The Internet as Psychological Laboratory Revisited:

Best Practices, Challenges, and Solutions

Edward G. Sargis

Linda J. Skitka

and

William McKeever

University of Illinois at Chicago

Chapter prepared for Y. Amichai-Hamburger (Ed.) *The social net: The social psychology of the Internet*. Oxford, UK: Oxford University Press.

The Internet as Psychological Laboratory Revisited:

Best Practices, Challenges, and Solutions

People increasingly incorporate the internet into how they live, work, and play. The internet enables people to connect with family and friends, find news and information, and to work more effectively. Scholars have powerful new tools including Google Scholar, societal listservs, web portals for manuscript submissions, and alternative ways to collect data. The goal of this chapter is to review some of the ways social psychologists use the internet to collect data, best practices for web-based data collection, and emerging issues in web-based data collection in psychology such as sampling, data quality, and security.

How Are Social Psychologists Using the Web in their Research?

Before turning to issues of best practices, we first examined the ways in which social psychologists are using the web to collect data. To this end, we reviewed the content of nine journals that published empirical research in social psychology in 2009 and 2010. Of the 1547 articles we reviewed, 173 (11%) reported at least one study that used the Internet to collect data remotely. Of the total 265 studies reported in the 173 articles, 92 (35% of the total studies) used the web to facilitate a lab study, such as to collect pre-measures from participants who also completed part of the study in the lab. The other 173 studies (65% of the total studies published) were completed entirely online (see Table 1). This is a substantial increase in the number of published studies in social psychology that used internet methods compared to 5 or 6 years ago, when the base rate was closer to 1% (Skitka & Sargis, 2005, 2006). The highest publication rate of internet based studies were published in the field's flagship journal, the *Journal of Personality and Social Psychology,* followed closely by *Personality and Social Psychology Bulletin.* In sum, internet-based research is increasingly a mainstream practice in social psychology, and web-based data collection may even be interpreted as a sign of quality given the percentage of these papers appearing in the top-tier journals in the field.

Ninety-six percent of the studies in our sample were translational, 4% were novel, and none reported phenomenological research. Translational research entails taking a methodological approach developed off-line, such as a questionnaire, and "translating" it into something that can be deployed over the internet. Novel research goes beyond translational research methods to develop new and creative ways of using the internet in research, and phenomenological studies explore the potentially unique impact of web-based social interaction on people's thoughts, feelings, and behavior (Skitka & Sargis, 2005). The percentage of novel studies in our current sample is similar to what we found in previous analyses (8% in Skitka & Sargis, 2005, and 5% in Skitka & Sargis, 2006). In our previous reviews, however, nearly half of the papers we found that used the internet to facilitate data collection were examples of phenomenological research, such as how internet use relates to well-being and depression. Our current review found virtually no examples of phenomenological research in the social psychological journals we reviewed in 2009 and 2010.

Further investigation suggests that interest in the phenomenology of internet use has not waned, but where scholars are publishing this research has shifted away from social psychological journals to more specialized journals that have emerged in recent years [e.g., *Cyberpsychology, Behavior, and Social Networking (CSBN)* and *Computers in Human Behavior (CHB)*]. A quick glance at the table of contents of CSBN and CHB, for example, indicates that research interest in how the internet affects people's day-to-day lives is vibrant and on going.

In summary, there is considerable growth in the number of scholars who are turning to the web to facilitate data collection. Most researchers are adapting methods commonly used off-line for online use, such as modifying paper and pencil questionnaires to be online measures instead. Moreover, this research appears to be well received by the scholarly community, and is faring particularly well at the top-tier journals in social psychology. We turn next to the emerging literature on best practices in web-based research, issues associated with probability and non-probability web-based sampling, and issues of data security.

Best Practices

Much of the research on best-practices for web-based data collection is being conducted by public opinion and survey researchers and methodologists, who share social psychologists' increasing enthusiasm for using the web to facilitate data collection (see Couper, 2008; Das, Ester, & Kaczmirek, 2011; see also Gosling & Johnson, 2010). These researchers have identified some of the unique challenges associated with web-based research, and a number of best practices for implementation of internet studies.

One of the major challenges of turning to web-based research is the loss of a certain amount of control, such as controlling whether participants carefully read and understand instructions, a tendency to drop out of the study before finishing due to boredom, task demands, or other considerations, and a tendency to provide mindless responses. The choices researchers make when designing web-based research can have a significant effect on either reducing or exacerbating these kinds of problems.

Overall Look and Feel of the Study

Experts generally agree that surveys should appear scholarly and professional (e.g., Couper, 2008; Fraley, 2004) and particular attention should be paid to usability (Couper, 2008). There are an infinite number of ways one can customize online measures, and there may be a temptation to make one's web page look elaborate or incorporate attractive designs features that do little to improve data quality. It turns out that the relative simplicity or complexity of designs, however, does not make much of a difference in data quality. For example, one study varied whether content was presented in a plain style (a simple text-based, black and white survey), whereas another used a graphic style (e.g., it included an organizational logo and varying colors, Walston, Lissitz, & Rudner, 2006), and whether the study was presented as publicly or privately funded. Completion rates were higher for the graphic style when it was government sponsored and displayed a logo for the U.S. Department of Education, but there was not an overall main effect for whether the study was simply or more complexly designed. That said, an aesthetically displeasing layout, such as one that uses a mixture of fonts, asymmetrical layouts, and contrasting rather than consonant color schemes can harm response rates, increase skipped questions, and skew the data toward more negative beliefs and opinions (Mahon-Haft & Dillman, 2010). A scholarly and professional appearance therefore appears to be important to web survey design, but adding graphic bells and whistles does not.

Visual Elements in Web-based Research

At its core, the internet is a visual medium and it is easy to use rich images in web-based research. It is often presumed that graphical elements help keep respondents engaged and therefore might prevent drop-out. One should not assume that the potential impact of visual elements on participant responses, however, will be neutral. Participants can interpret visual images as meaningful information for deciding how to respond. For example, participants who saw a picture of a woman jogging reported their own health to be worse than those who saw an image of a woman in a hospital bed (Couper, Conrad, & Tourangeau, 2007). Another study found that people reported higher support for protecting animals when animal pictures accompanied text than when they did not (Shropshire, Hawdon, & Witte, 2009). Although these findings might suggest how to design effective persuasive appeals, they also suggest that choices about including visual information in studies should be made with care. Moreover, the belief that the increased visual appeal of these elements improves response rates and/or decreases dropout rates is not supported by the data (Shropshire, et al., 2009).

Multi-item versus Single-item Pages

By changing a few settings or a few lines of code, researchers can choose to have all survey items individually, in particular groupings, or as a single continuing page. Presenting multiple items per page reduces completion times –something that can also reduce dropout rates (Toepoel, Das, & Van Soest, 2009; Vehovar, Manfreda & Batagelj, 2000), but only if people are not required to scroll down the page to see all the items (Toepoel et al., 2009).

When multiple items are grouped together on a screen, they tend to have greater inter-item correlations then when presented individually (Couper et al, 2007; Toepoel et al., 2009). From an organizational and scale reliability standpoint, it may make sense to group items on a screen together that are conceptually similar. Researchers should be aware, however, that the resulting correlations among these items might be inflated and groupings could mask random error that one might observe if items were presented one per screen.

Progress Bars

Many web-based studies include a text or graphics based progress indicator that lets participants know how much of the survey remains. The guiding assumption is that providing information about progress is likely to increase completion rates. Although some studies support the notion that progress bars enhance completion rates (e.g., Conrad, Couper, Tourangeau, & Peytchev, 2010; Couper, Traugott, & Lamias, 2001), other studies indicate that progress bars have little or no effect on completion rates (Heerwegh & Loosveldt, 2006; Matzat, Snijders, &

van der Hoorst, 2009), and yet others indicate that the presence of progress indicators reduce completion rates under some circumstances (Crawford, Couper, & Lamias, 2001; Conrad et al., 2010).

One reason for the mixed evidence of the usefulness of progress bars is due to how these bars are designed to work. Progress bars often use surface characteristics of a survey, such as the number of questions completed by a participant relative to the total number of questions as the reference point for displaying progress. However, these indicators can distort or over-estimate how much time is required to finish study. For example, when a study is programmed to skip certain questions as a function of responses to prior questions, progress bars based on the total number of items are likely to under-estimate progress. In addition, some questions take longer to answer than others which can limit the information value of progress bars. For example, having a progress bar is associated with higher drop-out rates when participants encounter several open-ended items at the beginning of a survey largely because participants assume the remainder of the survey will be similarly slowly paced (Crawford et al., 2001). Moreover, feedback of slow progress early in a study is associated with greater attrition than when participants receive slow progress feedback later in the survey. Faster progress feedback early in a study yields perceptions of greater interest and shorter completion times (Conrad et al., 2010). All other things being equal, time-consuming questions such as open-ended responses should therefore be placed at the end rather than beginning of studies, especially if progress feedback will be provided to participants.

Even though most participants prefer to have a progress indicator when given a choice (Heerwegh & Loosveldt, 2006), other research found that when participants had to click a button to check their progress, only 37% of participants bothered to check at all, and the vast proportion of those who did check only did so only once (Conrad et al., 2010). Taken together, progress bars may therefore not be as important for facilitating completion rates as most web researchers assume, and researchers should consider the relative trade-offs of using them in any particular study.

Response Formats in Web-based Research

There are several choices of response formats one can use in web-based research. Radio buttons, drop-down menus, sliders, and open-ended text boxes are commonly used response options (see Figure 1 for an example of each). Radio button scales and drop-down menus both allow users to select from a number of available options, whereas slider scales ask participants to place their responses on a continuum. When radio buttons and slider scales are used, every choice option is displayed on the screen along with the question. Drop-down menus, however, often hide most or all available response options until users click on a box and/or scroll through a menu.

Radio button scales generally yield higher quality data than either slider scales or drop-down menus (Couper, Tourangeau, Conrad, & Crawford, 2004). Drop-down menus yield more missing data than radio button scales (Healy, 2007) and are vulnerable primacy and recency effects (Couper et al. 2004; Galesic & Yan, 2011; Healy, 2007). Although problematic for these reasons, drop-down menus are nonetheless useful for collecting factual information about participants, for example age, education, or country of origin (Couper et al. 2004).

Slider and radio button scales yield equally reliable scales (Cook, Heath, Thompson, & Thompson, 2001; Couper, Tourangeau, Conrad, & Singer, 2006). The use of slider scales in online surveys, however, is associated with higher drop-out rates relative to radio button scales (Couper et al., 2006), perhaps because slider scales place higher cognitive demands on participants (Funke, Reips & Thomas, 2011). Slider scales also have a number of other limitations relative to other scale options, including that respondents' browsers must be configured to run JavaScript (required to program a slider scale), which can make these items take longer to load. One study found that the number of people who exited a study before even declining to participate (i.e., presumably before the survey fully loaded) was 16-18% higher for a survey programmed with slider-scales than other versions of the same survey, probably because the study took an average of 12 extra seconds to load (Walston et al., 2006).

Although JavaScript has some downsides, most survey software solutions (e.g., Qualtrics) nonetheless rely on Java or other client-side programs, to facilitate the collection of detailed internet paradata (e.g., IP addresses, when participants access a survey, and how long participants take to complete it). JavaScripts can also enable more nuanced paradata including tracking changes in user responses as they complete a measure, and to track lurkers (i.e., those that look at all of the survey questions without answering). Thus, the potential benefits of incorporating JavaScript into one's study may outweigh the risks of higher drop-out rates.

Response Option Spacing, Labeling, and Alignment

Research on the alignment of items and response options in web-based studies has been facilitated by the identification of heuristics participants' tend to use when completing web-based surveys (Tourangeau, Couper, & Conrad, 2004, 2007; see Toepoel & Dillman, 2011a for an overview). For example, respondents tend to assume that the visual midpoint of a scale is the typical or middle response ("the middle is typical" heuristic). This heuristic is particularly important when deciding where to place nonsubstantive (e.g., *Don't Know*) response options relative to more substantive response options within a scale. For example, when nonsubstantive responses are grouped with more substantive response options (*Slightly, Moderately*), responses are pulled in the direction of the visual midpoint of the scale. When a visual dividing line between substantive and non-substantive response options is present, however, the true midpoint of the scale is perceived as equal to the conceptual midpoint (Tourangeau et al., 2004). Uneven spacing of response options also affects responses. When spaces between items at one end of a scale are longer than another, respondents are more likely to choose more extreme responses (Tourangeau et al., 2004). Including a verbal or numeric label for each response option attenuates the effects of spacing (Toepoel & Dillman, 2011b; however see Schwartz, 1996 for how numeric labels can potentially bias results). Therefore, when constructing response scales, ideally all scale options would be evenly spaced, and each option should have its own verbal label (Toepoel & Dillman, 2011a, Tourangeau et al., 2004, 2007). If researchers want to have non-substantive response options, they should be visually separated from the scalar responses.

Open-ended Items

Another commonly used response format is a text box for open-ended questions. One issue to consider with open-ended questions is the amount of space to make visible for user responses. In HTML programming there are two important parameters one can set for each text box – the size of the box that is displayed, and the maximum number of characters that can be entered into the box. Because of this, the survey designer can choose to display a small box, but allow for a large amount of text to be entered (or vice versa).

Text box size and written instructions affect the quality of answers to open-ended questions (Smyth, Dillman, Christian, & McBride, 2009). Increasing the size of the text box increases the response quality among those who responded to the survey late in the fielding period, but not early. More importantly, regardless of text box size, participants who received instructions that they should not limit their response to the size of the box gave higher quality responses than those who did not (Smyth et al., 2009).

Text box size also affects the quality of text-based quantitative data. For example, participants asked to think of 10 acquaintances and then to indicate how many of them were of various ethnicities in text boxes associated with each ethnic category, should provide answers that sum to 10. When participants were asked to do this task, they were nearly twice as likely to provide an inappropriate response if provided a large rather than small response box (e.g., instead of entering a number as instructed, participants would enter “about three”, or “between four and five,” Couper, Traugott, & Lamias, 2001)). Thus, text boxes should be customized for the size of an appropriate response.

We have found that including an open-ended text box with the question, “Is there anything you would like to add or would like the researchers to know?” is particularly useful to include as the final item in an on-line study. Because it is last, it will not hurt completion rates, and responses often provide critical insight into either problems with the implementation of the study (e.g., unclear questions, formatting problems on one or another browser), and sometimes can be a rich source of information about the topic of study.

Preventing and Detecting Satisficing

Satisficing is the tendency for participants to use minimal cognitive effort to plausibly respond to a survey question (Krosnick, 1991). Rather than give a thoughtful appraisal of choice alternatives, a satisficing participant selects the least effortful response. Examples of satisficing can include failing to discriminate carefully between response categories (e.g., *Somewhat* versus *Very Much*) or choosing answers at random. Satisficing can occur for a number of reasons. Many participants in online studies are primarily motivated to obtain an incentive (for example, see the discussion of Mechanical Turk below), rather than motivated to provide thoughtful responses. Web participants are also vulnerable to any number of distractions that could interfere with their ability to concentrate or accurately complete measures (phone calls, and other distractions in the environment).

Satisficing is a bigger concern in web-based studies than those conducted using other methods. For example, web studies tend to yield more "*Don't Know*" responses and to have less differentiation in responses than data collected using telephone surveys (Fricker, Galesic, Tourangeau, & Yan, 2005) or face-to-face interviews (Heerwegh & Loosveldt, 2008). In a study with a sample of over 23,000 participants, Johnson (2005) found a 6% rate of satisficing responses (operationalized in this study as the participant selecting the same response category nine or more consecutive times) on a Big Five measure of personality measure, which was much higher than the 0.9% rate found when using pencil-and-paper versions of the measure.

There are many potential strategies to detect possible satisficing. For example, one can examine the amount of time participants spend answering questions, and exclude those who respond too fast to have carefully considered them. Another simple approach is to include several reverse-scored items interspersed throughout a questionnaire because satisficing participants often consistently choose responses only on one end of scales (e.g., Heerwegh & Loosveldt, 2008; Johnson, 2005). Savvy participants, however, may vary their responses throughout a measure without reading their content (see our discussion of professional participants in the section on sampling). Thus, another method to detect satisficing is to include instructional manipulation checks (IMCs, Oppenheimer, Meyvis, & Davidenko, 2009). IMCs are simple instructions embedded in a study that instruct the participant to select a particular response or to ignore a particular question. For example, in a computer-based administration of measures in a lab study, Oppenheimer et al. (2009) presented participants with instructions to click the title at the top of the page rather than select a response. Forty-six percent of the sample failed this IMC. When those participants were excluded from the data set, there was a corresponding increase in statistical power, despite the reduction in sample size (Oppenheimer et al. 2009, Study 1). When participants were forced to retry a failed IMC before continuing, the quality of their subsequent responses improved and they became indistinguishable from those who initially passed the IMC (Oppenheimer et al., 2009, Study 2).

When feedback is the primary incentive for participants' involvement in a study, they are unlikely to satisfice (Gosling, Vazire, Srivastava, & John, 2004; Johnson, 2005). Moreover, people who choose to participate in a study out of personal interest are less likely to satisfice than those who have agreed to be a member of an on-line panel or subject pool (Chang & Krosnick, 2009). Although maximizing the interest-value of one's study is one strategy to reduce satisficing, we suggest including IMCs to provide some protection and detection. One possibility is including an IMC at the beginning of a study (e.g., a short reading comprehension test that must be passed to continue to the real study), which would not only detect satisficers, but would probably lead unmotivated participants to drop out early as well.

Populating Your Study

Fifty-five percent of the studies we reviewed for this chapter used college students to populate their studies even though they collected data remotely on the web. The advantages of online data collection with college student samples are many, including automated data entry, running many participants simultaneously without the need to contend with scheduling hassles and space constraints, and limiting staff time to programming the study. To the extent that the subject pool at a given university is set up to easily allow participants to participate in studies online, or the university is willing to allow researchers to distribute e-mail blasts requesting students' participation in studies, it is not surprising that college student samples are a popular option for populating studies. There are also web site portals that allow researchers from universities without subject pools to have access to college student participants.

Although university subject pools are typically inexpensive and accessible ways to populate studies, it is increasingly possible to use community samples. For example, in addition to providing a very user-friendly shell for designing web surveys, Qualtrics also sells access to an opt-in panel of possible participants. Many researchers have also had success posting Craig's List ads and recruiting hundreds of participants in relatively short periods of time, often for no incentive or a small incentive such as a lottery.

MTurk

Increasingly popular is turning to Amazon's Mechanical Turk (MTurk) for participants (e.g., Alter, Oppenheimer, & Zemla, 2010; Erikson & Simpson, 2010). MTurk is a crowdsourcing marketplace that allows users to distribute work to a larger number of potential workers. Work is broken down into one-time tasks (HITs, or Human Intelligence Tasks) that workers are paid to complete. Potential workers browse among posted tasks and can complete tasks for which they qualify. "Requesters" (those requesting work to be done) can use either a set of pre-existing qualifications (e.g., a given country of origin, workers 18 years of age or older, or even how many HITs a worker has submitted in his/her lifetime) or set unique qualifications such as completing a brief screening questionnaire. Tasks are typically simple enough to require only a few minutes to complete, and workers can sort tasks by reward level and length of time to complete. Rewards for completing HITs can be as low as $0.01, and rarely exceed $1.00. When translated into an hourly wage, workers are estimated to be willing to complete HITs at a return of about $1.40 per hour (Horton & Chilton, in press). Requesters set up an Amazon account and fund it for the purpose of paying workers, and funds are automatically transferred from the Requester to the Worker's account when a HIT is completed. Moreover, Amazon.com has numerous pages instructing users how to set up an MTurk account, qualify workers, etc., all of which is quite user-friendly.[1]

There has been considerable interest in describing the demographics of MTurk samples. Early reviews of MTurk samples indicated that about 70-80% were from the United States (Ipeirotis, 2009; Ross et al., 2010). Due to changes in the way Amazon.com is willing to pay non-U.S. workers (they recently added the option to be paid in cash instead of in gift cards), there has been a very recent increase in non-U.S. workers on MTurk. For example, Indian workers now make up approximately 34% of MTurk workers (e.g., Eriksson & Simpson, 2010; Paolacci, Chandler, & Ipeirotis, 2010—keep in mind, however, that one can qualify workers based on nationality).

A closer examination of current U.S. workers reveals that they are more often female (65%), slightly younger, more highly educated, and lower in income than the national average. Only a small percentage of U.S. workers claim MTurk as a primary source of income (about 14%), but a majority indicated that earning additional income is a primarily motivation for completing tasks on MTurk (61%). That said, many MTurk workers claim they participate in part for entertainment (41%) or for just "killing time" (32%) (Paolacci et al., 2010). Taken together, the demographics of MTurk U.S. workers are similar to other opt-in internet samples, but taken as a whole, MTurk samples are more diverse than most other opt-in panels due to increased levels of

[1] At present, there are some challenges for non-U.S. researchers to become requesters. See Buhrmester (2010) for work-arounds and continuing updating of an MTurk guide for social scientists.

participation of people globally (Buhrmeister, Kwang & Gosling, 2011; Paolacci et al., 2010), something that may be an advantage for some researchers.

Data quality on MTurk seems to be comparable to college student subject pools. One study that compared the degree of failure on instructional manipulation checks for college student and MTurk samples found that college students were more likely to provide thoughtless responses (6.47%) than were those on MTurk (4%) (Paolacci et al., 2010), but survey completion rates were higher with college students (99%) than MTurk (92%). Moreover, effect sizes were quite similar in college student and MTurk samples when asked a number of common judgment and decision making questions (Paolacci et al., 2010).

Problems with Non-Probability Samples on the Web

Access to "opt-in" samples, such as MTurk, is relatively easy and inexpensive, but does have some downsides. Yes, opt-in panel members look in many ways like college students and internet users in general, but that does not mean that they are representative of the population at large. For example, as of December 2010 it was still the case that 33% of Americans do not use the internet (Pew Internet and Life Project, 2010a), and the adoption curve has largely plateaued at between 73 and 77% penetration since 2005. Blacks and Hispanics are between 11-24% less likely to be on-line than their White peers, and only 46% of American adults age 65 or older and 63% of those with incomes under $30,000 a year use the internet. Internet use is also highly correlated with education (Pew Internet and Life Project, 2010b). Although many differences between internet users and non-users disappear once one accounts for these demographic differences in internet use, an examination of differences between internet users and non-users who completed the 2000, 2002, 2004 and 2006 General Satisfaction Survey (GSS) revealed that internet users are more liberal on some social issues than non-users, and were more sociable and optimistic. Moreover, these findings were remarkably stable over time (Robinson & Steven, 2009). Other comparisons of web-users and non-users found that users are also higher in trust of others, have broader social networks, and generally believe that people are more fair than are non-users (Lenhart et al, 2003). Opt-in samples of web-users are also more politically knowledgeable and engaged than are random samples of the population (Chang & Krosnick, 2009).

In addition to problems associated with differences between internet users and non-users that could introduce bias into web-based research, is the problem of volunteerism. Studies based on self-selected volunteers – especially from large and largely unknown populations—are subject to non-measurable biases. Although all studies are prone to multiple sources of error, two known problems with opt-in panels include the inability to calculate estimates of true sampling error (the difference between a sample statistic used to estimate a population parameter and the actual but unknown value of the parameter) and problems with coverage (when all members of the population do not have an equal or known probability of being included in the sample—a serious problem with opt-in studies). When one samples from a known population, these kinds of errors can be legitimately estimated and adjusted for in data analysis, because one can calculate the probability of inclusion in the sample. Although researchers calculate "standard errors" all the time, they are not scientifically or mathematically informative when one does not have a probability sample of the population. Moreover, to the extent one has a biased sample, collecting large samples just multiplies the bias instead of reducing it.

Our goal in raising these issues is not to say non-probability samples have no value. When the goal of social psychological research is to document whether two variables relate to each other or to test theoretical propositions, it may not be as important to get the strength of the association precisely correct: Learning that the variables relate is sufficient to reject the null hypothesis (Petty & Cacioppo, 1996). However, when the goal is to make claims about effect sizes and the generalizability of a finding in a population, sample quality matters, and there is mounting evidence that opt-in web-based research is not as accurate as research using probability sampling either on the web or not (see especially Yeager et al., 2009).

Marketing research can provide some examples of the problems associated with the accuracy of opt-in samples. For example, General Mills conducted the same concept test with two samples drawn from the same opt-in panel, but the two studies yielded completely divergent recommendations about whether the company should launch the product. It ultimately turned out that one sample had much more experience taking web-based surveys, and for whatever reason, this explained which sample had a less positive impression of the product than the other (for more about this example and others, see Baker, 2008). In short, despite being drawn from the same panel, the conclusions reached by the two studies were quite different largely because the panel was (a) not representative in the first place, and (b) there is no way to randomly sample from opt-in panels—people choose when to participate, and there can be systematic reasons why they choose to participate at any one time rather than another (e.g., it's the end of the month and people may need an influx of cash, or a project like implicit.org may be mentioned in the press which drives traffic to the site one week, but not another).

A related problem is that there is a greater than chance likelihood that some respondents in opt-in panels are study "professionals." As noted earlier, 14% of those surveyed on MTurk used their participation as a primary source of income. Other research has estimated that 10% of panel participants account for 81% of study responses in the 10 largest opt-in web panels, and 1% of participants account for 34% of responses (Langer, 2009). In short, a small number of highly motivated participants are providing the vast majority of responses to studies using opt-in panels. Professionals are also more likely to try to game the system, and to know what characteristics are most likely to lead to pay-off in screening questionnaires, which can introduce a host of yet other problems (Langer, 2009).

Although social psychologists have not become terribly concerned about these issues as yet, others have. For example, the *New York Times* publication standards state that “Self-selected or ‘opt-in’ samples, including the internet, e-mail, fax, call-in, street intercept, and non-probability mail-in samples—do not meet The Times’ standards, regardless of the number of people who participate” (see http://www.nytimes.com/packages/pdf/politics/pollingstandards.pdf). The Associated Press and Washington Post have similar policies. It might be somewhat embarrassing to admit that many of us in the scientific community have lower standards than the press on what counts as quality data (social psychology is not alone: for a detailed discussion, see Langer, 2009).

Accessing Probability Samples on the Web

There are a number true probability national panels available for research. The Longitudinal Internet Studies for the Social Sciences (LISS) panel is a true probability sample of households in the Netherlands, with about 5000 households and 8000 total participants. The LISS sample was drawn from national population registers, and potential participants were approached by mail, telephone, or in-person with an invitation to participate in scientific research. If potential participants did not have access to the web, they were loaned equipment. In 2010, a special sample of immigrants stratified by region was added to the panel. Funding for maintaining the panel is provided by the Netherlands Organization for Scientific Research, researchers from anywhere in the world can apply for access, and proposals are evaluated through peer review.

Knowledge Networks (KN) is the only company so far to build an internet enabled probability sample panel in the U.S., and began building its panel by soliciting participation by calling people using random-digit-dialing (RDD) recruitment methods. The KN panel now includes about 30,000 households and 43,000 adults. RDD involves generating random numbers associated with a known area code and exchange, and calling people with the request to participate. Because widespread cell phone use is beginning to erode the effectiveness of RDD, KN switched to address-based-sampling (ABS) several years ago, which bases participant recruitment on mailing recruitment materials to randomly selected residential addresses (see DiSogra, 2010). To ensure that they built a sample that was independent of whether people have prior access to the internet, KN, like LISS, offers participants with a free device to connect to the internet if needed, and pays participants' ISP charges as part of an incentive to participate. Every household member age 13 and up is given their own KN account, and they are asked to complete 1 to 2 studies per month. KN has also recruited a number of nationally representative specialty panels, including Hispanic, teacher, and physician panels.[2]

Unlike LISS, KN is a for-profit enterprise and one about equally geared toward conducting commercial and government/academic research. Researchers therefore generally require grant funding to buy access to the KN panel. However, some scholars concerned about data quality in the social sciences wrote a large National Science Foundation grant to facilitate greater research

[2] A third representative panel of respondents is available in Germany through Forsa.Omninet. Because (a) very few specifics about its sampling procedures are available, (b) there is little or no evidence of academic use of this panel, and (c) the existence of considerable negative press attention about alleged biases in their political polling (e.g., an alleged tendency to push poll), we decided not to cover this firm in any detail in this chapter.

access to true probability samples in the U.S. (the Time-sharing Experiments in the Social Sciences (TESS) program (see http://www.tessexperiments.org/ for details). The program is open to any faculty member, postdoctoral fellow, or graduate student affiliated with any social science or social science-related department anywhere in the world, with the only requirement being that the study use an experimental design. Proposals are brief (5 pages), and are subject to peer review. TESS has now funded more than 250 studies.

Because LISS and KN are sampling from known populations (the Netherlands and the U.S., respectively), it is possible to estimate sampling errors and to generate sample weights for the data, which will increase the accuracy of study conclusions. Both panels are much less prone to coverage biases or infiltration by professionals because they do not allow people to opt-in, but instead recruit participation within their full respective national populations (KN estimates that its panel coverage is at 97% of the U.S.). Another advantage of these panels is that LISS is entirely free for academic use, and there are ways to obtain free access to KN as well. Both panels also maintain a great deal of information about their panelists, so it is possible to recruit representative samples of (for example) specific minority groups, parents of children under the age of 10, or equal numbers of political ideologues, which will be a very attractive feature for many researchers.

Incentives

The vast proportion of social psychological research still relies on college student subject pools for research participants (see Feldman-Barrett, 2005; Henry, 2008; Sears, 1986 for problems associated with social psychology's over-reliance on student samples). The usual incentive for college students to participate has been fulfilling course requirements or earning extra credit. Although firms like KN and LISS have their own incentive policies, researchers using opt-in or other convenience samples need to explore incentives besides course credit, including either pay for service in the form of PayPal payments, on-line gift cards, payments to Mechanical Turk accounts, or offering “lottery tickets” and the chance of winning a larger incentive. A meta-analysis found that incentives increased the likelihood that a participant would (a) respond to a study by 19% and (b) finish the study measures by 27% (Göritz, 2006).

Incentives can take many forms, something we explored in our review of internet-based studies in social psychology. Because most samples in our review were college students, the most frequent incentive was course credit (32%). For non-student participants, the most common incentives were money or gift certificates (these incentives were used 25% of the time in our full sample). Researchers have some options as to how to package incentives. For example, one option is to give every participant a small incentive, for example, studies using MTurk might offer between 15 and 25 cents for a completion. Another common approach is to offer a chance to win a larger prize upon completion of the study in the form of a lottery (used by 17% of the studies reviewed). Lotteries have the advantage that for a limited, pre-specified amount of funds, the researcher can collect data from an unlimited number of participants.

Lotteries can increase participation rates in online surveys and lead to fewer incomplete responses than a small token incentive, particularly for one-time studies rather than longitudinal panel designs (Bosnjak & Tuten, 2010, Göritz, 2010). Telling participants they will know whether they won a lottery immediately upon completing their participation improves responses rates by 6% relative to a condition that offers delayed notification (Tuten, Galesic, & Bosnjak, 2004). Lotteries are therefore effective strategies for incenting participation, and are generally more economical than other approaches.

A non-monetary incentive that some participants may find appealing is feedback. This was the incentive in 3% of the studies in our sample. One advantage of web-based measurement is the ability to instantaneously compute individualized feedback for participants. Websites like projectimplicit.net and outofservice.com have collected data from massive numbers of participants with the incentive of feedback alone. Promises of feedback significantly increase participation rates relative to no feedback controls, and nearly to the same level as a lottery condition with delayed notification of lottery winners. A lottery with immediate notification, however, has a stronger incentive effect than the promise of immediate feedback (Tuten et al., 2004).

Data Security

Data security is fast becoming a major issue in internet-based research. Researchers have an obligation to protect sensitive information collected from research participants, in particular, sensitive information that can be linked directly to specific participants. Ideally, data would be collected without any identifiers. Depending upon the nature of one's research, however, it may be necessary to collect certain identifiers. Sometimes this information is collected for practical purposes such as collecting email addresses to allow one to notify winners when a lottery is a participation incentive. Regardless, Institutional Review Boards (IRBs) are increasingly concerned about data security in general, and of identifiable data in particular. Although a full treatment of data security is beyond the scope of this review, we review some basic guidelines.

Secure Data Transfers

Data transfer represents a major vulnerability to data security—that is, any movement of data from one server to another, from a computer to a back-up drive, sending data by e-mail, etc. A motivated hacker has no problem accessing unsecured data during data transfers. One solution is to make sure that information is passed through an encrypted connection using hypertext transfer protocol secure (HTTPS). Normal, unsecured web traffic is transferred, unaltered, using regular hypertext transfer protocol (HTTP). When using HTTPS, the information being sent between the user and the server is encrypted. Anyone intercepting the transmission of data would be unable to read the data. For a HTTPS session to occur, the server must present the user's browser a validated third party security certificate such as (e.g., one generated by VeriSign, Westfall & Ma, 2010).

To see whether your host server is HTTPS compliant, simply change the "http" in the web address of the questionnaire or experiment to "https". The data will be encrypted if the page displays normally after this change. (Note: it is also important that any other web addresses that the survey will pass information to also use "https" in their URL, e.g. subsequent web pages). The steps for making a server accept HTTPS connections is beyond the scope of what we can cover here, but there are many instructive resources on the web, and this well within the skillset of most information technology staff members (presuming your home university does not block their use --some do to protect their own systems, Thiele & Kaczmirek, 2010).

Researchers should also use secure connections, such as HTTPS when they download data remotely from a survey host such as SurveyMonkey or Qualtrics. Most survey software shells can be accessed via a secure connection and are themselves password protected. In addition, there are free secure file transfer protocol programs available that will encrypt data transfers from a server to the researcher. If HTTPS is available use it; if it is not, one should minimally alert potential participants that the data being collected will not be secured during transfer, and could therefore be vulnerable.

Secure Storage

Another potential security vulnerability lies in the storage of data. Once sensitive data leaves a server, it is important that protections are put in place to protect data on local machines. An easy way to secure data storage is file encryption. Although there are commercial products available, there are also many free sources of encryption software. Before shopping around for encryption software, be sure to check with your local IRB about any requirements they may have about data security (e.g., the authors' university requires NIST compliant encryption). Encryption software will make password protected "file containers" that can protect data on any kind of computerized storage device ranging from USB drives to cloud based systems such as Dropbox.

Passwords

Passwords are usually the first line of defense between a would-be attacker and data. Passwords are used to protect accounts for survey software shells, access to self managed servers, and the encryption software just mentioned. It is important that the passwords used in these contexts are "strong" passwords. A strong password is one that is (a) between 8 and 14 characters, contains letters, numbers, and non-alphanumeric characters, (b) does not correspond with any other passwords the user has for any other websites or systems, and (c) does not use any common words. One useful strategy is to use a mnemonic: Pick a sentence you are likely to remember, such as "I love to dance the Cha-Cha" and use the first letter of each word to yield: Il2dtCC (we used 2 instead of "t" for "to" because most passwords require at least 1 number). Alternatively, one can use a random password generator (there are many available on-line, e.g., http://www.pctools.com/guides/password/). Given the increasing need for more complex passwords, many are finding password-management software such as LastPass or KeePass useful. This software is often free or charges a nominal monthly fee (fees usually also enable extra features). It encrypts and stores all your passwords, and some programs automatically plug in your password at appropriate sites. The advantage of these services is that the only password you will need to remember is the one to your password protection program.

The landscape of security threats and solutions is constantly changing. Although data security is important for a number of reasons, IRBs (and especially those with rigorous government oversight due to the number of grants received at a given site) are increasingly requiring data security plans be included with all new research proposals and renewals. Therefore these protections will no longer be simply desirable, but are likely to be mandated.

Conclusion

The internet has evolved into an important tool for social psychological research. The internet's ability to connect vast numbers of people and the richness of information that can be displayed and collected makes it an ideal research tool in many respects. The penetration of internet-based research being published in top-tier social psychological journals has skyrocketed in recent years and is likely continue to grow. As we learn more about the potential challenges of web-based research (e.g., a tendency to drop-out or satisfice, maintaining data security), we are also increasingly learning more about how to avoid them. Similar to the growing interest in turning to the web for research, is a burgeoning interest in research on best practices of web-based research. We encourage researchers interested in these issues to keep in touch with these developments as much as possible. Fortunately—and perhaps not surprisingly, given the topic-- a website has emerged as a major clearinghouse for information about best practices for web-based research (WebSM.org), something we encourage researchers interested in using the web for their research to explore whenever confronted with choices or decisions about designing the strongest study possible.

References

Alter, A. L., Oppenheimer, D. M., & Zemla, J. C. (2010). Missing the trees for the forest: A construal theory account of the illusion of explanatory depth. *Journal of Personality and Social Psychology, 99,* 436-451.

Baker, R. (2008). A web of worries: Online research has been booming but after 12 years of exponential growth, is it losing its luster? *Research World,* June 2008, 8-9.

Bosnjak, M., & Tuten, T. L. (2003). Prepaid and promised incentives in web surveys: An experiment. *Social Science Computer Review, 21*, 208-217.

Buhrmester, M. (2010). Amazon Mechanical Turk guide for social scientists. Retrieved July 4, 2011 from http://homepage.psy.utexas.edu/homepage/students/buhrmester/MTurk%20Guide.htm.

Buhrmester, M., Kwang, T., & Gosling, S. D. (2011). Amazon's mechanical turk: A new source of inexpensive, yet high-quality, data? *Perspectives on Psychological Science, 6*, 3-5.

Chang, L., & Krosnick, J. A. (2009). National surveys via RDD telephone interviewing vs. the Internet: Comparing sample representativeness and response quality. *Public Opinion Quarterly, 73,* 641 – 678.

Conrad, F. G., Couper, M. P., Tourangeau, R., & Peytchev, A. (2010). The impact of progress indicators on task completion. *Interacting with Computers, 22*, 417-427.

Cook, C., Heath, F., Thompson, R. L., & Thompson, B. (2001). Score reliability in web or internet-based surveys: Unnumbered graphic rating scales versus Likert-type scales. *Educational and Psychological Measurement, 61*, 697-706.

Couper, M. P. (2008). *Designing effective web surveys*. New York, NY, US: Cambridge University Press. Couper, M. P., Conrad, F. G., & Tourangeau, R. (2007). Visual context effects in web surveys. *Public Opinion Quarterly, 71*, 623-634.

Couper, M. P., Tourangeau, R., Conrad, F. G., & Singer, E. (2006). Evaluating the effectiveness of visual analog scales: A web experiment. *Social Science Computer Review, 24*, 227-245.

Couper, M. P., Tourangeau, R., Conrad, F. G., & Crawford, S. D. (2004). What they see is what we get. *Social Science Computer Review, 22*, 111-127.

Couper, M. P., Tourangeau, R., & Kenyon, K. (2004). Picture this! Exploring visual effects in web surveys. *Public Opinion Quarterly, 68*, 255-266.

Couper, M. P., Traugott, M. W., & and Lamias, M. J. (2001). Web survey design and administration. *Public Opinion Quarterly, 65*, 230-253.

Crawford, S. D., Couper, M. P., & Lamias, M. J. (2001). Web surveys: Perceptions of burden. *Social Science Computer Review, 19*, 146-162.

Das, M., Ester, P., & Kaczmirek, L. (Eds.). (2011). *Social and behavioral research and the internet: Advances in applied methods and research strategies*. New York, NY, US: Routledge/Taylor & Francis Group.

DiSogra, C. (2010). Update: Address-based sampling nets success for KnowledgePanel recruitment and sample representation. *Accuracy's Impact on Research: A Knowledge Networks Newsletter,* Spring, 1- 2.

Eriksson, K., & Simpson, B. (2010). Emotional reactions to losing explain gender differences in entering a risky lottery. *Judgment and Decision Making, 5,* 159 – 163.

Feldman-Barrett, L. (2005). How random is that? *APS Observer,* Retrieved June 29, 2011 from http://www.psychologicalscience.org/observer/getArticle.cfm?id=1838.

Fraley, R. C. (2004). *How to conduct behavioral research over the internet.* Guilford Press.

Fricker, S., Galesic, M., Tourangeau, R., & Yan, T. (2005). An experimental comparison of web and telephone surveys. *The Public Opinion Quarterly, 69*(3), pp. 370-392.

Funke, F., Reips, U. D., & Thomas, R. K. (2011). Sliders for the smart: Type of rating scale on the web interacts with educational level. *Social Science Computer Review, 29*, 221-231.

Galesic, M., & Yan, T. (2011). Use of eye tracking for studying survey response processes. In M. Das, P. Ester, L. Kaczmirek, (Eds.), *Social and behavioral research and the internet: Advances in applied methods and research strategies.* (pp. 349-370). New York, NY, US: Routledge/Taylor & Francis Group.

Göritz, A. S. (2006). Incentives in web studies: Methodological issues and a review. *International Journal of Internet Science, 1*, 58-70.

Göritz, A. S. (2010). Using lotteries, loyalty points, and other incentives to increase participant response and completion. In S. D. Gosling, & J. A. Johnson (Eds.), *Advanced methods for conducting online behavioral research.* (pp. 219-233). Washington, DC, US: American Psychological Association.

Gosling, S. D., & Johnson, J. A. (Eds.). (2010). *Advanced methods for conducting online behavioral research*. Washington, DC, US: American Psychological Association.

Gosling, S., Vazire, S., Srivastava, S., & John, O. (2004). Should we trust web-based studies? A comparative analysis of six preconceptions about internet questionnaires. *American Psychologist, 59,* 93 – 104.

Healey, B. (2007). Drop downs and scroll mice: The effect of response option format and input mechanism employed on data quality in web surveys. *Social Science Computer Review, 25*, 111-128.

Heerwegh, D., & Loosveldt, G. (2006). An experimental study on the effects of personalization, survey length statements, progress indicators, and survey sponsor logos in web surveys. *Journal of Official Statistics-Stockholm, 22*, 191-210.

Heerwegh, D., & Loosveldt, G. (2008). Face-to-face versus web surveying in a high-internet-coverage population: Differences in response quality.*72*, 836-846.

Henry, P. J. (2008). Student sampling as a theoretical problem. *Psychological Inquiry, 19,* 114 -125.

Horton, J. & Chilton, L. (in press). The labor economics of paid crowdsourcing. *Proceedings of the 11th ACM Conference on Electronic Commerce.*

Ipeirotis, P. (2009). Turker demographics vs. internet demographics. http://behind-the-enemy-lines.blogspot.com/2009/03/turker-demographics-vs-internet.html. Accessed June 30, 2011.

Johnson, J. A. (2005). Ascertaining the validity of individual protocols from web-based personality inventories. *Journal of Research in Personality, 39*, 103-129.

Krosnick, J. A. (1991). Response strategies for coping with the cognitive demands of attitude measures in surveys. *Applied Cognitive Psychology: Special Issue: Cognition and Survey Measurement, 5*, 213-236.

Langer, G. (2009). *Survey reporting standards*. Paper presented at the Survey Quality Conference, Harvard University Program on Survey Research.

Lenhart, A., Horrigan, J., Rainie, L., Allen, K., Boyce, A., Madden, M., & O'Grady, E. (2003). The ever-shifting Internet population: A new look at Internet access and the digital divide. *The Pew Internet and American Life Project.*

Mahon-Haft, T. A., & Dillman, D. A. (2010). Does visual appeal matter? effects of web survey aesthetics on survey quality. *Survey Research Methods, 4*, 43-59.

Matzat, U., Snijders, C., & van der Horst, W. (2009). Effects of different types of progress indicators on drop-out rates in web surveys. *Social Psychology, 40*, 43-52.

Oppenheimer, D. M., Meyvis, T., & Davidenko, N. (2009). Instructional manipulation checks: Detecting satisficing to increase statistical power. *Journal of Experimental Social Psychology, 45*, 867-872.

Paolacci, G., Chandler, J., & Ipeirotis, P.G. (2010). Running experiments on Amazon Mechanical Turk. *Judgment and Decision Making, 5,* 411-419.

Petty, R. E., & J. T. Cacioppo. (1996). Addressing disturbing and disturbed consumer behavior: Is it necessary to change the way we conduct behavioral science? *Journal of Marketing Research, 33,*1-8.

Pew Internet and Life Project (2010a). Internet adoption, 1995 – 2010. http://www.pewinternet.org/Trend-Data/Internet-Adoption.aspx, downloaded June 30, 2011.

Pew Internet and Life Project (2010b). Demographics of internet users. http://www.pewinternet.org/Trend-Data/Whos-Online.aspx, downloaded June 30, 2011.

Robinson, J., & Steven, M. (2009). Social attitude differences between internet users and nonusers. *Information Communication and Society, 12,* 508 – 524.

Ross, J., Irani, L., Silberman, M. S., Zaldivar, A., & Tomlinson, B. (2010). Who are the crowdworkers?: Shifting demographics in Mechanical Turk. In *CHI EA '10: Proceedings of the 28th of the international conference extended abstracts on human factors in computing systems,* pp. 2863 – 2872. New York, NY: ACM.

Schwarz, N. (1996). *Cognition and communication: Judgmental biases, research methods and the logic of conversation.* Hillsdale, NJ: Erlbaum.

Sears, D. O. (1986). College sophomores in the laboratory: Influence of a narrow data base on social psychology's view of human nature. *Journal of Personality and Social Psychology, 51,* 515 – 530.

Shropshire, K. O., Hawdon, J. E., & Witte, J. C. (2009). Web survey design: Balancing measurement, response, and topical interest. *Sociological Methods & Research, 37*, 344-370.

Skitka, L., & Sargis, E. (2005). Social psychological research and the internet: The promise and peril of a new methodological frontier. In Y. Amichai-Hamburger (Ed.) *The social net: The social psychology of the Internet* (pp. 1-26). Oxford, UK: Oxford University Press.

Skitka, L. J., & Sargis, E. G. (2006). The internet as psychological laboratory. *Annual Review of Psychology, 57*, 529-555.

Smyth, J. D., Dillman, D. A., Christian, L. M., & McBride, M. (2009). Open-ended questions in web surveys: Can increasing the size of answer boxes and providing extra verbal instructions improve response quality? *Public Opinion Quarterly, 73*, 325-337.

Thiele, O., & Kaczmirek, L. (2010). Security and data protection: Collection, storage, and feedback in internet research. In S. D. Gosling, & J. A. Johnson (Eds.), *Advanced methods for conducting online behavioral research.* (pp. 235-253). Washington, DC, US: American Psychological Association.

Toepoel, V., Das, M., & Van Soest, A. (2009). Design of web questionnaires: The effects of the number of items per screen. *Field Methods, 21*, 200-213.

Toepoel, V., & Dillman, D. A. (2011a). How visual design affects the interpretability of survey questions. In M. Das, P. Ester, L. Kaczmirek, M. Das, P. Ester & L. Kaczmirek (Eds.), *Social and behavioral research and the internet: Advances in applied methods and research strategies.* (pp. 165-190). New York, NY, US: Routledge/Taylor & Francis Group.

Toepoel, V., & Dillman, D. A. (2011b). Words, numbers, and visual heuristics in web surveys: Is there a hierarchy of importance? *Social Science Computer Review, 29*, 193-207.

Tourangeau, R., Couper, M. P., & Conrad, F. (2004). Spacing, position, and order: Interpretive heuristics for visual features of survey questions. *Public Opinion Quarterly, 68*, 368-393.

Tourangeau, R., Couper, M. P., & Conrad, F. (2007). Color, labels, and interpretive heuristics for response scales. *Public Opinion Quarterly, 71*, 91-112.

Tuten, T. L., Galesic, M., & Bosnjak, M. (2004). Effects of immediate versus delayed notification of prize draw results on response behavior in web surveys: An experiment. *Social Science Computer Review, 22*, 377-384.

Vehovar, V., Manfreda, K. L., & Batagelj, Z. (2000). Design issues in web surveys. Paper presented at the *Proceedings of the American Statistical Association, Survey Research Methods Section,* 983–988.

Walston, J. T., Lissitz, R. W., & Rudner, L. M. (2006). The influence of web-based questionnaire presentation variations on survey cooperation and perceptions of survey quality. *Journal of Official Statistics - Stockholm, 22*, 271-291.

Westfall, J. E., & Ma, A. (2010). *Locking the virtual file cabinet: A Researcher's guide to internet data security.* Unpublished Manuscript.

Yeager, D.S., Krosnick, J., Chang, L. C., Javitz, H., Levendusky, M., Simpser, A. & Wang, R. (in press). Comparing the accuracy of RDD telephone surveys and Internet surveys conducted with probability and non-probability samples. *Public Opinion Quarterly.*

Table 1.
Target journals that published articles reporting on research conducted on the Web, total articles published during 2009-2010 and penetration of Web-based research

Journal	Number of articles that reported Internet research 2009-2010	Total number of articles published in 2009-2010	Penetration (% of articles that reported on Internet research)
Asian Journal of Social Psychology	4	61	7%
Basic and Applied Social Psychology[a]	4	38	11%
British Journal of Social Psychology	2	81	2%
European Journal of Social Psychology	13	136	10%
Journal of Applied Social Psychology	20	246	8%
Journal of Experimental Social Psychology	40	384	10%
Journal of Personality and Social Psychology	47	295	16%
Personality and Social Psychology Bulletin	37	258	14%
Social Psychology and Personality Science[b]	6	48	13%
Total	**173**	**1547**	**11%**

[a]At the time of coding, only year 2009 of Basic and Applied Social Psychology was available electronically.

[b]At the time of coding only year 2010 of Social Psychology and Personality Science was available.

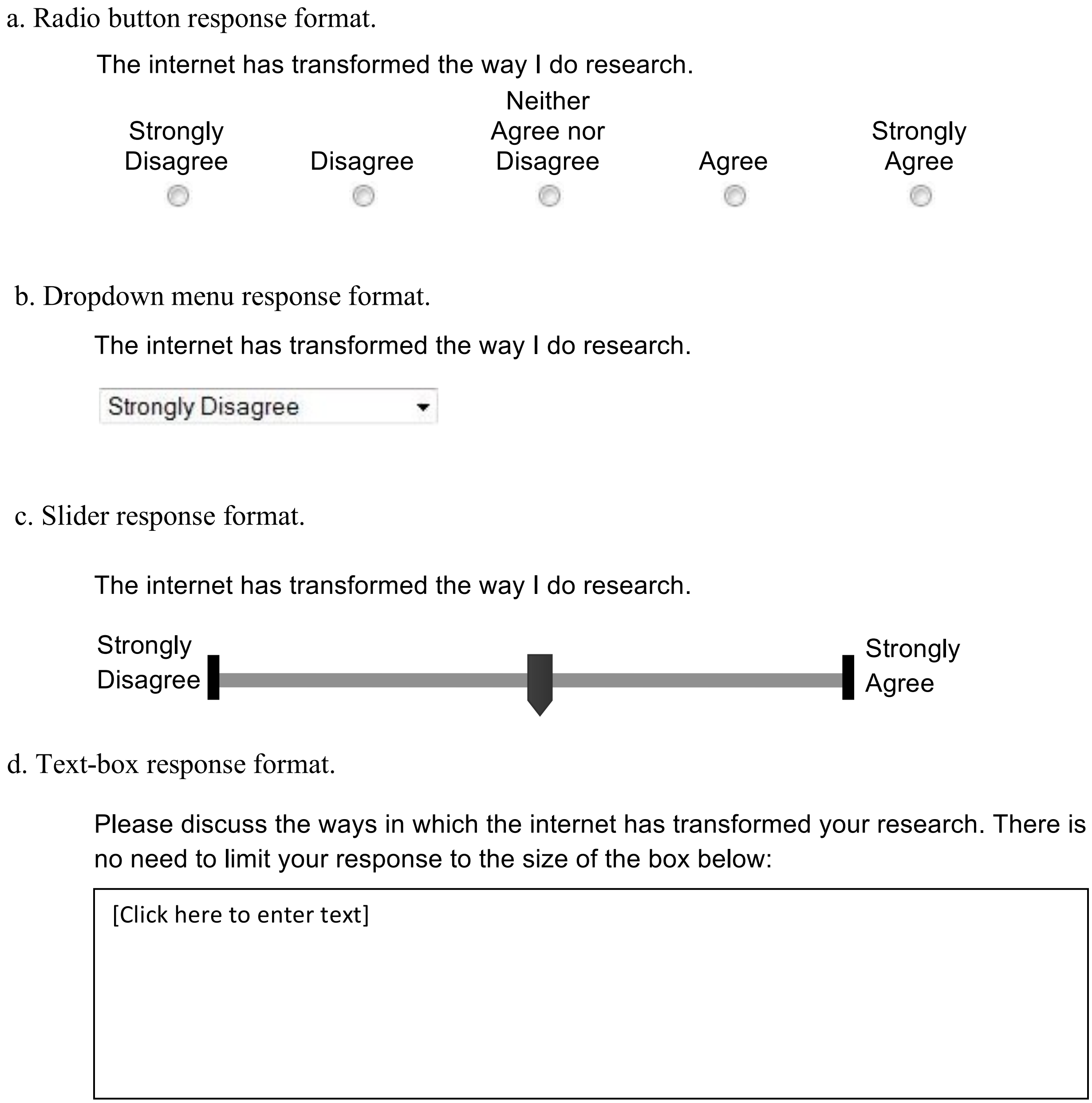

Figure 1. Examples of radio button, dropdown menu, and slider response formats.