 25,000 messages, is the use of one-half of one percent fewer emotional words in email exchanges within disadvantaged neighborhoods substantively different from what is found in neighborhoods with less economic and racial inequality (Hampton 2010)? Or, in a corpus of more than three million messages, does a change of 0.1% in positive/negative words translate to a meaningful change in emotional state (Kramer et al. 2014)? Trace data cloud traditional statistical inferences. In datasets with a very large number of cases, p-values are much more likely to approach zero (Lin et al. 2013a). For example, a trace-data analysis of Facebook users' voting behavior found that those who were cued that their friends had voted were 0.39% (t-test, $p = 0.02$) more likely to vote (Bond et al. 2012). Although statistically significant according to a traditional social science cutoff of $p < 0.05$, is such a finding either substantive or significant in a dataset with more than 6 million cases?

Research questions that focus on the use of a single platform or medium are most likely to benefit from the validity and population coverage of trace data. In this context, as concerns over sample generalizability are removed, the advantage of population data is clear. However, attempts to generalize findings from the analyses of trace data on a single system to other systems, or to broader populations, face the same hurdles as other methodologies when demonstrating cross-population generalizability. The population of Facebook users, Twitter users, and even the users of a single mobile phone carrier are not a random selection of the population. As argued by Hargittai (2015) and demonstrated on data from multiple sources of trace data, including social media (Hampton et al. 2011) and mobile phones (Gonzales 2014), users self-select for digital platforms based on a variety of characteristics, including age, education, sex, race, ethnicity, geography, socioeconomic status, and technological skill.

Trace data from a single platform or medium almost necessarily imply that the focus is on a single channel of communication. When used as data for social network analysis, the omission of ties to actors outside a bounded network can omit central, influential, or supportive members of a personal network (Wellman 1999). Attempting to generalize beyond the platform replicates a problem encountered with cyberethnography—studying an online relationship in isolation from offline relationships. Such an approach does not represent how digital technologies are used and integrated into everyday life.

To argue that trace data are inherently superior to probability samples because of survey nonresponses ignores the extensive literature that suggests survey estimates achieved through random digit dialing (RDD) and similar approaches are generally unaffected by lower response rates (Keeter et al. 2006, Singer 2006). Probability samples collected through telephone surveys (especially those that conduct interviews over both traditional and mobile phones and those that are weighted to match the demographic composition of the population) continue to provide accurate data on most political, social, and economic measures (Kohut et al. 2012). In addition, well-designed survey measures of exposure to digital technologies often demonstrate criterion validity through moderate to strong correlations with trace data (Burke et al. 2010, Goulet 2012, Hampton et al. 2012).

Some argue that although trace data, specifically social media data, may not represent the broader population, the correlation between trace data and the outcome of some surveys demonstrates that these data adequately cover the "research topics under study" (Schober et al. 2016, p. 184). Proponents suggest that additional comparisons between social media data and survey data across topic domains may "through a range of (not yet fully understood) possible mechanisms" demonstrate that trace data represent "the larger population's opinions and experiences" (Schober et al. 2016, p. 185). This argument is based on the observation that some social media content can correlate with broader public opinion on issues such as elections. This correlation is not a result of probability sampling, but of some process whereby social media data mirror broader collective expectations (Margolin et al. 2016), public attention (Jungherr et al. 2016), media framing, and agenda setting for the relative success of a candidate or issue. Some scholars expect that over time and through a large number of comparisons to survey data, it will be possible to identify topic domains in which social media data can substitute for probability samples of broader public opinion in the population (Schober et al. 2016). However, this approach still lacks a theory that is as rigorous as sampling theory (Hansen et al. 1953) and leaves open the very real possibility of finding spurious correlations (Lazer et al. 2014).

Trace data may not generalize to the broader population or across platforms, but they also may not be comparable within platforms over time. Digital media platforms undergo constant revision and updating. Assumptions that users of social media have an equal opportunity to be exposed to all content contributed by other users and other sources are faulty. Digital technologies often use algorithms that bias opportunities for exposure to content (Hamilton et al. 2014, Rader 2017). Not only does this pose challenges for ensuring construct validity, but a researcher may not be aware of changes made to an algorithm that affects measures made over time, an issue that is not present with changes to a survey.

Many researchers have made comparisons between trace data and survey data, but the parallels between big data approaches and qualitative methods, such as ethnography and focus groups (Lin et al. 2013b), are at least as strong. The difficulties and inequalities of access are common to both ethnographic and trace-data research. Negotiating entry into the field is a defining process of ethnographic work. Big data researchers face similar negotiations to gain access to trace data from media companies (boyd & Crawford 2012). As a result of privileged access and the context-specific nature of their data, these approaches share common issues with replicability. When trace data are collected from a single platform or medium, they can be understood as a case study. As with other case studies, a deep understanding of a single setting is the desired outcome, but generalizability is impossible (Stoecker 1991), and replicability over time (as a result of changes to algorithms and the user base) is unlikely (Burawoy 1998). The inductive approach, in which researchers begin with data and look for patterns that contribute to theory development, is the cornerstone of qualitative methods. It is consistent with the data-driven or data-mining approach of many studies that utilize trace data and often reject hypothesis testing (Schober et al. 2016).

Experiments and the Digital Lab

Scholars have paid considerable attention to the potential that digital technologies offer to create new opportunities and a new approach for experimental research within the social sciences and sociology in particular (Radford et al. 2016, Watts 2011). True experiments provide a level of confidence in the validity of causal conclusions that cannot be achieved through other research designs.

The lab. Lab-based studies of the social implications of digital technologies were among the earliest methods employed in the study of digital technologies. This work focused on organizational studies of how technologies, such as email and groupware (software designed to allow people to work together), were affecting relationships in the workplace (Sproull & Kiesler 1991). Despite the early contributions of several prominent sociologists of knowledge and technology (Goodman & Sproull 1990), the body of lab-based research that deals explicitly with sociological questions pertaining to newer digital technologies is relatively sparse. Despite the ability to clearly demonstrate time order and the association between independent and dependent variables, and to reduce or eliminate confounding variables, lab-based work is often grouped under the heading of "usability studies" (Wellman 2004). However, there are recent examples of lab-based studies that focus on clear sociological questions, including the study by Stefanone et al. (2012) of perceived social capital on Facebook and the activation of social support, and the groundbreaking work of Karahalios, Sanvage, and colleagues (Eslami et al. 2015), who explored how social media algorithms are related to a perception of social ties.

Although the lab has not been central to the sociological study of digital media, the same is not true of psychology. Psychologists have embraced lab-based work and primarily true experiments in their study of new technologies, such as video games, to examine emotions, violence, and psychological traits, such as empathy (Bushman & Anderson 2015, Velez et al. 2016). The willingness within psychology to use lab-based experiments has contributed to a growing psychological literature in digital media on topics it has traditionally shared with sociology, but which it increasingly dominates. These include how the use of digital media affects social support and prosocial behaviors, such as altruism (Greitemeyer 2011, Shaw & Gant 2002).

Quasiexperimental. Ethical and practical problems can make random assignments and the confines of the lab difficult for the study of sociological questions. Quasiexperimental studies can be more suitable, in that they are conducted in naturalistic settings and have the benefit of utilizing a comparison group or groups, although they lack benefits of random assignment of subjects. Quasiexperiments are just as rare in the study of digital technologies. Examples include a series of studies by Hampton (2007) in which he designed and deployed a series of information and communication technologies in three Boston-area neighborhoods and used a fourth neighborhood as a comparison group. The residents of the four neighborhoods were interviewed once per year for three years. Interviews were combined with trace data to study how use impacted the formation of local social ties and community engagement. In a follow-up study, Hampton (2010) released a publicly accessible website designed to allow neighborhood groups to form digital groups online. The site was ultimately adopted by more than 100,000 users, and trace data of adoption and usage patterns were used to compare civic engagement between advantaged and more disadvantaged communities (Gad et al. 2012, Hampton 2010). Other examples of experiments in the field, although without the comparison group utilized in true quasiexperimental design, include Kwon et al. (2014), who recruited confederates to explore network exposure and mobilization to join a local advocacy group.

Online experiments. Golder & Macy (2014) call this the virtual laboratory. Although advocates of computational science and big data often frame this approach as something entirely new, scholars from a variety of disciplines have been recruiting participants through the Internet for online experiments since at least the mid-1990s (Reips 2001). The advantages of this approach include the low cost of participant recruitment; access to large, diverse, or specialized samples of participants; automation of the experimental manipulation; a reduction in the obtrusiveness of the experimenter; and the speed at which subsequent iterations of an experiment can be deployed (Golder & Macy 2014, Kraut et al. 2004). When compared with the traditional laboratory, disadvantages include the lack of control that the researcher exerts over the environment where the research is conducted (e.g., distractions and access to outside information) and the ability to verify a participant's characteristics (e.g., age and gender) (Kraut et al. 2004, Mason & Suri 2012).

Although online experiments are not especially new, the online infrastructure to facilitate such experiments is more accessible and has increased the ease in conducting such experiments. The most common example of this infrastructure is Amazon's Mechanical Turk (AMT), a platform that has attracted hundreds of thousands of people who are willing to complete relatively small tasks for small amounts of money. A task that takes only a few minutes to complete may pay less than 25 cents, with an additional 20% to 40% commission paid to Amazon. Bohannon (2016) has reported the average pay for an AMT worker at $3–$8/hour. Originally designed to automate tasks that computers cannot easily do, such as identifying duplicate web pages and matching images to product pages (Pontin 2007), AMT has broadened into a publicly accessible web platform that allows anyone to "crowdsource" small tasks (Howe 2006), including online experiments.

Mason & Suri (2012) provide a thorough overview of the procedure for how to use AMT to recruit participants, execute a task, review the results, and pay participants. A substantial body of work has emerged to document the strengths and weaknesses of using AMT for social science experiments (e.g., Paolacci & Chandler 2014). Not surprisingly, participants in experiments completed using AMT tend to be both socioeconomically and ethnically more diverse than experimental populations composed of students (Casler et al. 2013). They also tend to be younger, more educated, and less conservative, and are less likely to be employed full time than the general adult population (Berinsky et al. 2012, Paolacci et al. 2010, Shapiro et al. 2013). Findings are mixed about the reliability of AMT participants on experimental tasks (Rouse 2015) and how much attention participants pay to tasks (Goodman et al. 2013).

Online Surveys

Researchers have been conducting surveys online since at least the late 1980s (Kiesler & Sproull 1986). Although many different platforms are available to administer online surveys (e.g., Qualtrics and SurveyMonkey), as with online experiments, the platform of choice to recruit participants is AMT. Survey researchers have embraced AMT for its reduced cost when compared with RDD and its higher participant diversity in comparison with samples of university students. AMT makes it relatively easy for researchers to access a large number of willing survey participants in a short period of time. As with online experiments, online surveys may suffer from issues related to low participant attention and a tendency to consult outside sources for information (Clifford & Jerit 2014). Some researchers have reported that AMT participants are more attentive to instructions than other participants (Hauser & Schwarz 2016). My own experience with a 20-minute survey administered through AMT with a sample of slightly more than 1,000 participants found that more than 20% failed manipulation checks designed to detect participants who were not providing valid responses.

Participants necessarily opt in to participate in online panel surveys. Although sampling methods do vary, with very rare exceptions (Keeter & Weisel 2015), online surveys consist of nonprobability samples. Nonprobability samples, including convenience sampling, are prone to selection bias and have no theory to support statistical inference. Attempts to reduce bias in nonprobability survey samples have used methods such as sample matching, network sampling, and estimation and weight adjustment methods (Baker et al. 2013). Such approaches may reduce error in some nonprobability samples, but the tools to evaluate data quality based on these approaches are limited and depend highly on theoretical assumptions about the population and survey measures. However, if researchers can find ways to overcome the opt-in problem of online sampling, allowing for probability sampling, online surveys could quickly become a gold standard. Current levels of household Internet penetration in the United States are now higher than household telephone penetration at the time that scholarly opinion of RDD switched from skepticism and distrust to broad acceptance (Klecka & Tuchfarber 1978, US Bur. Census 1975).

DISCUSSION

This review has highlighted some of the dominant methods and their strengths and weaknesses in the study of digital technologies. Often, reviews of this type can appear to be blindly zealous or overly critical of a particular approach. I hope that this review does not slant toward either extreme. The reader should not leave with the impression that the study of digital technologies suffers from serious methodological shortcomings, nor that it has reached a maturity (or insularity) where methodological choices are rarely disputed. Like other areas of sociological inquiry, there are contested areas of methodological concern. These concerns include issues unique to this area of study, such as questions about the scope of cyberethnography, the validity of trace data relative to other approaches, and the analytical division between on- and offline interaction. Other issues have a more established literature that can be borrowed from related fields, such as those related to obtaining valid and reliable measures of media exposure through surveys. Some issues may be resolved through pedagogical changes within the social sciences, such as teaching the use of relational databases along with traditional statistical packages. Still other issues, such as the complexity of measuring the time-use of digital technologies, may require that some instruments, such as the ATUS, receive significant revision. My hope is that this review serves as a starting point to assist researchers in the evaluation of the strengths of different approaches and to document some of the challenges faced by those studying digital technologies.

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