Crowdsourcing in Observational and Experimental Research

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Crowdsourcing in Observational and Experimental Research

A substantial fraction of the observational and experimental data collected in the social sciences is now coming from crowdsourcing platforms. The steady shift towards crowdsourced samples that has occurred over the last decade means that it is more important than ever to be acquainted with the characteristics and dynamics of such samples. This chapter aims to familiarize computational social scientists with crowdsourced samples, and in particular with what has become the most popular source of such samples across the social sciences: Amazon Mechanical Turk (MTurk). The chapter will answer several questions: Who joins the MTurk platform as a worker and why? How do MTurk samples compare to traditional samples in survey and experimental research, such as undergraduate students? What challenges can researchers expect to face on MTurk? What are the ethical concerns that these online workplaces bring to the surface? We hope the answers to these questions will be useful to a variety of computational social scientists: aspiring survey and experimental researchers who want to familiarize themselves with the main characteristics of crowdsourcing; experienced researchers who seek a deeper understanding of the implications of their methodological choices; and outsiders who want to get a peek at how social science is conducted in the present and will be conducted in the future.

Why so successful? An introduction to MTurk

MTurk is an online labor market, founded by Amazon in 2005, that connects a large pool of businesses and individuals that need tasks to be completed with workers (MTurkers) who are willing to complete them. Originally, MTurk was designed as an “artificial artificial intelligence” platform that performed tasks that are difficult for computers yet simple for people to do. These activities include tagging pictures or coding text for content or sentiment, creating the humanannotated data sets necessary for machine learning algorithms, and transcribing audio files. Since 2008, MTurkers have increasingly been used by academics as participants for survey and experimental research. After little more than a decade, studies using MTurk samples are widespread if not routine in social science. Reviews of sample composition in top-tier journals suggest that more than a third of all published papers in social psychology (Anderson et al., 2019), consumer psychology (Goodman & Paolacci, 2017), cognitive psychology (Stewart et al., 2017), and some subspecialties of clinical psychology (Miller et al., 2017) rely on at least some MTurk data.

Compared to traditional student samples or commercial online samples, MTurk offers advantages in terms of population size and diversity, cost, speed, and flexibility. First and foremost, MTurk can connect researchers instantly with thousands of participants. Prior to MTurk, most social scientists relied on college student samples, which were often smaller, slower to recruit, and only readily available at specific times in the year. In contrast, MTurk can guarantee to the average researcher a large population at any given time (about 16,000, according to a conservative estimate) and a similar turnover to a university pool (Stewart et al., 2015); the overall MTurk population might be well over 100,000 (Difallah et al., 2018), and depending on the research design it is feasible to recruit tens of thousands of unique participants within a reasonable time frame.

Relative to traditional convenience samples composed of college students or residents of college towns, the MTurk population is also remarkably diverse in terms of age, education, income, race, profession, political affiliation, and many other characteristics (Casey et al., 2017). This means that researchers not only have easy access to a diverse sample of the (US) population, but also that it is possible to recruit relatively large samples of hard-to-find populations. In the past researchers have been able to reach populations of specific theoretical, social, or methodological interest on MTurk, for example people of a certain ethnicity, people with particular life experiences such as veterans, or those with specific psychopathological symptoms (Chandler & Paolacci, 2017).

MTurk also presents considerable logistical advantages for observable and experimental research conducted using surveys. Foremost among these is that it provides a secure and far more flexible platform by which to easily manage recruitment and payment. Research conducted in physical labs (and by extension, online samples that recruit from the same pool) usually employs participants for set increments of time (e.g., a half hour). In contrast, MTurk workers are paid by the minute, allowing researchers to avoid paying for time they will not use.

Replicability

While the practical advantages of MTurk ensured a quick expansion of its use in academic research, many have questioned the reliability, validity, and more generally the quality of data collected on MTurk. As a first step to ensure its legitimacy as a data source, many researchers started comparing results between MTurk and more traditional subject pools, either by replicating classic experiments with MTurk samples or by running parallel identical experiments in multiple subject pools (Bartneck et al., 2015; Behrend et al., 2011; Casler et al., 2013; Coppock, 2018; Goodman et al., 2013; Mullinix et al., 2015; Paolacci et al., 2010; Smith et al., 2016).

In studies running parallel experiments, MTurk samples have produced results comparable to student samples, campus samples, and other online samples (Goodman et al., 2013; Paolacci et al., 2010). Importantly for concerns about generalizability, results obtained on MTurk also compare favorably to those observed in more representative samples of the population, obtaining effects that are consistently in the same direction and usually of the same approximate magnitude (Coppock, 2018; Mullinix et al., 2015; Weinberg et al., 2014). For example, Mullinix and colleagues (2015) found that 29 out of 36 experimental effects were statistically significant in the same direction on MTurk and within a nationally representative sample. In general, correlations between variables observed on MTurk are very similar to those observed in the population as a whole (Snowberg & Yariv, 2018), though relationships between political views and other variables do frequently differ (Zack et al., 2019).

Overall, these results suggest that MTurk samples can be compared favorably to samples used for academic research in the past; on the other hand, there are still a number of characteristics and respondent dynamics unique to MTurk that researchers must be aware of in order to maximize validity and data quality. In the remainder of this chapter, we will provide a description of who MTurk workers are, addressing the ways in which they are similar to and the ways in which they differ from the general population; furthermore, we will discuss the reasons they are on the platform and what the main drivers of their behavior on the platform are. Next, we will focus on the characteristics unique to MTurk that threaten the reliability, validity, and quality of the data collected and provide corresponding solutions. We finish with a discussion of ethical concerns related to carrying out academic research on MTurk in a responsible manner.

MTurkers: who are they and why do they work?

Demographic characteristics of MTurk workers

Recent estimates show that most of the workers on MTurk are from the US (75%) followed by India (16%) and in much smaller proportions Canada, Great Britain, Philippines, and Germany (1.1%–2.7%; Difallah et al., 2018). For a description and comparison of the Indian MTurk demographics, see Boas et al. (2018). As virtually all HITs (i.e., human intelligence tasks, the way tasks are labeled on MTurk) with keyworks “survey”, “research”, or “psychology” are restricted to the US population (Difallah et al., 2015), the remainder of this description of MTurk demographics will focus on the US subject pool.

Like any Internet sample, MTurk workers tend to be younger on average than the adult population they are drawn from. To illustrate, 20%, 60%, and 80% of US MTurk workers are born after 1990, 1980, and 1970 respectively. In the broader US population, these proportions are

20%, 40%, and 60%. The two populations also differ on other characteristics that are correlated with age: MTurkers tend to have lower household income and higher levels of education (Casey et al., 2017; US Census Bureau, 2016).

Compared to the US population, MTurk workers are both more likely to be unemployed (Casey et al., 2017) and more likely to have a white-collar rather than a blue-collar job (Castille et al., 2019). In terms of distribution across industries, however, the occupations among MTurkers are representative of the general population (Huff & Tingley, 2015). Finally, compared to the US population, MTurk workers tend to be less religious (Lewis et al., 2015), on the Democratic side of the political spectrum (c.f. Levay et al., 2016), less likely to be married (Berinsky et al., 2012), and more likely to identify as LGBTQ (Casey et al., 2017).

While age and other demographic traits explain many of the differences between MTurk samples and the general US population, it may be difficult, conceptually and statistically, to explain all of them. Levay et al. (2016) administered the ANES (American National Election Studies) questionnaire to an MTurk sample and found that, while MTurk workers do differ significantly from the national sample on a wide range of socioeconomic, political, personal, religious, and behavioral characteristics, most differences are not entirely eliminated when controlling for age, gender, race, and ethnicity, and some differences are not explained at all. Importantly, it is possible to obtain an MTurk sample that is more representative of the US population, by under- or oversampling workers with specific demographic characteristics to meet representative quotas; however, as the presence of unexplained differences between MTurk and the general population suggests, true “representativeness” may be conceptually elusive and operationally difficult to achieve.

Psychographic characteristics of MTurk workers

Along with demographic differences, there are also psychographic differences between MTurk workers and other samples and the general US population. In a large sample of MTurk workers

(*N* = 10,000), Casey and colleagues (2017) found workers to be less extroverted, slightly less conscientious and emotionally stable, and more open to experience than the general US population. MTurk workers also score higher on clinical measures of social detachment, implying social isolation and aversion (Hargittai & Shaw, 2020; McCredie & Morey, 2018), and report higher levels of social anxiety (Arditte et al., 2016; Shapiro et al., 2013). Likewise, there is suggestive evidence that workers may score higher on autism spectrum disorder features (for a discussion see J. Chandler & Shapiro, 2016). Independent of whether these differences can be explained by the younger age of the sample, these results emphasize that one should be cautious while generalizing from MTurk research on social interactions to people in general.

MTurk workers also score differently on several other clinical measures. They demonstrated higher scores on depression, phobia, suicidal ideation, and traumatic stress scales. Ophir et al. (2019) find that, in comparison to responses to the CDC National Health survey, MTurk workers display a higher incidence of what would qualify as major depression (11.0% vs 3.6%). For depression at least, differences between workers and the population as a whole cannot be explained by mere demographic differences. Various sociodemographic and health and lifestyle variables (e.g., income, work status, exercise) explain only 42.7% of the difference in depression prevalence between the two samples (Ophir et al., 2019; see also Walters et al., 2018). Again, these results warn against attempts to achieve representativeness by matching samples based on demographic quotas.

Workers also differ from the general population on a number of other behavioral and attitudinal measures. As might be expected from people who use a specialized online platform, they are more likely to be more skilled at using the Internet and more likely to adopt technologies (Hargittai & Shaw, 2020). Relatedly, Walters et al. (2018) found that MTurk workers were less likely to be vaccinated or smoke and more likely to exercise, even after adjusting for demographic covariates.

Understanding worker motivation

It is important to understand why people are motivated to participate in MTurk and the contextual factors that define their experience on the platform. MTurk is rarely a workers' primary source of income, with only 13.8% reporting it as such (Paolacci et al., 2010). Almost 60% of workers spend less than 12 hours weekly on the platform (Kaufmann & Schulze, 2011), consistent with the large segment of the pool that reports to be employed full time. However, earning money is in fact the primary reason workers use the MTurk platform (Chen et al., 2019; Kaplan et al., 2018; Litman et al., 2015), and likely for this reason workers wish more work was available to them (Berg, 2015; Yang et al., 2018).

While workers largely participate for money, they also have other motivations that may influence how much they participate or (more likely) the kinds of tasks they prioritize. Workers report a variety of intrinsic motivations, such as developing skills, "gaining self-knowledge" (Litman et al., 2015), community identification (Kaufmann & Schulze, 2011), and simply "killing time" (Paolacci et al., 2010). These motivations seem to drive the kinds of tasks that workers decide to complete. For example, workers motivated to develop competence report that they are more likely to select challenging tasks, while those with social motives report that they prefer tasks requiring coordination or cooperation with other workers (Pee et al., 2018).

Research has also explored the effect of intrinsic motivation on worker productivity. Chandler and Kapelner (2013) find that portraying work as meaningful (i.e., the work was necessary to assist medical researchers) resulted in higher likelihood of participation and higher quantity of output; when the same work was portrayed as meaningless (i.e., it was not going to be used), quality of work decreased. Rogstadius and colleagues (2011) find that framing the task as "helping others" resulted in better quality output. On the other hand, Shaw and colleagues (2010) tested a number of intrinsic incentives (nonfinancial competition with other workers, reminders of the importance of the work, being thanked in advance for doing the work, being primed for good work by answering a questionnaire, being told they were trusted to do the work to the best of their ability) and found that they did not result in better performance than a control condition or financial incentives.

Data quality

Understanding workers' motivation has important consequences for data quality. The quality control mechanism that is built into MTurk hinges upon workers' motivation to earn money: requesters can reject workers' submissions if they consider them not to be of sufficient quality, which results in foregone payment. Workers are also assigned a reputation score based on the proportion of their work that is approved, and this score determines access to future tasks when these tasks select for approval rate. While simple, this kind of reputation score enables people to participate in economic transactions with strangers with relative confidence. As implied by studies of MTurk replicability, it also motivates most workers to make a good faith effort when completing studies. However, data quality remains one of the chief concerns among those who consider crowdsourcing their samples. The separation between researcher and participants is a unique challenge: There is no easy way to verify whether people are who they say they are (or even that they are people – see section on "Fraudulent Worker Profiles"), and it is difficult to control where, how, and why MTurk workers participate in research. Though the MTurk reward system can reduce misbehavior, potential quality issues exist as a logical consequence of workers' motivations to earn as much as possible while managing their reputation. We discuss some of these implications later.

Fraudulent survey responses

Since workers are highly motivated to complete HITs, they will do their best to qualify for tasks. This is a major concern for studies that select workers on self-reported characteristics, because workers may lie to gain access to them. Most studies find that only a minority of workers will lie about their identity to gain access to a study; however, minimal rates of misreporting at the broader MTurk population level can translate into substantial fraudulent responses in a study that targets a rare subpopulation (Chandler & Paolacci, 2017). For example, when recruiting a specific kind of worker with an incidence rate of 5%, a 1% fraud rate will lead to almost 17% (0.01/(0.05 + 0.01) of responses being fraudulent.

Fraud can have a serious impact on data quality. Importantly, impostors may try to adjust their responses in a manner that is consistent with how they believe they should respond given their claimed identity. In some cases, this can contribute to obscure true effects, similar to what non-systematic measurement error does. The political attitudes of people who fraudulently claim affiliation with a political party are less extreme than the attitudes of those who are truly affiliated with that party (Siegel & Navarro, 2019). Likewise, fraudulently depressed workers report more depressive symptoms than nondepressed workers but fewer depressive symptoms than truly depressed people (Chandler et al., 2020, Study 1). In other circumstances, including fraudulent responses can lead to spurious effects. For example, people who report to be red-blue colorblind (which is biologically impossible) claim to be unable to distinguish blue numbers on a red background (Kan & Drummey, 2018), and men who claim to be women report a preference for pink products not held by actual women (Sharpe Wessling et al., 2017).

Given this tendency, explicitly stating screening criteria and asking workers to self-select into studies is the worst way to recruit workers with specific characteristics. Instead, workers should be unobtrusively screened for desired characteristics. However, if workers learn that they have been screened out, some may attempt the HIT again and change their responses to gain eligibility. Some of these workers can be blocked (e.g., through placing a cookie in the users' browser[1] or by blocking multiple attempts from the same IP address[2]). However, the easiest way to minimize fraud is to conceal decisions about study eligibility from the worker. One way of doing this is running a large-scale pretest to measure the variables of interest (or obtain these from existing data sources[3]) and to then recontact the eligible workers with the focal research. Another option is to recruit workers for a survey that includes measures of the characteristics of interest and then immediately invite workers with the desired characteristics to complete a second survey in exchange for an additional "bonus" payment.

Fraudulent worker profiles

Some workers will also lie about certain characteristics when setting up their account in order to gain access to more or better paying HITs (Chandler et al., 2020). Survey tasks are particularly desirable to workers, but most of them require US residency. This creates a strong incentive to fake US residency. A first line of defense against this type of misreport is that to confirm US residency, workers must acquire a US bank account and social security number, which undergoes an unknown verification process by Amazon. More recently, researchers seeking US workers have used tools to require a US IP address as well.

In 2018 there was a surge in US-based human-generated, but extremely low-quality, responses (Chmielewski & Kucker, 2020). The increase was caused in part by non-native (and non-language-proficient) English speakers that originate mostly in India and Venezuela (Kennedy, Clifford, Burleigh, Waggoner et al., 2018) (though these workers may also have made use of automated form-fillers to provide responses). These workers are able to avoid IP restrictions by logging on to virtual machines located in US data centers to simulate US IP addresses (Dennis et al., 2018). Fortunately, these type of workers' access to studies can be reduced using tools that compare worker IP addresses or geolocations to a database of known fraudulent addresses (Prims et al., 2018). As fraudulent profiles, by definition, generate low-quality responses, researchers can minimize their impact by employing measures to identify poor-quality data (discussed in the "Data Quality" section).

Attrition

Compared to experiments conducted in physical labs, where participants are supervised, MTurk workers can leave a study at any time. This has given rise to concerns about attrition, that is, that participants begin a study but do not complete it. Attrition on MTurk is highly dependent on study characteristics, with levels obtained by faculty members in a single department ranging from 0% to 77.6% (Zhou & Fishbach, 2016). The potential impact of attrition on study results is determined by the overall attrition rate of a study, the difference in attrition rates between conditions, and the correlation between the probability that a study participant will drop out and their response on the dependent variable (for a detailed discussion see Deke & Chiang, 2017). Attrition can be particularly problematic when differential attrition rates are high and act disproportionally on participants with particular characteristics, creating confounds (Deke & Chiang, 2017).

It is particularly important for researchers to minimize attrition in their studies. The most common reasons workers abandon a task is that it requires more time than anticipated (reducing the effective hourly rate) and that it includes unclear instructions and "glitches" (Han et al., 2019; Kaplan et al., 2018). This suggests that researchers should be clear upfront about the effort and time it takes for participants to complete the task and ensure that the task is pilot tested before launching it.

Researchers can also try to avoid (or at least measure) differential attrition across experimental conditions. Some experimental studies require more effort out of participants in some conditions or require them to consider more unpleasant topics (Rinderknecht, 2019). When differential attrition across conditions is a concern, participants could be exposed to all experimental conditions (albeit in different orders) and the analysis restricted to those who complete the entire study (Hauser et al., 2018). Finally, researchers should collect and report measures of attrition; they can also collect individual difference measures early in the experiment, so that they can test whether certain characteristics contributed to attrition and check that final experimental groups do not differ on key variables (Hauser et al., 2018).

Non-naivete

Another difference between MTurk workers, lab samples, and to an extent also other online samples is that MTurk workers are likely to have participated in many more studies. This concern is compounded by the fact that a majority of the studies on MTurk are actually taken by a small and highly active proportion of the overall population. Illustratively, Chandler and colleagues (2014) found that 10% of workers completed 41% of the HITs, and that especially the most productive ones were familiar with paradigmatic experiments in the social sciences (e.g., trolley problem). This suggests that, if participant naivete is an important requirement for the interpretation of results of the study, certain common paradigms may not be suitable for use on MTurk.

Experiences in prior studies can also change participant responses. Returning to the issue of participant fraud, there is some evidence that participants who learned information about eligibility criteria in one study (owning a VR headset) applied this information when answering the first question of a later study, leading to a dramatic increase in the number of participants who claimed to own VR headsets (Chandler & Paolacci, 2017). Prior experience can also influence responses to questions not directly tied to incentives. One area of substantial concern is the impact of repeated experience on some tasks leading to improved performance on measures of ability. Practice effects have been repeatedly observed on measures of cognitive ability (e.g., Chandler et al., 2014; Stagnaro et al., 2018; Woike, 2019) but may also extend to other measures (e.g., tests of creativity, Oppenlaender et al., 2020). These kinds of practice effects can undermine the predictive power of measures if they lead workers of even moderate ability to score perfectly on the measure (a ceiling effect) and can cause spurious correlations between over-practiced measures that are themselves correlated with worker experience (Woike, 2019, but not always; for a discussion see Stagnaro et al., 2018). For studies that use measures of ability as an outcome measure, the increased variation of scores that results from including a mix of people who have and have not been exposed to the items could make it harder to detect the impact of experimental treatments, because most tests of statistical significance assess differences in average scores between treatments relative to differences in individual scores within treatment groups.

Practice effects can also lead people to mindlessly apply "correct" answers above and beyond any improvement in underlying ability. Woike (2019) observed that workers would apply the correct answer from a previous exposure to measures of ability to superficially similar later questions with different answers. Similarly, Chandler and colleagues (2015) find that multiple exposures to the same experimental material can reduce effect sizes, especially when participants are assigned to a different condition the second time. One interpretation of this finding is that information from prior experimental treatments comes to mind, regardless of whether it is explicitly contained within a study. In its most extreme form, people can simply cut and paste responses to difficult or unpleasant questions to avoid answering them. In one study, around 5% of participants seemed to copy and paste responses to a commonly used experimental text prompt used to induce a feeling of powerlessness (Rinderknecht, 2019), making it unlikely that this writing task had the desired psychological effect. Importantly, and consistent with the previous discussion, repeated participation seems not to be a concern for studies that rely on automatic processes (Zwaan et al., 2018).

It is therefore important to ensure that workers do not repeatedly participate in the same or similar studies. Workers cannot be relied upon to correctly report having completed a certain study before. Large proportions of workers who had completed a study before claimed that they had not, and self-reporting of prior participation is not a reliable predictor of attenuated effects in a later study (Chandler et al., 2015). However, researchers can limit the number of non-naïve workers in their study. When conducting a series of related experiments, workers who have completed earlier studies can be excluded from completing later studies. Likewise, workers with lots of prior experience can be excluded from participating if there are concerns that this experience is problematic (e.g., it makes it likely that participants are familiar with a study procedure and this familiarity might threaten validity). Amazon allows requesters to limit the number of prior tasks eligible workers have completed. Likewise, Cloud Research allows researchers to exclude workers who are known to have completed many research studies.

Cross talk

To the frustration of many workers, Amazon’s reputational system is designed to ensure that requesters can find high-quality workers, but not vice versa. As a result, workers have created a number of communities in which they can share information about specific requesters and tasks. These communities raise the concern that participants could share details of studies that researchers do not want revealed until after the study is complete, such as different experimental treatments, the use of deception, or the availability of bonus payments for specific workers. The presence of discussions about posted studies is potentially concerning, because it both influences readers' perceptions of the study and quickly drives them to complete it: one study of a large sample of tasks found that when a HIT is posted in a discussion forum, participation rates increase by nearly 60% (Yang et al., 2018).

Edlund and colleagues (2017) analyzed the discussions posted on a forum about posted studies and found that 9% of the comments included key information and an additional 30% important information or information about qualification. However, it is unclear how likely a given study is to end up in a discussion board and how many workers may in fact stumble upon this information, especially in absence of an incentive to do so. In fact, Chandler and colleagues (2014) find that, in a survey of 300 participants, only 13% report ever seeing the content of a study discussed online. Furthermore, Edlund and colleagues (2017) found that simply asking the participants not to discuss the experiment online was successful in eliminating the problem. Monitoring MTurk forums (e.g., on Reddit) is still a sensible recommendation when cross talk might threaten the validity of one's study.

Distraction

Since workers complete surveys in an unsupervised environment, researchers cannot ensure that they are paying attention – MTurk workers have reported that they often complete multiple surveys at the same time or that they complete surveys while doing other activities, such as watching TV (Chandler et al., 2014). Moreover, because MTurk workers are paid per HIT, there is a concern that they may rush through surveys without paying close attention to survey materials. Indeed, Smith and colleagues (2016) find that compared to a US panel, MTurk workers completed a survey about 50% faster. This has led to many concerns about "satisficing" behavior, straight-lining (giving the same answer to all questions), answering at random, or answering without reading the materials (called, among others, careless or insufficient effort responding) (Berinsky et al., 2014; Curran, 2016; Huang et al., 2015; Kim et al., 2017; Meade & Craig, 2012).

Importantly, through an extensive review of the literature and further experiments, Thomas and Clifford (2017) find that MTurk workers display rates of inattention no higher than student samples or other online samples. Exclusion rates based on screener items (i.e., questions used to identify and subsequently exclude problematic respondents) range from 2% to 52% depending on the difficulty and extent of screener question – no different from the range observed in the lab (6%–46%) or in other online panels and samples (5%–63%). These findings are consistent with the finding that distractions in web surveys do not necessarily impact data quality (Wenz, 2019). However, that average rates do not differ does not imply that MTurkers will be invariably attentive, and inattention is likely to remain a reason of concern for many researchers. We describe later a number of methods that, alone or in conjunction with one another, have been reliably shown to improve data quality.

Identifying and removing poor-quality responses

Poor data responses are often assumed to introduce noise into data. When a source of noise is uncorrelated with a variable of interest, it makes it more difficult to observe the potential effect of that variable. For example, in experimental studies where treatment condition is randomly assigned, careless participants tend to decrease observed treatment effects (Kennedy, Clifford, Burleigh, Jewell et al., 2018). However, the effects of including poor-quality responses is not as predictable. In the context of correlational data (e.g., observed associations between participants' responses to different questions), random responses can add noise as they do to experiments, reducing observed effect sizes. This is especially true when sets of items with opposite meanings are collapsed together to form a single score (Chmielewski & Kucker, 2020). In practice, however, careless responses to different questions are non-independent (because they come from the same person; Presser, 1984) and are thus correlated, which can inflate observed correlations. To complicate matters further, differences in the means and the distributions of the true and careless responses are also captured by these analyses, which can suppress, inflate, or in some cases even reverse the sign of correlations observed within each group (for a detailed discussion see Chandler et al., 2020). For example, Chandler and colleagues (2020) found that in an uncleaned data set, higher educational attainment is associated with increased social anxiety and depression, but when poor-quality responses are removed, more education is associated with decreased social anxiety and depression. Therefore, poor-quality responses cannot be necessarily offset by increasing the statistical power of a study. We provide later some suggestions for identifying poor-quality responses.

Response speed

One option is to identify workers who have completed the task implausibly quickly. Researchers have developed a number of different benchmarks based on reading speed or benchmarked survey data. Recommendations for surveys with any (offline) population are to use a two-second per item rule (based on four to seven word items with a five-point Likert scale; Huang et al., 2012) or 300 milliseconds per word (Zhang & Conrad, 2014). However, because MTurk workers may complete surveys faster than other samples for benign reasons such as experience with the format (Kees et al., 2017; Smith et al., 2016), Wood and colleagues (2017) suggest a more conservative limit of one second per item. Since items can vary in length, and some pages may include a lot of text in addition to/instead of the items, we recommend using a rule based on a words-per-minute reading speed. Following Carver (1992), we suggest 600 words per minute (100 milliseconds per word) as the maximal speed for text comprehension. In practice, this means one should count the words on a page, divide it by 10, and flag every participant completing that page in less than the resulted number of seconds (e.g., on a 173-word page, the cutoff would be 17.3 seconds). Our rule is consistent with Wood et al. (2017) assuming an average item length of about 10 words.

Analysis of response patterns

Researchers can also identify workers who provide illogical or unlikely responses, for which several methods exist (see Curran, 2016, for a review). Researchers can identify problematic respondents informally by inspecting data for unusual values (e.g., more than eight children) or combinations of values (e.g., unemployed with a household income >$150k). Open-ended responses can also be a valuable source of data. Responses that are irrelevant, appear to be copied from elsewhere, are only one or two words long, or are written in all caps are all indications of potential data quality issues.

Some researchers have developed more quantitative methods of identifying unusual data such as counting strings of questions with the same response to identify participants who straight-line (that is, give the same answers to all items in a scale); examining the consistency between different scales or parts of scales (Curran, 2016); and examining intra-individual response variability, which measures the standard deviation of responses for each participant, whereby high standard deviations denote random responding, while low standard deviations imply straight-lining (Marjanovic et al., 2015).

Screener questions

It is much easier to assess data quality when questions are included in the survey that have patterns of responses that can be verified as logical, plausible, internally consistent, or sensitive to the content of the study. These “screener” questions have been shown to be effective at increasing the power of the experiment and reducing noise in the data without introducing significant sampling bias (Thomas & Clifford, 2017). A variety of different types of screener questions exist. Researchers have included factual questions to verify that workers paid attention to critical instructions (Kane & Barabas, 2019; Oppenheimer et al., 2009), questions with logically impossible responses (e.g., “while watching the television, have you ever had a fatal heart attack?”; Paolacci et al., 2010), and batteries of questions with unlikely responses (assuming that reporting many rare experiences or beliefs is a signal of data quality; Maniaci & Rogge, 2014).

The design and content of each individual study determine which techniques are used to achieve data quality; however, generally, we recommend a combination of a speed check, a screener item (e.g., an infrequency question), a specific screener such as a comprehension check, and an IP test for suspicious IPs. See Chandler et al. (2020) for an exhaustive description of each technique and where and when it will work best.

Beyond convenience samples

Most researchers use MTurk to conduct simple survey experiments. However, workers are used to complete a much wider variety of tasks, and the platform is easily linked to external sites. This facilitates the implementation of study designs that are more complex than questionnaires. For example, many researchers conduct studies in which small or even large groups of workers interact with one another (cf. Arechar et al., 2018). Researchers have also experimented with using MTurkers as research assistants in various parts of the research process, including screening articles for literature reviews (Krivosheev et al., 2017; Mortensen et al., 2017), acting as “sensors” to collect data on behalf of researchers (Lukyanenko & Parsons, 2018), stimulus creation (Sina et al., 2014), survey item creation (Holland et al., 2016), testing (Edgar et al., 2016), and content coding (Benoit et al., 2016; Conley & Tosti-Kharas, 2014; Leeper, 2016). Moreover, researchers leveraged MTurk to conduct labor field experiments, observing how actual workers respond to different forms of incentives (Fest et al., 2019).

Ethics

Especially in the early years of the platform, the lack of rules and regulations and the anonymity of workers led to a situation in which strong norms about the ethical treatment of MTurk workers were not in place. First and foremost, researchers are encouraged to not let the anonymity of and distance from their research participant allow them to relax common standards. These include seeking the approval of institutional review boards, ensuring participants read and agree to a consent form, and that they are correctly debriefed if necessary. More uniquely to MTurk, efforts have been made to examine and understand the ethical issues surrounding the worker-requester relationship. Guidelines have been suggested, for example by the Dynamo Initiative (Salehi et al., 2015). Fair compensation, fairness in the extent to which work is accepted or rejected, and privacy are three main ethical concerns that we discuss in this section.

Compensation

Completing HITs on MTurk is considered to be a form of self-employment; as labor laws have been slow to update to the unfamiliar nature of the crowdsourcing format, the working relationship between requesters and the "crowd" is almost entirely unregulated, and MTurk workers have very little or no benefits or protection (Felstiner, 2011). This has been reflected in the level of compensation – researchers, especially in the past, often underpaid workers (as little as $0.01 per HIT) or even asked them to complete HITs for free (Hara et al., 2018; Mason & Suri, 2012; Mason & Watts, 2009), perhaps revealing beliefs that voluntarily completing surveys is not necessarily equivalent to work. Importantly, working on MTurk entails a lot more than just taking a HIT – it includes searching for HITs, informing oneself on the reputation of unfamiliar requesters, communicating with other workers and requesters, spending additional time deciphering unclear HIT descriptions or instructions, etc. Taking this unpaid "overtime" into account, Hara et al. (2018) find that only 4% of workers earn more than the federal minimum wage, while the average wage amounts to $2/h.

Complaints by workers have led to many calls to conform HIT payments to minimum wage levels (e.g., $7.25/h; Pittman & Sheehan, 2016; Salehi et al., 2015; Williamson, 2016). Payments on the site have increased over time (Difallah et al., 2015), and recent analyses suggest that MTurk workers are now more positive about their interactions with academic requesters (Moss et al., 2020).

There are many voluntary steps that researchers can take to maximize the extent to which workers are compensated fairly for their work. First and foremost, one should carefully measure and honestly communicate completion times for the HIT, setting payment rates accordingly at a minimum of $0.12 per minute ($7.25/h). Researchers should ensure the HIT instructions are clear and there are no problems that will take additional worker time to solve. Finally, returning (rejecting) HITs is one of the biggest factors driving down real wages (Hara et al., 2018), underlying the need for HIT instructions to be designed to minimize mistakes that will lead to rejections.

Rejection

Requesters have full control over whether to accept a worker's HIT submission; as requesters do not have to forfeit the work if it is rejected, there is an incentive to reject more than the strictly necessary. Requesters rejecting good work is one of the most-voiced complaints, mentioned in a 2016 study by 52% of workers (Brawley & Pury, 2016). Workers also complained about mass rejections, being rejected due to technical difficulties, and being rejected or blocked from HITs without being given a reason.

In contrast to these complaints, Matherly (2018) highlights a positivity bias in the use of the reputation system on MTurk. Data quality in academic research is more of a subjective judgment; leniency and reciprocity principles, and fear of retaliation, sway researchers in favor of accepting all work. Moreover, some IRBs' guidelines demand full payment for all participants. Since (currently) rejecting a participant's work automatically denies their payment, some researchers are bound to accept all work regardless of data quality. Finally, identifying and rejecting low-quality work is time consuming – rejected workers also tend to contact requesters to complain or find out why they were rejected, resulting in additional time costs. The result is that the reputation system may become only mildly diagnostic of worker quality and then only at the very highest levels (contrary to earlier indications that a 95% threshold suffices, Peer et al., 2014). There is an argument for researchers to reject work more often, in order to allow the reputation system to function. If researchers do choose to reject low-quality respondents, they should keep in mind to only reject when the data quality is poor beyond a reasonable doubt and to provide explicit reasons for rejection to the workers that are aligned to expectations.

Privacy

Researchers can undermine MTurk workers' privacy by asking directly for sensitive information, aggregating data from various HITs, unauthorized information sharing, phishing/malware, etc. (Xia et al., 2017). Despite being concerned for their own privacy (e.g., Kang et al., 2014), workers may provide personal information to avoid the consequences of noncompliance (Sannon & Cosley, 2018). Importantly, WorkerIDs cannot be directly linked to personal information. However, perhaps they might point to a specific individual when they are linked through multiple experiments with data that is granular enough (e.g., postal code, age, sex, etc.). It is thus particularly important for researchers to ensure that they never store identifiable information (e.g., while posting data on public repositories).

Conclusion

Crowdsourced samples, of which MTurk is the foremost example, are inexpensive, convenient, and plentiful. It is likely that they will be a feature of academic research for a long time to come, and as such, researchers are advised to acquaint themselves with the unique characteristics and dynamics of such samples. Crowdsourced samples are perhaps less different from more traditional student and online samples than we have been led to believe, and most of the best practices that have been successful in the past at ensuring study subjects are attentive and conscientious carry over seamlessly to studies run on a crowdsourcing platform. On the other hand, anonymity, distance, and lack of researcher oversight on participants give rise to a number of concerns and unique challenges that we have detailed and addressed in this chapter. MTurk is a continuously evolving marketplace that responds to changing social forces and incentives. An awareness of these dynamics is essential to ensure academics have a deeper understanding of their methodological choices and can continue to use this valuable resource to its full potential.

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[1] The Qualtrics survey-building platform has this as an available feature named “prevent ballot box stuffing” under survey options.

[2] Some third-party platforms that run experiments on MTurk, such as CloudResearch (formerly Turk Prime) and Positly, have this as an available feature.

[3] Both Amazon and Cloud Research maintain data sets of workers with specific characteristics. Researchers can also select eligible participants from studies they have conducted in the past.