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Contact

Daniel J. Power, Ph.D.
Professor of Management and Information Systems
Department of Management
University of Northern Iowa
Cedar Falls, IA 50613
(319)273-2987
daniel.power@uni.edu

Rassule Hadidi, Dean
College of Management
Metropolitan State University
Minneapolis, MN 55403-1897
(612)659-7295
rassule.hadidi@metrostate.edu



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Editors' Comments

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Transforming Agriculture: Exploring Precision Farming Research Needs

Daniel J. Power

University of Northern Iowa, Daniel.Power@uni.edu

Rassule Hadidi

Metropolitan State University, Rassule.Hadidi@metrostate.edu

Abstract

Information Technology, Information Systems, Decision Support and analytics play an increasingly important role in the practice and science of agriculture. Precision farming or precision agriculture uses tools like sensors, the global positioning system (GPS), Cloud data storage, and analytics and decision support tools to increase efficiency and effectiveness of land, labor and machines used in farming. JMWAIS publishes a wide mix of scholarship and research related to Information Systems and Information Technology. Given our origins in the Midwest United States we also encourage and publish articles especially relevant to our region. Precision farming is an important topic for Midwest US.

Keywords: Precision agriculture, information and communication technology, data analytics

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1. Overview

According to the United States Department of Agriculture (www.usda.gov), the Midwest United States produces a wide diversity of agricultural products, including corn and soybeans. The Midwest U.S. "represents one of the most intense areas of agricultural production in the world" and has a large impact on the global economy. The Midwest U.S. is the nation's and the World's breadbasket. In 2017, farmers in Midwest U.S. sold more than \$76 billion in corn, soybeans, livestock, vegetables, fruits, berries, and nursery/greenhouse plants. There are over 127 million acres of fertile agricultural land in the Midwest U.S. and approximately 75% of that area is planted in corn and soybeans each year. Agriculture, the science or practice of farming and production of food and other goods, is an essential activity that supports human life. Information Technology and Information Systems (IS/T) play an increasingly important role in the practice and science of agriculture. IS/T have become essential to efficient and effective agriculture and precision farming.

The Journal of the Midwest Association for Information Systems (JMWAIS) at URL <http://jmwaiss.org/> promotes research and scholarship about IS/IT in general and given our regional origins we especially encourage articles that meet specific regional needs. Precision agriculture and farming is a critical topic for Midwest U.S.. The application of Information Technologies, including the Internet of Things (IoT), automation and machine learning, and Artificial Intelligence (AI), is transforming agriculture and farming. More applied research on these applications can influence the future of farming.

In approximately 8000 B.C. when farming communities were initially established, the population of planet Earth was around 5 million people. On July 30, 2019, the World population was approximately 7.595 billion people, cf., www.census.gov/popclock/. To feed the growing population, more efficient and more effective farming developed to provide an expanded food supply. To meet the food needs of a global population expected to reach 10.85 billion people on July 4, 2100, more efficient and better technology-supported farming is needed. Computerized decision support and analytics using new data is central to site specific crop management and better farm management. Studying and creating new capabilities to use the technologies of precision farming will feed our growing population.

2. Defining Precision Farming

According to Covey (1999), "Precision farming is an integrated agricultural management system incorporating several technologies. The technological tools often include the global positioning system, geographical information systems, yield monitoring, variable rate technology, and remote sensing." He notes that "just having information about variability within the field doesn't solve any problems unless there is some kind of decision support system (DSS) in order to make VRT recommendations." VRT is an acronym for Variable Rate Technology.

Farms.com explains "precision agriculture, also known as precision farming, is a broad term commonly used to describe particular farm management concepts, sometimes referred to as satellite farming or site-specific crop management (SSCM). The term first came into popular use with the introduction of GPS (global positioning systems) and GNSS (global navigation satellite systems) as well as other methods of remote sensing which allowed farm operators to create precision maps of their fields that provide detailed information on their exact location while in-field.... The use of decision support systems (DSS) is often incorporated into precision agriculture as it pertains to managing the information collected through spatial and temporal practices."

The HGCA Glossary (2009) defines precision farming as "management of farming practices that uses computers, satellite positioning systems, and remote sensing devices to provide information on which enhanced decisions can be made. Sensors can determine whether crops are growing at maximum efficiency, highly specific local environmental conditions can be identified, and the nature and location of problems pinpointed. Information collected can be used to produce maps showing variation in factors such as crop yield or soil nutrient status, and provides a basis for decisions on, for example, seed rates and application of fertilizers and agrochemicals, as well for the automatic guidance of equipment." Pierce and Novak (1999) point out that precision agriculture enables farmers to do the right things, in the right places, in the right times, and with the right methods.

Wolfert, Ge, Verdouw, and Bogaardt (2017) suggests that precision farming or smart farming's future may result in a continuum of two scenarios. One option is a "closed system that the farmer is part of a highly integrated food supply chain" and the other is an open and collaborative system that "the farmer and every other stakeholder in the chain network is flexible in choosing business partners as well as the technology" for the food production side (p. 60).

3. Decision Support for Farming

The goal of analytics and decision support is to help a decision maker choose an action associated with a decision situation that will change the identified state or process in a way that makes it more favorable. Farming remains risky and subject to many uncontrollable factors. Given the increasing complexity of farming, more and better decision support and information can help make farming more profitable and more sustainable.

Russo and Dantinne (1997) suggested five steps for creating precision farming decision support:

1. Identify environmental and biological states and processes in the field that can be monitored and manipulated to improve crop production.
2. Choose sensors and supporting equipment to record data on these states and processes.
3. Collect, store, and communicate the field-recorded data.
4. Process and manipulate the data into useful information and knowledge.
5. Present the information and knowledge in a form that can be interpreted to make decisions.

Lowenberg-DeBoer (1996) argued that "Long run profitability of precision farming technology depends on the development of management systems that link inputs applied with yields harvested on specific sites. These management systems will be some combination of computerized decision support systems and the accumulated wisdom of experienced managers. Decision support systems require databases. Wisdom comes with long experience. These management systems will be site specific. Generic decision support systems will be developed, but their performance on your farm will be enhanced by data from your farm." Precision agriculture is no longer the "infant technology" discussed by Lowenberg-DeBoer, but the need to improve decision support and collect and share data remains and has become more urgent.

In 1998, Davis, Casady and Massey explained "As important as the devices are, it only takes a little reflection to realize that information is the key ingredient for precise farming. Managers who effectively use information earn higher returns than those who don't." GPS (Global Positioning System) and sensor technologies make precision farming possible, but databases of historical information, analytics, and decision support enable farmers to effectively use the data gathered from using the technology tools.

Pierpaloli, Carli, Piganti, and Canavari (2013) state that "precision agriculture is a fairly new concept of farm management developed in mid-1980s" (p. 62). In their article, they focus on precision agriculture (PA) technology adoption from the lens of ex-post research technology adoption and then focus on technology acceptance for PA. Their adoption model focusses on factors classified into three drivers of adoption which they classify as competitive and contingent factors, socio-demographic factors, and financial resources.

In general, the goal of Information Technology, analytics, and decision support is to help farmers manage their farms better. Precision farming decision support applications include advising about 1) what to plant where, 2) when and where to apply chemicals and in what amounts, and 3) when to harvest. There is also a role for decision automation in precision farming. Real-time decision automation can control the application of chemicals in the field based on GPS data, soil data, crop and decision rules. Software creates an integrated, precision farming system from disparate hardware components and historical and real-time data.

Research investigating precision agriculture, precision farming, and agriculture decision support and analytics is appropriate for submission to JMWAIS. We encourage more research in this important topic area.

The Journal of the Midwest Association for Information Systems (JMWAIS) remains a double-blind, peer-reviewed, quality focused, and open-access online journal. JMWAIS strives to ensure that original Information Systems research broadly defined from scholars linked to the Midwest United States is widely shared and disseminated. Articles that are published in JMWAIS are available from the AIS eLibrary and at <http://jmwaiss.org/>. DOI registration complements our purpose.

4. Overview of the contents of this issue

This issue of the journal includes a tutorial and two traditional research articles:

Jacob Young and Kristie Young in their tutorial for the use of Amazon's Mechanical Turk provide a timely set of guidelines and best practices for researchers on how to use this platform to safeguard the quality of the collected data. They further recommend that more attention needs to be paid by reviewers and editors on how data is collected for research purposes.

Sharma and Biros in their article suggest that a major barrier to the adoption of healthcare related wearable devices is the lack of trust by potential users of these kinds of devices. Hence, they have conceptualized a user's trust model for adopting these devices.

Bansal and Redfearn examine the role corporate social responsibility initiatives play in the weakening in trust and its restoration in cases where a data breach has occurred and the CEO of the affected corporation issues an apology. The study considers four scenarios and concludes that the corporate social responsibility initiatives may play a role in privacy concerns.

We appreciate and wish to acknowledge the contributions of reviewers for this issue of the journal, including David Biros (Oklahoma State University), Omar El-Gayar (Dakota State University), Yi "Maggie" Guo (University of Michigan, Dearborn), Joey George (Iowa State University), Hasan Kartal (University of Illinois Springfield), Barbara Klein (University of Michigan, Dearborn), Dahui Li (University of Minnesota Duluth), Alanah Mitchell (Drake University), Anne Powell (Southern Illinois University – Edwardsville), Troy Strader (Drake University), and Abhishek Tripathi (University of Nebraska, Omaha),

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Author Biographies



Daniel J. Power is a Professor of Information Systems and Management in the College of Business Administration at the University of Northern Iowa. Power serves as the editor of the Journal of the Midwest Association for Information Systems (JMWAI), DSSResources.com, PlanningSkills.com, and Decision Support News. His research interests include the design and development of decision support systems and how these systems impact individual and organizational decision behavior.



Rassule Hadidi is Dean of the College of Management, Metropolitan State University, Minneapolis, Minnesota. His current research areas of interest include online and blended teaching and learning pedagogy and its comparison with face-to-face teaching; MIS curriculum development and quality assessment; cloud computing and its applications for small and medium-sized enterprise; and quality of online information. He is the First Hanson Professional Services Faculty Scholar; served as the President as well as the At-Large Director of the Midwest Association for Information Systems and is the founding Managing Editor of the Journal of the Midwest Association for Information Systems. He is a member of Board of Directors of the Society for Advancement of Management.

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Don't Get Lost in the Crowd: Best Practices for Using Amazon's Mechanical Turk in Behavioral Research

Jacob A. Young

Bradley University, jayoung@fsmail.bradley.edu

Kristie M. Young

Illinois State University, kmyou3@ilstu.edu

Abstract

The use of Amazon's Mechanical Turk (MTurk) to conduct academic research has steadily grown since its inception in 2005. The ability to control every aspect of a study, from sampling to collection, is extremely appealing to researchers. Unfortunately, the additional control offered through MTurk can also lead to poor data quality if researchers are not careful. Despite research on various aspects of data quality, participant compensation, and participant demographics, the academic literature still lacks a practical guide to the effective use of settings and features in MTurk for survey and experimental research. Therefore, the purpose of this tutorial is to provide researchers with a recommended set of best practices to follow before, during, and after collecting data via MTurk to ensure that responses are of the highest possible quality. We also recommend that editors and reviewers place more emphasis on the collection methods employed by researchers, rather than assume that all samples collected using a given online platform are of equal quality. We also recommend that editors and reviewers place more emphasis on the collection methods employed by researchers, rather than assuming that all samples collected using a given online platform are of equal quality.

Keywords: Mechanical Turk, sampling, survey research, experimental research

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1. Introduction

Amazon Mechanical Turk (MTurk), an online crowdsourcing platform, has emerged as an attractive data collection method for both survey and experimental research (Buhrmester, Talaifar, & Gosling, 2018). Even though the use of MTurk has increased, authors still find themselves forced to defend the quality of data collected on MTurk to reviewers and editors. Lowry, D'Arcy, Hammer, and Moody (2016) had this to say on the issue:

A pattern has taken hold in which traditional organizational researchers, reviewers, and editors are quick to misconstrue and reject new methods while defending the “best practices” of paper surveys, which have been the methodology of choice for several decades. Although organizations themselves have implemented significant innovations, the published research on organizations has not undertaken innovation to the same degree. Traditionalists and the researchers who make up the reviewing system in the organization science and information systems (IS) fields are quick to downplay the legitimacy of new theories and methods, but they fail to apply the same level of scrutiny to their own traditions. This thwarts scientific progress. (Lowry et al., 2016, p. 233).

Critiquing the quality of all data during the review process is certainly important. However, we argue that the efficacy of MTurk as a research tool, as opposed to more widely accepted online panel services (e.g. Qualtrics, SurveyMonkey, Turkprime) or traditional paper surveys, should be judged based upon the qualification methodology employed by the researcher rather than the collection media itself (Landers & Behrend, 2015; Roulin, 2015). We argue that the use of all online panels, where researchers pay for a study instrument to be administered to a group of prequalified participants, reduces the validity and generalizability of behavioral research. The inability to confirm or even fully describe the procedures used to develop and validate a given sample is a major disadvantage to the use of these services because it forces authors, reviewers, and editors to blindly accept the quality of the panel. Therefore, we argue that sample reliability and study generalizability is greatly improved if researchers are required to document how they qualified their subjects instead of accepting panels qualified by such services.

Despite promising research on various aspects of MTurk, such as data quality (Behrend, Sharek, Meade, & Wiebe, 2011; Buhrmester, Kwang, & Gosling, 2011; Landers & Behrend, 2015; Paolacci, Chandler, & Ipeirotis, 2010; Peer, Vosgerau, & Acquisti, 2014; Shapiro, Chandler, & Mueller, 2013; Sprouse, 2011; Steelman, Hammer, & Limayem, 2014), participant compensation (Chandler, Paolacci, & Mueller, 2013; Deng & Joshi, 2016; Goodman, Cryder, & Cheema, 2013; Horton & Chilton, 2010; Kraut et al., 2004; Mason & Suri, 2012; Mason & Watts, 2009) participant diversity (Behrend et al., 2011; Buhrmester et al., 2011; Kaufmann & Veit, 2011; Kraut et al., 2004; Mason & Suri, 2012; Paolacci et al., 2010; Ross, Irani, Silberman, Zaldivar, & Tomlinson, 2010), and successful replications (Berinsky, Huber, & Lenz, 2012; Crump, McDonnell, & Gureckis, 2013; Horton, Rand, & Zeckhauser, 2011) the academic literature lacks a practical guide to the effective use of MTurk for survey and experimental research. Thus, the purpose of this tutorial paper is to provide behavioral researchers with a suggested set of best practices to follow when employing MTurk to ensure that future research is based on high-quality data. Due to our specific focus on MTurk, we only mention traditional best practices (e.g., Kerlinger & Lee, 2000; Pedhazur & Schmelkin, 1991; Shadish, Cook, & Campbell, 2002) when describing how to apply them on MTurk. Therefore, researchers must ensure that proper statistical and experimental procedures have been followed when using MTurk, just as they should with any other sampling method.

Although there are many possible uses for MTurk, we limited our paper to its use in survey and experimental research. Our suggested best practices build upon discussions found in prior literature (Cheung, Burns, Sinclair, & Sliter, 2017; Jia, Reich, & Jia, 2016; Jia, Steelman, Reich, & Jia, 2017; Lowry et al., 2016) in addition to knowledge gained through our personal use of MTurk. Cheung et al. (2017) discuss methodological concerns with MTurk and provide general recommendations based on the work of Shadish, Cook, & Campbell (2002). However, they provide little guidance on exactly how to address these concerns when using MTurk. Similarly, Jia et al. (2017) provide a table of recommendations with brief rationales, but also lack specific instruction on how to follow these recommendations when using MTurk. Further, Jia et al. (2017, p. 309) contend that MTurk is only suitable for research that can be “generalized to a variety of users and technologies” and samples populations with “diverse individual cognition.” We contend that if authors properly follow the best practices we outline in this paper, all types of behavioral research can be conducted on MTurk without diminishing data quality, especially when compared to other online sampling methods.

Another issue is that due to page limits, authors tend to provide brief explanations of their data collection procedures (Lowry et al., 2016). For example, in a study of industrial-organizational psychology journals, approximately one-third of the articles did not include any information on quality control measures (Cheung et al., 2017). Because of this, determining whether the sampling methodology was adequately implemented and examined during the review process is often difficult, regardless of the sampling method employed. Therefore, assessing whether our suggested best practices are being followed when collecting data via MTurk is difficult, and evaluating the techniques employed in studies that have been rejected and remain unpublished is impossible.

To address these issues, we discuss specific options and settings available in MTurk to employ best practices. First, we provide an overview of MTurk. Second, we propose best practices for working with Workers on MTurk. Third, we outline the suggested best practices in this tutorial with respect to phases of the sampling process: before, during, and after data collection. We conclude the tutorial by providing recommendations for authors, editors, and reviewers to aid in the assessment and reporting of data quality and collection procedures when using MTurk. We also compare and contrast our recommendations with those of Cheung et al. (2017), Jia et al. (2017), and Lowry et al. (2016) throughout our paper. We have provided appendices to help researchers outline the expectations and instructions to participants of studies conducted using MTurk.

2. Overview of Amazon Mechanical Turk

Crowdsourcing has been defined as “the paid recruitment of an online, independent global workforce for the objective of working on a specifically defined task or set of tasks” (Behrend et al., 2011, p. 801). Amazon Mechanical Turk is a crowdsourcing platform that serves as an online marketplace for individuals and businesses, referred to as *Requesters*, to hire independent contractors, referred to as *Workers*, to remotely perform a wide variety of jobs, referred to as *Human Intelligence Tasks* (HITs). Requesters choose the payment amount and participant qualifications. Requesters review work and determine if it should be accepted or rejected, or if a bonus payment is appropriate. Workers’ reputations are indicated by their HIT acceptance rate, while Requesters’ reputations are based on opinions shared by Workers on external websites. Behavioral researchers are most likely to use MTurk to solicit participants for surveys and experiments, and then conduct the study on other online research platforms, such as Qualtrics or SurveyMonkey. For an excellent introduction to MTurk and its uses in behavioral research, see Mason & Suri (2012).

2.1. Benefits of MTurk

Although Amazon does not reveal user information, several studies have reported on the characteristics of Workers and Requesters. Ipeirotis (2010b) determined that when compared to Internet users in general, Workers tend to be younger, mainly female, and have less income. It is estimated that there are currently over 100,000 users on MTurk, with at least 2,000 actives at any given time (Difallah, Filatova, & Ipeirotis, 2018). Demographic data for certain date ranges can also be obtained from Mechanical Turk Tracker (<http://mturk-tracker.com>) (Difallah, Catasta, Demartini, Ipeirotis, & Cudré-Mauroux, 2015; Ipeirotis, 2010a). As shown in Table 1, several studies have identified numerous benefits of using MTurk over other primary data sources. Further, MTurk is particularly useful in behavioral research (Behrend et al., 2011; Goodman et al., 2013), allowing surveys and experiments to be conducted online without sacrificing quality (Briones & Benham, 2017; Mason & Watts, 2009; Rogstadius et al., 2011; Sprouse, 2011). While Goodman et al. (2013) hypothesized that MTurk participants might disregard instructions if it is likely to lead to a higher payment, the study found that cheating was significantly reduced from 40.1 to 27.2 percent simply by asking MTurk participants to answer honestly.

Ultimately, MTurk provides researchers with greater control and flexibility at less expense than other online panel providers. MTurk’s pricing is far more transparent in that Amazon’s base fee is a percentage of the amount paid directly to Worker(s) for completing a HIT (20 percent for batches with fewer than ten assignments and 40 percent for batches with ten or more assignments) (Amazon Mechanical Turk, n.d.-b), where an assignment is referring to one completion of the HIT. Other online panel providers typically charge researchers a flat fee per respondent. Unfortunately, pricing using the flat fee approach is indicative of the challenge in obtaining a sample of the desired population rather than the actual payment made to each respondent, which obfuscates the sampling methodology. For example, researchers might be quoted a cost of \$50 per respondent to sample a niche target population with a short 10-minute survey, yet only \$5 of that fee is paid to each respondent. The remaining \$45 cost is incurred by the online panel provider in the recruitment and identification of the sample. Understandably, the online panel services do not want to reveal their internal cost structure, but the inability of researchers to report the true amount paid to respondents or the sample recruitment procedure used by the online panel service is problematic.

Category	References
Cost	Chandler et al., 2013; Goodman et al., 2013; Horton & Chilton, 2010; Kraut et al., 2004; Mason & Suri, 2012; Mason & Watts, 2009
Subject Pool Access	Behrend et al., 2011; Chandler et al., 2013; Goodman et al., 2013; Kraut et al., 2004; Lowry et al., 2016; Mason & Suri, 2012; Mason & Watts, 2009; Shapiro et al., 2013; Stewart et al., 2015
Subject Pool Diversity	Behrend et al., 2011; Buhrmester et al., 2011; Difallah et al., 2018; Kaufmann & Veit, 2011; Kraut et al., 2004; Lowry et al., 2016; Mason & Suri, 2012; Paolacci et al., 2010; Ross et al., 2010
Speed	Chandler et al., 2013; Goodman et al., 2013; Horton & Chilton, 2010; Lowry et al., 2016; Mason & Watts, 2009
Flexibility	Chandler et al., 2013; Kraut et al., 2004; Lowry et al., 2016; Mason & Watts, 2009
Attentiveness	Hauser & Schwarz, 2016
Anonymity	Chandler et al., 2013; Shapiro et al., 2013

Table 1. Advantages of using MTurk

2.2. Common Criticisms of MTurk

Some of the common criticisms of MTurk revolve around data verification, self-selection bias, and its appropriateness for sampling certain target populations. While all researchers should strive for perfect generalizability and validity, every study has its limitations. We contend that the control that researchers have when qualifying participants on MTurk is a substantial advantage over other online sampling methods.

Some of the benefits of online research might also negatively affect studies conducted using MTurk. For example, anonymity can certainly be beneficial to participants and reduce social desirability bias, but complete anonymity prevents researchers from verifying self-reported data (Cheung et al., 2017; Jia et al., 2017). Encouragingly, Rand (2012) found that most subjects answered reliably to demographic questions on MTurk. Unfortunately, one of the common misconceptions of MTurk is Workers falsely claiming to be residents of the United States (Jia et al., 2017). Previously, citizens of the United States were only required to provide either a social security number or an individual tax identification number upon reaching a certain level of earnings and international Workers were unable to perform any HITs without providing the necessary information found on IRS Form W-8BEN. Now, Amazon requires all Workers to provide valid taxpayer identification information when registering with Amazon Payments before they are permitted to complete a single HIT. This is explained in the frequently asked questions related to tax information on MTurk. Under “Tax Information for US Residents”, the answer to “Why am I asked to register with Amazon Payments?” states:

An Amazon Payments account allows you to transfer Amazon Mechanical Turk earnings to your bank account. We also require U.S. Workers to provide valid taxpayer identification information when registering with Amazon Payments. You must create an Amazon Payments account to work on HITs and your earnings may be subject to tax reporting with the Internal Revenue Service (IRS). To learn more, click here. (Amazon Mechanical Turk, n.d.-c)

Under “Tax Information for Non-US Residents”, the answer to “Why am I asked to provide my tax information?” states:

We require Workers to provide valid taxpayer identification information in order to comply with U.S. tax reporting regulations governed by the U.S. tax authority (Internal Revenue Service or "IRS"). The tax information interview collects the information needed to complete an IRS tax form (e.g. IRS Form W-8) which will be used to certify your non-U.S. status, determine if your earnings are subject to IRS reporting, and the rate of U.S. tax withholding (if any) applicable to your earnings. (Amazon Mechanical Turk, n.d.-c)

Amazon’s increased scrutiny for all new Worker accounts to address early issues with work performed by international participants might lead to a less diverse subject pool for studies requiring an international sample, but they have addressed much of the early criticism of MTurk with respect to sampling populations located in the United States.

Concerns have also been raised regarding self-selection bias (Cheung et al., 2017; Jia et al., 2017). We agree in the sense that there is no way to compel people to participate since everyone has autonomy. Yet, reduced verifiability and

self-selection bias are potential issues true of all online samples and not limited to MTurk. Self-selection by ineligible participants can be mitigated by following our suggested best practices. Since these concerns exist for all online panels, we argue that if other platforms that provide far less control are considered acceptable, a study properly conducted on MTurk should be, as well. Jia et al. (2017) also discuss when MTurk samples or organizational samples are appropriate. We feel that MTurk has wider applications than what they suggest. We agree that when the topic of interest is narrow and specific to an organization, then an organizational sample is necessary. However, MTurk's extensive pool of potential participants and researcher control make it more advantageous than traditional sampling methods for studies intended to be generalizable to the population at large.

2.3. Dangers of Naïve Use of MTurk

The attractive benefits of MTurk introduce additional burdens that researchers must properly address to collect quality data. Due to its short existence and the relative ease of publishing HITs, researchers with little to no experience with MTurk might be unaware of potential data quality issues and how to mitigate them prior to data collection. In the following sections, we outline our suggested practices for maintaining a healthy relationship with Workers, as well as methods researchers should employ before, during, and after data collection on MTurk to ensure collection of the highest quality data possible. The ordering of the suggested practices is intended to follow the stages in the research process as best possible, though researchers should be aware that some of the practices can and should apply to multiple aspects of study design, data collection, and analysis. Therefore, we highly encourage readers to fully read and understand all the best practices before collecting data on MTurk.

3. Best Practices for Working with Workers

In addition to ensuring data quality, it is critical for researchers to maintain a symbiotic relationship with participants. Treating workers with respect and dignity preserves MTurk and other platforms as acceptable sources of participants for conducting research. Gleibs (2017) reminded researchers of the importance of maintaining ethical treatment while using crowdsourcing services. The best practices suggested in this section, summarized in Table 2, can help researchers maintain this vital relationship when utilizing MTurk.

Number	Best Practice	How to Implement
3.1	Protect Study Integrity and Reputation	<ul style="list-style-type: none"> • Be aware of your reputation • Resolve any issues quickly
3.2	Provide Clear Expectations and Instructions	<ul style="list-style-type: none"> • State expectations regarding attentiveness, time commitment, and compensation • Include any study-specific restrictions that you expect Workers to follow
3.3	Provide Contact Information	<ul style="list-style-type: none"> • Provide Workers with an email address that will be monitored during data collection • Allow Workers to provide feedback after completing the study
3.4	Be Fair and Consistent	<ul style="list-style-type: none"> • Set payment at or above minimum wage • Establish an objective rubric for submissions • Include a statement in the HIT description of how work will be assessed
3.5	Maintain Worker Confidentiality and Anonymity	<ul style="list-style-type: none"> • Protect participant information • Only collect anonymous MTurk Worker IDs

Table 2. Best Practices for Working with Workers

3.1. Protect Study Integrity & Reputation

We believe that effective use of MTurk requires obtaining accounts on multiple websites to protect the integrity of studies, as well as one's own reputation among MTurk Workers (Mason & Suri, 2012; Paolacci et al., 2010). In this section, we discuss their benefits and the best practices to follow when using these additional accounts.

Workers, who commonly refer to themselves as "Turkers," often post reviews of Requesters on MTurk review websites, such as Turkopticon (<http://turkopticon.ucsd.edu/>) and Turker Nation (<http://www.turkernation.com>) (Cheung

et al., 2017; Jia et al., 2017; Mason & Suri, 2012). The use of these outlets might result in study-specific information, such as the location and answers to attention and manipulation checks, being shared with potential study participants, possibly invalidating the results of the study. Chandler, Mueller, & Paolacci (2014) concluded that cross-talk about study content among Workers was not a major problem. However, prohibiting participants from discussing the study on public forums and monitoring these websites during collection is still important to ensure that such disclosures have not compromised the integrity of the study.

The first version of Turkopticon (<https://turkopticon.ucsd.edu>) allows Workers to rate a Requester's "communicativity," "generosity," "fairness" and "promptness" on a scale of one to five, as well as submit detailed comments about their participation in a given HIT. The beta version of Turkopticon 2 (<https://turkopticon.info/>) has been modified to focus ratings on individual HITs rather than aggregate all ratings for each Requester. The rating criteria has also evolved to include items related to terms of service violations, technical issues, completion time, approval/rejection time, and whether the Worker would recommend the HIT to others. The HIT review form of Turkopticon 2 can be seen in Figure 1.

Tell Other Workers About This HIT

HIT title

🇺🇸 Reward
the HIT

Requester Name

Requester ID
the Requester

This HIT violates TOS [see TOS]

This HIT is broken (technical issue prevents completion, e.g. broken images, bugged submit button, etc.)

Approximately how long did it take you to complete each HIT? *

minutes seconds

I don't know

I didn't finish the HIT

Was the requester communicative and responsive? *

I did not contact the requester.

No, the requester did not respond to my satisfaction

Yes, the requester responded to my satisfaction

Approximately how long did it take to approve or reject? *

days hours

I'm still waiting

How much of your work was rejected? *

All Some None

All rejections were overturned

Would you recommend this HIT to others? *

No opinion No Yes

You can give additional information, context, or constructive comments below.

Submit review

Figure 1. Turkopticon 2 HIT Review Form

In addition to the Turkopticon websites, Requester reputation ratings are readily available to potential Workers who are using Internet browser plugins or have manually installed scripts (<https://turkopticon.info/install>). If the plugin or script is installed, Workers can quickly gain insight on the Requester's reputation in the Turkopticon community while

browsing available HITs on MTurk. This information is provided by a pop-up box that can be accessed simply by hovering the mouse cursor over the small icon inserted in front of the Requester's name for each HIT. A side-by-side comparison of Requester ratings as seen on MTurk using browser scripts for the original Turkopticon and beta version of Turkopticon 2 is provided in Figure 2.



Figure 2. Comparison of Old and New Turkopticon Ratings as Viewed on MTurk

Requesters (based upon the original Turkopticon) and HITs (based upon Turkopticon 2) with a poor reputation among Workers might struggle to attract study participants, and those who do elect to participate might not provide reliable data. Therefore, Requesters should be aware of their reputation and strive to resolve any issues Workers might have as reasonably and swiftly as possible. Reviewing valuable feedback from Workers can also help researchers improve future HITs and their standing in the MTurk community. For those who discover that they have poor reputations on these services, we recommend following our best practices under a new Requester account. This will provide a clean slate and allow the researcher to build a positive reputation over time. Aside from that, we do not encourage researchers to create new accounts unless compelling justifications can be given. The goal of this paper is for researchers to adopt best practices so MTurk will remain a mutually beneficial research platform. Repeatedly creating new accounts to avoid maintaining a poor Requester reputation is unethical and counter to the spirit of our recommendations.

3.2. Provide Clear Expectations and Instructions

Researchers should ensure that they have provided detailed expectations in the HIT description for potential participants to review on MTurk. They should also be upfront about compensation and time required (Paolacci et al., 2010) and notify participants that they will be removed for inattentiveness (Jia et al., 2017). Some have suggested that stating the scientific importance of a study might reduce participant inattentiveness (Fleischer, Mead, & Huang, 2015; Goodman et al., 2013). However, researchers should make sure that study instructions do not invalidate responses by priming participants (Cheung et al., 2017). Further, restating these expectations again on the research platform being used prior to the participants' commencement of the study is always wise.

Despite the fact that MTurk Workers conduct their work in an unsupervised and uncontrolled environment, research has shown that Workers will respond to specific instructions that restrict certain behavior, such as looking up answers on the Internet (Goodman et al., 2013). Cheung et al. (2017) advise asking participants to reduce extraneous factors by using a certain Web browser or finding a quiet place to complete the task. Providing clear directions for acceptance is also important because there are many tasks on MTurk where priming is not a concern. For example, approximately 13% of submitted HITs are returned, giving Workers an opportunity to improve their work and have it accepted (Hara et al., 2018). However, resubmitting work is not an option for surveys and experiments since it would invalidate the results. Therefore, we suggest that researchers clearly outline the expectations and instructions for participants to improve the likelihood of achieving acceptable results. We have provided recommended language in Appendices A and B. We have also provided a supplementary file that includes alternate code to use for the HIT expectations on MTurk which prevents access to the study link until the HIT has been accepted, as shown in Appendix C.

3.3. Provide Contact Information

Providing direct contact information to potential participants prior to the commencement of a study is always a good practice and likely required by institutional review boards (IRBs). This should be done within the HIT instructions. Providing Workers with an email address that is associated with an institution or research organization is likely to increase the study's legitimacy. As we discuss in more detail below, researchers should also be available during the data

collection process, because some Workers will email the researchers directly with questions, concerns, or to report technical issues. Also, email clients might filter messages sent to Requesters via the MTurk messaging system into spam folders. Therefore, researchers should be sure to monitor the email address associated with their MTurk Requester account during the data collection process and resolve any issues as quickly as possible. We also recommend that researchers include open-response questions for Workers to provide HIT-related feedback within the study instrument (Mason & Suri, 2012). Such feedback often pertains to confusing directions and issues experienced with the functionality of the instrument.

3.4. Be Fair and Consistent

Offering compensation relative to the task length for a given HIT has been shown to impact participation from MTurk Workers and reasonable compensation can be expected to yield quality data (Buhrmester et al., 2011). Although some MTurk Workers will accept HITs for little compensation, and Requesters are not bound by minimum wage laws since Workers are considered independent contractors, this is considered poor practice on ethical grounds. Additionally, low compensation is likely to increase data collection time and can negatively impact Requester reputation (Mason & Suri, 2012). Thus, researchers should ensure that they fairly compensate Workers for the time spent participating in the study (Jia et al., 2017; Lowry et al., 2016). At a minimum, we suggest that compensation be set at or above the hourly minimum wage in relation to the anticipated length of time to complete the HIT. Since some participants will take longer than others, we recommend that the minimum rate be based upon the completion time for the 75th percentile from a pilot study. For example, based upon the current minimum wage in the United States of \$7.25, a survey expected to take most participants approximately 20 minutes to complete (i.e., based upon completion times obtained during pilot testing) should pay participants approximately \$2.50. This is not only ethical but has also been shown to be a factor for participant motivation (Deng & Joshi, 2016; Kaufmann & Veit, 2011) and can result in improved data quality (Buhrmester et al., 2011).

The most effective metric for determining Worker quality is the HIT acceptance rate. Fairness and consistency when approving and rejecting submitted work for HITs are critical. Adhering to community norms when rejecting work and explaining why the work was rejected is also important (Paolacci et al., 2010). Approving all submissions without assessing work quality increases data collection costs and reduces the effectiveness of the metric for other Requesters, whereas rejecting every instance of questionable work is likely to reduce the Researcher's reputation among Workers. Therefore, researchers must take reasonable steps to maintain a delicate balance between approval and rejection that is appropriate for the interests of both parties.

Since the HIT acceptance rate is critical to assessing Worker quality and the rejection of work often results in negative Requester reviews, we recommend that researchers be proactive by establishing clear criteria for reviewing work prior to publishing a HIT on MTurk. Our suggested approach is for researchers to establish an objective rubric for poor, marginal, acceptable, and excellent submissions based upon the requirements and expectations for the study in question. Researchers can then assess the standards for a given study by collecting pilot batches.

Once the quality of a submission has been determined, we recommend that researchers refer to the matrix provided in Table 3 to determine whether to accept the work, whether to provide a bonus to the Worker, as well as whether additional communication with the Worker is warranted. Doing so will allow for a more objective and efficient work approval process.

Work Quality	Accept Work?	Provide Bonus?	Send Message?
Poor	No	No	Yes
Marginal	No	Yes	Yes
Acceptable	Yes	No	No
Excellent	Yes	Yes	Yes

Table 3. Work Approval Matrix

Poor data would consist of submissions that clearly indicate the Worker did not put forth an honest attempt. For example, providing the same response for every question in a 100-item survey indicates insufficient effort. In such cases, researchers should reject the work and send Workers an explanation for why their work was rejected. We believe that this is the best way for researchers to preserve their Requester reputation, while also maintaining the integrity of the HIT acceptance rate. However, if the work involves completing a survey or participating in an experiment, we recommend that these explanations be given in general terms to protect the integrity of the study.

Marginal data consists of submissions that appear to be honest attempts yet fail to meet the stated expectations for acceptable work. For example, submissions that fail an unacceptable number of attention check questions would be considered marginal. Researchers should pay special attention to how they handle poor to marginal submissions. Our suggested approach for marginal submissions is to reject the work, provide the Worker with a detailed explanation outlining the reason(s) for doing so, and provide a bonus payment to compensate the Worker for taking the time to participate in the study. Ideally, we recommend that researchers provide a bonus amount equivalent to accepted work to Workers who spent the expected amount of time participating in the study. The use of a bonus payment simply serves as compensation for time spent producing work of marginal quality, while also preserving the integrity of the HIT acceptance rate as a measure of Worker quality. This might appear to reward Workers for rejected work, but qualitative responses from Workers have indicated that they would prefer to preserve a high acceptance rate rather than receive a monetary bonus since poor acceptance rates limit the HIT opportunities available to them in the future.

Obviously, researchers should accept data that meet the criteria for acceptable and excellent submissions. However, if possible, we suggest that work that meets the criteria for excellent submissions also be rewarded with additional compensation through bonus payments. In addition to meeting the standard for acceptable work, an excellent submission might also include extensive qualitative information related to the study's context or feedback on the behavior of the study instrument. Sending a message that thanks them for their excellent submission and the use of a bonus payment provides positive reinforcement to the Worker and shows that the researchers appreciate the Worker's thoughtful participation in the study. These small gestures help preserve the number of quality respondents available to participate in future research conducted on MTurk.

Researchers would be wise to include a statement in the HIT description of how they will assess work. For example, the following statements would explain the suggested method: "We will review work within [X] hours. Honest, attentive, and complete responses will be accepted. Your work will be rejected if it does not satisfy our quality standards. If your work is rejected, you will be compensated for your time through a bonus payment." This informs potential participants that Workers who submit honest attempts will always be compensated for their time. Adopting these suggested practices will help researchers protect their reputation among Workers while also maintaining the HIT acceptance rate as a reliable measure of Worker quality.

3.5. Maintain Worker Confidentiality and Anonymity

Before granting approval for a proposed study, IRBs often require assurances from researchers that they will maintain participant confidentiality and/or anonymity. Even though Amazon prohibits Requesters from requesting personally identifiable information and MTurk Workers benefit from several features designed to protect their identities (Amazon Mechanical Turk, n.d.-c), such as anonymized Worker IDs, instances might occur where a Worker reveals their identity to the researcher.

Though unlikely to affect most researchers, Requesters should also be aware of the potential tax implications of data collection on MTurk. If a Requester pays an individual Worker more than \$600 in a fiscal year, the U.S. Internal Revenue Service (IRS) requires the Requester to send the Worker a 1099-MISC form for tax purposes. When necessary, Amazon will provide Requesters with Worker information, such as name, Social Security number, and address to satisfy this requirement. The potential for Requesters to receive such sensitive personal information only increases the importance of maintaining Worker confidentiality.

A more likely disclosure occurs when an MTurk Worker communicates with a Requester via email (Mason & Suri, 2012). Workers will often use personal email accounts to ask questions, raise concerns, or dispute the rejection of submitted work. Such communication is highly likely to include the Worker's MTurk ID. Hence, researchers must take their responsibility to protect participant information seriously and prevent any knowledge of identifiable participants from influencing how they conduct or analyze the data from the study.

Jia et al. (2017) recommend the collection of IP addresses when conducting external HITs. We disagree with this practice for multiple reasons. First, collecting IP addresses has the potential to identify Workers. Second, the use of proxies, such as a virtual private network (VPN) or the Tor anonymity network, reduces the reliability of IP addresses as an indicator of a user's physical location. Third, legitimate Workers might share the same IP address, which further decreases its usefulness in screening participants. Jia et al. (2017) also suggest including additional qualitative questions with the intent to establish Worker identity while simultaneously mentioning in a footnote that requesting or collecting personally identifiable information is against Amazon's terms of service. Not only does this violate Amazon's policies, it is also likely to violate IRB guidelines. Any effort to reduce Worker anonymity is unethical and will likely result in negative Requester reputation for the researcher since review sites now prompt Workers to report violations of MTurk's

terms of service (see Figure 1). Additionally, the anonymity that MTurk provides Workers should be viewed as an advantage because anonymous participants are less likely to succumb to social desirability bias. Therefore, we highly discourage researchers from collecting or requesting any such information.

4. Best Practices Before Collection

Regardless of the participant recruitment method employed, researchers must carefully plan their studies. However, this is especially true for data collected on MTurk due to the freedom and flexibility it provides. The best practices suggested in this section, summarized in Table 4, help researchers establish proper methods for soliciting, identifying, and collecting high-quality respondents from the desired population when using MTurk.

Number	Best Practice	How to Implement
4.1	Create & Secure Amazon Accounts	<ul style="list-style-type: none"> • Create accounts for MTurk and AWS • Enable two-step verification • Adopt a generic Requester name • Use unique email addresses for each account
4.2	Create a Qualification Test	<ul style="list-style-type: none"> • Create custom MTurk Qualification Types • Ask study-specific qualification questions • Broadly state HIT title, instructions, and qualification test items • Set the HIT visibility to private
4.3	Filter Workers	<ul style="list-style-type: none"> • Restrict access using MTurk features • Require no greater than a 97 percent HIT approval rate • Consider limiting the number of HITs approved
4.4	Generate Unique Completion Codes	<ul style="list-style-type: none"> • Randomly generate and assign a unique completion code to each respondent
4.5	Test Your HITs	<ul style="list-style-type: none"> • Use the MTurk Developer Sandbox • Collect a pilot batch before the full collection • Include qualitative questions to identify issues

Table 4. Best Practices Before Collection

4.1. Create & Secure Accounts

We suspect that many researchers new to MTurk already have personal Amazon.com accounts they use to purchase goods and services online. Nevertheless, we recommend that researchers create separate accounts on Amazon when conducting research on MTurk for a few reasons. First, proper account security includes using unique logins for each account. If one account is compromised, access to additional accounts will not be affected. Given the sensitive nature of academic research and the assurances of anonymity and confidentiality given to participants, researchers should also enable two-step verification, which is available in the Advanced Security Settings under Login & Security. Second, we advise that researchers adopt a generic Requester name. Using a personal Amazon account on MTurk can result in the researcher's name being revealed as the Requester for each HIT. While we do encourage researchers to share identifiable contact information with participants, disclosing such information can be done within the HIT instructions rather than Requester name. Third, when creating separate Amazon accounts for research purposes, we suggest that researchers use unique, non-work email addresses. If/when a researcher changes employer, they run the risk of losing access to their Requester account since Amazon's only method of contact and verification for MTurk Requesters is the email address associated with the account. This would be especially unfortunate for researchers with positive Requester reputation ratings.

While a standard Amazon.com account is all that is needed to access MTurk, we also recommend creating an Amazon Web Services (AWS) account (<https://aws.amazon.com>) to access the advanced features available through MTurk Developer Tools (<https://requester.mturk.com/developer>). Leveraging the capabilities of the MTurk Developer Tools and the associated Application Programming Interface (API) allows researchers to create Qualification Tests and to test the functionality of their HITs prior to collecting data. Amazon provides a helpful chart, which has been reproduced in Table 5 and outlines the other major benefits of using the command line tools and API as opposed to the standard web

interface. The Developer Tools require that the Requester's account be linked with an AWS account. Doing so allows the Requester to register for the MTurk Developer Sandbox and download the AWS Software Development Kit (SDK).

Creating and Managing Your Work	Web Interface	Command Line Tools	API
Start with our sample HTML templates	✓		
Create HITs visually with an HTML editor	✓		
Create and manage your HITs in batches	✓	✓	
Manage HITs created via the CLT or API		✓	✓
Define HITs in XML		✓	✓
Host HITs on your own server		✓	✓
Can be integrated into back-end systems			✓
Create notifications indicating when HITs are updated			✓
Managing the Workforce	Web Interface	Command Line Tools	API
View Worker Approval Rate on your HITs	✓		
Create custom Qualifications	✓	✓	✓
Assign a Worker a Qualification	✓	✓	✓
Revoke a Worker's Qualification	✓	✓	✓
Use system Qualifications with your HITs	up to 5	up to 10	up to 10
Use custom Qualifications	up to 5	up to 10	up to 10
Block Worker from submitting future HITs	✓	✓	✓
Remove a block from a Worker	✓	✓	✓
Give a Worker a bonus	✓	✓	✓
Email a Worker			✓

Table 5. Tool Comparison Table (reproduced from Amazon Mechanical Turk, 2018)

4.2. Create a Qualification Test

There are a few different approaches to qualifying Workers for HITs. Requesters can create a separate HIT for a qualification survey, include qualification questions at the beginning of a study, or use custom Qualification Types. We do not recommend creating a separate HIT for qualifying participants unless the study's budget allows for offering a higher than usual payment for a longer qualification survey. Workers tend to set alerts and sort the available HITs by the reward amount. Since most qualification surveys are likely to be short and low paying, these HITs will be buried at the bottom of the list and result in a slower qualification process. We also do not recommend including qualification questions in the research instrument itself. This is likely to frustrate Workers who fail to meet the desired qualifications after beginning a HIT since it might be perceived as a "bait-and-switch" tactic.

Instead, we recommend the use of custom MTurk Qualification Types. This allows Requesters to limit the availability of a costlier and time-consuming HIT to only those who meet the desired criteria. This can be achieved prior to full-scale data collection by limiting the HIT only to Workers who have successfully obtained a custom Qualification Type. One of the major advantages of custom Qualification Types is that there are no fees paid to Workers who attempt to qualify. Workers only earn compensation after successfully qualifying and having their work accepted for the HIT. Since a high paying HIT can attract many potential participants, using custom Qualification Types is a highly cost-effective method of qualifying participants for targeted samples. However, since Requesters do not incur fees when using the custom Qualification Type method, we encourage researchers to be mindful of the Workers' time by limiting the length of the qualification and only including items or tasks that are necessary for determining eligibility. Abusing the Qualification Type to avoid paying Workers is highly unethical and might result in the Requester's account being terminated by Amazon.

When developing a Qualification Test, researchers should carefully consider qualification requirements and make sure the sample characteristics are as close to the target population as possible (Cheung et al., 2017; Lowry et al., 2016). Cheung et al., (2017, pg. 357) suggest including “questions that would only be answered affirmatively by someone who had the desired characteristics, such as their job title, work schedule, and salary.” We discourage aggressive attempts to verify the employment status of Workers as it would violate their anonymity. However, we agree that ability can be assessed by having participants demonstrate that they have the requisite knowledge, skills, and abilities of the desired population.

Ensuring that the HIT title, instructions, and qualification test items are broadly stated is important so that Workers are not influenced to answer dishonestly simply to meet the desired target population characteristics. Signals that would reveal to participants the purpose of the study or eligibility requirements should be avoided (Cheung et al., 2017) and neutral wording can also help alleviate social desirability bias (Jia et al., 2017). For example, if a study calls for a sample of full-time employees who hold management positions at publicly traded firms in the United States, Workers might be asked to answer: 1) Please indicate your current employment status [35 hours a week or more; Less than 35 hours a week; I am not currently employed]; 2) Which of the following most closely matches your position in the organization? [intern; entry level; manager; owner]; 3) Please indicate whether your firm is privately owned or publicly traded [privately owned; publicly traded; not applicable]; 4) Which of the following best describes the organization of your employer? [for-profit; not-for-profit; government; other]. Based upon these example survey items, one could program the Qualification Test to automatically grant the custom Qualification Type to Workers who report working 35 hours or more in a management position for a publicly traded, for-profit organization.

Researchers can use Amazon's MTurk Developer Tools to create and manage custom Qualification Types. The Quiz Qualification method allows for automatic approval of Workers that meet the specified criteria, permitting qualified Workers to participate in the study immediately. Chandler, Mueller, and Paolacci (2014) provide detailed instructions on how to assign qualifications using command line tools or the web interface. Qualification surveys can also be used to ask subjects if they would like to be contacted about future studies (Mason & Suri, 2012) in order to form a pool of Worker IDs for further research (Chandler et al., 2014). If researchers are planning to conduct multiple studies that require different target populations, the relevant qualification questions can be combined into a single survey HIT. The data can then be used to generate multiple MTurk Qualifications. However, this should be done as a standalone HIT with appropriate compensation provided.

Lastly, if a Custom Qualification Test is being used, we also suggest setting the HIT Visibility to private, which is in the Worker Requirements section of the HIT properties. This allows the HIT to be visible to all Workers, but only those who have successfully obtained the custom Qualification can preview the HIT. Those who have not yet qualified will be provided a link to the Qualification Test.

4.3. Filter Workers

Generalizability and the ability to achieve reliable statistical inference is a primary concern in academic research. One of the most critical steps before collecting data is ensuring that the methods used will result in a representative sample drawn from the target population. In addition to custom Qualification Types, MTurk also provides several features that researchers can use to filter the number of eligible respondents, such as the master qualification, premium qualifications, HIT acceptance rate, Worker location, and number of HITs accepted.

MTurk offers Requesters the ability to restrict acceptance of HITs to MTurk “Masters”, who are Workers deemed by Amazon to be high-quality participants. However, there are a few drawbacks to the use of Masters. First, the process for attaining Master status is not transparent, forcing Requesters to blindly accept Amazon's judgment of Worker quality. Second, the use of Masters increases the cost of data collection by an additional five percent. Third, the pool of MTurk Masters is highly unlikely to be representative of the target populations for most research. We do not recommend using Masters unless convincing justification can be given.

MTurk introduced Premium Qualifications in 2016 (Amazon Mechanical Turk, 2016). Premium Qualifications are an attempt to categorize Workers based on regularly-sought criteria instead of forcing Requesters to include additional qualification questions into each HIT. For an additional fee, ranging from \$0.05 to \$1.00 per assignment, Requesters can filter the pool of Workers by the predefined list of over 130 Premium Qualifications, such as gender, industry, employment status, and job function. While the idea behind Premium Qualifications is attractive, especially to those publishing HITs that do not require accurate samples of certain populations, we discourage academic researchers from using this feature for a couple of reasons. First, just as with other online panel services, researchers cannot verify the methodology employed by MTurk. Although we recognize that the introduction of Premium Qualifications is likely to

reduce the chances of Workers changing their reported characteristics from HIT to HIT, we recommend that Requesters perform their own Qualifications to maintain control and transparency. Second, since there is no additional cost for researchers to create a custom Qualification Test to assign custom Qualification Types to Workers, the surcharge for Premium Qualifications makes this feature less appealing.

Requesters can set eligibility criteria for each HIT using MTurk's built-in features for filtering participants, such as location and approval rate. Since Amazon has strengthened the standard location field for MTurk's Workers by forcing the disclosure of tax information, it can now be used reliably. This can be selected under the "Advanced" tab when setting up a HIT on MTurk by choosing to "Customize Worker Requirements", as shown in Figure 3. Requesters can then set the Worker's location as a qualification filter, allowing or restricting Workers based upon the region(s) selected.

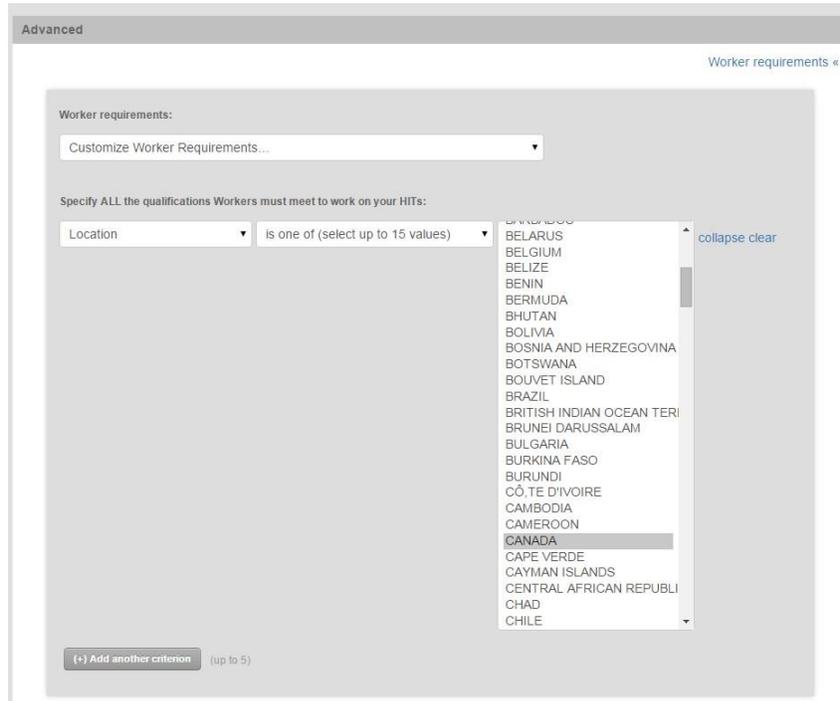


Figure 3. Location Worker Requirement

The reputation of MTurk Workers has been found to be an accurate predictor of Worker quality and successful completion of attention check questions (Peer et al., 2014). Cheung et al. (2017) and Jia et al. (2017) also mention the usefulness of Worker reputation. By using these filters, Requesters can be sure that Workers have achieved a desired Worker HIT approval rate and have had an acceptable number of HITs approved. Amazon suggests requiring Workers to have at least a 95 percent approval rate and 1,000 approved assignments (Amazon Mechanical Turk, n.d.-a). However, we feel that this recommendation is likely too restrictive for most academic research. Although most of the work that is conducted on MTurk consists of short, repetitive tasks, we suggest requiring no greater than a 97 percent HIT approval rate to allow for Workers who have up to a three percent rejection rate to participate. Since MTurk assigns a 100 percent approval rating to Workers who have completed fewer than 100 HITs, we also suggest that researchers set a minimum of 100 approved HITs to ensure that the approval rating is effective, and that Workers have some familiarity with MTurk before participating.

Jia et al. (2017) suggest increasing the sample size to lower the proportion of professional MTurk Workers. While limiting the number of professional Workers might be desirable for certain studies, simply collecting more responses is unlikely to significantly alter the proportion because the entire population of Workers has an equal opportunity to participate. Instead, if professional Workers are undesirable, we suggest that researchers consider filtering out professionals by limiting the number of HITs approved to fewer than 10,000 with an additional HIT qualification. However, researchers should be aware that using more restrictive reputation thresholds could potentially skew the participant pool and relying solely upon the HIT acceptance rate and the number of accepted HITs to qualify Workers is not advisable. Also, "professional" survey takers are not unique to MTurk as they are just as likely to participate in

studies facilitated by other online panel providers, which prevents researchers from having any control over the qualification process.

4.4. Generate Unique Completion Codes

Researchers usually prefer to use other platforms that are better suited for collecting such data in conjunction with MTurk. For example, researchers can include a link in the HIT to their study instrument on Qualtrics or SurveyMonkey. Therefore, researchers need to be able to determine that a Worker claiming to have completed the HIT has in fact submitted the data collected in another platform. The most common method is to use a completion code to approve external hits (Mason & Suri, 2012), such as a combination of letters and/or numbers (e.g. "U8L4F9") at the conclusion of the study that the Worker can enter into MTurk after participating. Some researchers might elect to use a static code for each batch to avoid verifying unique codes for each submission, although this increases the risk of participants sharing the code with other Workers to obtain payment for a HIT they did not complete. As we discuss in Best Practice 6.1, the verification process for unique completion codes can be quite painless if the researcher is comfortable with basic functions in Microsoft Excel. Therefore, we recommend the use of unique completion codes that are randomly generated and assigned to each participant. This can be achieved in Qualtrics through the built-in random number generator. For example, a random, six-digit, numeric completion code can be generated and stored in an Embedded Data field (Figure 4), and then be displayed in the survey using Piped Text (Figure 5). Though this approach would allow for the possibility of the same completion code to be assigned to multiple respondents, randomization and a large range of values makes this an unlikely event.



Figure 4. Creating the Completion Code as an Embedded Data Field in Qualtrics

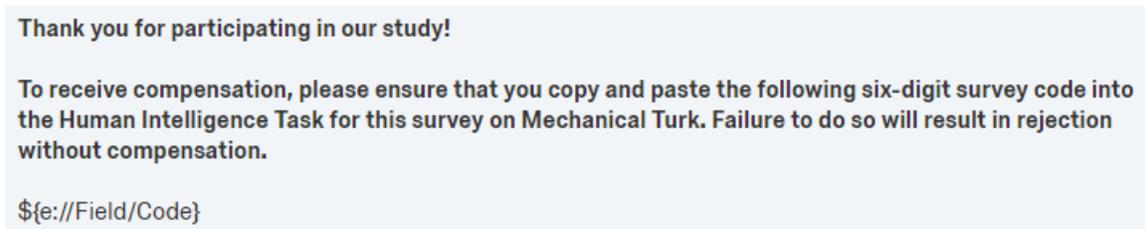


Figure 5. Using Piped Text to Display the Completion Code in Qualtrics

4.5. Test Your HITs

Poorly implemented HITs are likely to result in Workers leaving negative ratings and comments, so we highly recommend that researchers carefully test each aspect of the HIT, including any Qualification Tests, to confirm that they perform as intended. The first step is to test the HIT in the MTurk Developer Sandbox. Although the sandbox mimics the functionality of the production environment, HITs published in the Developer Sandbox are not visible to Workers. This allows Requesters to experiment with new uses for MTurk and to test the behavior of their HITs prior to publishing.

Once the researcher is satisfied with a HIT in the Developer Sandbox, we recommend that it be published in the production environment using a pilot batch with a limited number of assignments to verify that nothing was overlooked during the sandbox testing. Researchers should treat the pilot batch as if it were a real collection to test their rubric and approval methods. Work from the pilot batch should be classified according to the Work Approval Matrix, but we encourage Requesters to approve most work unless the Worker clearly did not put forth a reasonable effort.

Researchers should also include additional qualitative questions to identify any issues related to the technical behavior of their HIT and to gauge Worker opinion on the planned compensation relative to completion time. For example, replicating questions from the Turkopitcon review form would provide insight on how Workers are likely to view the HIT and allow researchers to mitigate these concerns prior to full data collection. Once the HIT is ready for full data

collection, researchers should reduce the number of HIT-related questions as much as possible and include an open-response text box for Workers to relay any issues.

5. Best Practices During Collection

The nature of conducting studies using MTurk requires researchers to pay close attention to their HITs while they are in progress. As will be discussed in section six, more detailed data analysis should always be conducted to determine whether responses are suitable to be included in the study. In this section, we focus on the suggested practices to follow while collecting data on MTurk to ensure timely decisions can be made with respect to evaluating work on MTurk. The best practices we recommend in this section are summarized in Table 6.

Number	Best Practice	How to Implement
5.1	Capture MTurk Worker ID	<ul style="list-style-type: none"> • Use JavaScript to capture and store participant Worker IDs with individual responses
5.2	Repeat Study-Specific Qualification Questions	<ul style="list-style-type: none"> • Compare responses from qualification test to verify participant consistency and honesty
5.3	Collect Data in Batches	<ul style="list-style-type: none"> • Collect data in multiple batches • Resolve issues before full data collection
5.4	Promptly Remove Disqualified Participants	<ul style="list-style-type: none"> • Include attention check, manipulation check, and ability questions • Automatically disqualify Workers who exceed acceptable quality control thresholds • Automatically categorize Workers who are removed from the study
5.5	Exclude Repeat and Ineligible Participants	<ul style="list-style-type: none"> • Prevent repeat responses by excluding Worker IDs collected from prior attempts • Employ multiple approaches when excluding Workers

Table 6. Best Practices During Collection

5.1. Capture MTurk Worker ID

One of the most useful pieces of information that a researcher can gather while conducting studies on MTurk is the Worker ID, which is a randomly generated string of thirteen or fourteen alphanumeric characters assigned by Amazon to each MTurk Worker account. The Worker ID can be used to establish MTurk Qualifications, ensure the same respondent is participating in longitudinal studies, or to exclude past participants from repeated attempts. However, the Worker ID is not associated with data collected outside of MTurk without following additional steps. Some researchers might simply ask Workers to enter their Worker ID in a field within the study. However, this approach is likely to result in errors, especially if the Worker mistakes certain characters for numbers and vice versa. Even copying and pasting Worker IDs might result in extra spaces being appended to the end. Both issues can complicate the work approval process when an exact match for a given Worker ID cannot be found, potentially resulting in erroneously rejecting otherwise acceptable work. Therefore, we recommend that researchers use a script to append the Worker ID to the end of the URL for the study to automatically associate it with the participant's response on the researcher's platform of choice. A straightforward set of instructions for obtaining the Worker ID from MTurk and collecting it in Qualtrics was provided by Peer, Paolacci, Chandler, & Mueller (2012) and was later extended by Shawn Zamechek (2015). Since the Worker ID serves multiple purposes not available with other methods, we highly recommend that researchers take advantage of this feature and make certain that the Worker ID is accurately captured for each response. We have provided a modified version of this code as a supplementary file. The result of the code can be seen in Appendix C.

5.2. Repeat Study-Specific Qualification Questions

If MTurk Qualifications have been established prior to collecting study data, we suggest that the full-scale research instrument repeat the same qualification questions to verify their accuracy. By comparing the answers for each respondent from the qualification survey and the full-scale data collection, researchers can identify questionable participants. This helps eliminate any Workers who might have answered dishonestly or simply guessed the desired

target population characteristics during the qualification survey, as well as Workers who might have experienced a change in their demographic status (e.g., changed jobs) between answering the qualification survey and participating in the full study.

5.3. Collect Data in Batches

Although the number of eligible participants available on MTurk is dependent upon the target population, we advise researchers to collect data in multiple batches due to the speed in which HITs are attempted by Workers. Issues that might arise during data collection are difficult to address while hundreds of attempts are in progress. Limiting the size of each batch can avoid this problem (Mason & Suri, 2012). This is especially important for researchers with limited budgets since it would be unethical to withhold payment due to any unforeseen issues with the data collection. Therefore, starting with a smaller test batch is encouraged before collecting larger sample sizes.

Another reason for employing batch collection is the short time between the initiation and conclusion of a HIT. Even though it is possible to collect thousands of responses quickly, there could be unknown issues with generalizability due to temporal bias if a sample is collected over such a narrow timeframe (Casey, Chandler, Levine, Proctor, & Strolovitch, 2018). Thus, it would be advisable to collect data in smaller batches that are initiated at different times and days of the week. One should also keep the target population in mind when developing a collection schedule. For example, unless tax season is particularly relevant to a study's purpose, it would not be wise to seek participation from tax preparers in the United States during late March or early April because it is unlikely for the true target population to be active and fully represented on MTurk while experiencing an increased workload.

Lastly, Amazon changed the cost structure of MTurk in 2015. Previously, the fee charged to Requesters for conducting work on MTurk was 10 percent of the amount paid to Workers, including bonus payments. However, the fee is now 20 percent for HITs with up to nine assignments and 40 percent for HITs with 10 or more assignments. While the additional work involved in manually managing nine assignment HITs would be considerable, conducting small batches is a way for Requesters to reduce the cost of conducting a study on MTurk. Fortunately, the batch creation process can be automated using various programming languages, such as Python ("MTurk Documentation for Boto 3", n.d.) and R (Carter, 2017), which helps reduce cost and avoid temporal bias.

5.4. Promptly Remove Disqualified Participants

Common techniques for ensuring data quality in academic research include the use of attention check questions (ACQs), reverse-coded questions, and manipulation check questions (MCQs) (Cheung et al., 2017; Jia et al., 2017; Lowry et al., 2016; Oppenheimer, Meyvis, & Davidenko, 2009). Mason & Suri (2012) also encourage including questions that discourage spammers and bots. Lastly, researchers should avoid questions with answers that are easily found online (Goodman et al., 2013).

Establishing criteria and methods for assessing data quality should be done for all research studies, but the use of MTurk introduces unique issues that researchers must consider when identifying and removing disqualified participants. Jia et al. (2017) recommend removing participants who fail quality controls after data collection. Some have even suggested that allowing participants to have multiple attempts to complete the study would improve data quality (Cheung et al., 2017). Sprouse (2011) suggests increasing the desired sample size by 15 percent to account for rejection rates. However, we disagree with these approaches. First, we argue that researchers should set *a priori* thresholds for what is an unacceptable number of failed checks for a given study. Second, researchers should use survey logic to promptly remove participants who have exceeded quality control thresholds and prevent them from reattempting the study. Third, if you're following Best Practice 5.3, you can simply collect additional batches until the desired sample size has been obtained. Following these recommendations will prevent the final sample from including data from inattentive participants and avoid researchers unnecessarily paying for additional attempts that should not be kept in the final sample.

Jia et al. (2017) also note that some IRBs might feel that disqualifying and removing participants violates their right to withdraw from a study without penalty or loss of benefit. However, we argue that being disqualified from a study for inattentiveness is not equivalent to voluntarily withdrawing from a study. Further, we feel that this situation can be avoided by including a "withdraw from the study" option on all screens of the study instrument. This allows participants to voluntarily remove themselves from the study and be directed to a short survey on why they wish to withdraw. Not only does this allow researchers to be notified of any concerns as they occur, but it also allows for such instances to be handled on a case-by-case basis. Researchers can still provide reasonable compensation to Workers through the bonus payment feature on MTurk.

Failing to compensate and/or communicate with disqualified participants is likely to result in reduced reputation ratings for the Requester. Therefore, consistent with the earlier recommendation to clearly communicate with Workers, we encourage researchers to include notification messages if a Worker's participation is terminated for any reason. This should be incorporated into the study design to inform Workers of the general reason for their removal (i.e., "Your responses failed to meet our quality control standards"). If the notification message is too specific (i.e., "You answered attention check questions incorrectly"), the disqualified Worker can compromise the study's integrity by warning potential participants. Informing these participants that they will still receive compensation for the time spent working on the HIT should also be included in disqualification messages when appropriate.

Manually determining the proper payment for these participants is more laborious because their work will not appear on MTurk since they are unable to submit a completion code. However, if additional embedded data fields are associated with each notification message, researchers can quickly analyze the entire data set to identify those who were disqualified for various reasons. In Qualtrics, this can be achieved using branch logic in the Survey Flow. A standard field can be set using the "Flag Response As Screened-Out" option in a custom end of survey message. However, we recommend using a custom embedded data field so that multiple values can be stored that indicate when and why the participant was removed from the study, as shown in Figure 6. In this example, the first if statement will be triggered if a participant incorrectly answers one of three attention check questions. The participant will be immediately removed from the study, provided a custom end of survey message, and the REMOVED embedded data field associated with their response will show ATTN. The second if statement will be triggered if the participant elects to voluntarily withdraw from the study. Before receiving this custom end of survey message, they will be redirected to additional questions to solicit feedback on why they elected to withdraw. Incorporating automated categorization logic simplifies the review process, especially when hundreds of responses are being collected. Simply reviewing the REMOVED embedded data field allows researchers to quickly pay these participants by uploading a batch of Worker IDs to be awarded a bonus payment. Even though the data from disqualified participants is likely unusable, clear communication and reasonable compensation is still greatly appreciated by Workers and helps encourage future participation in behavioral research.

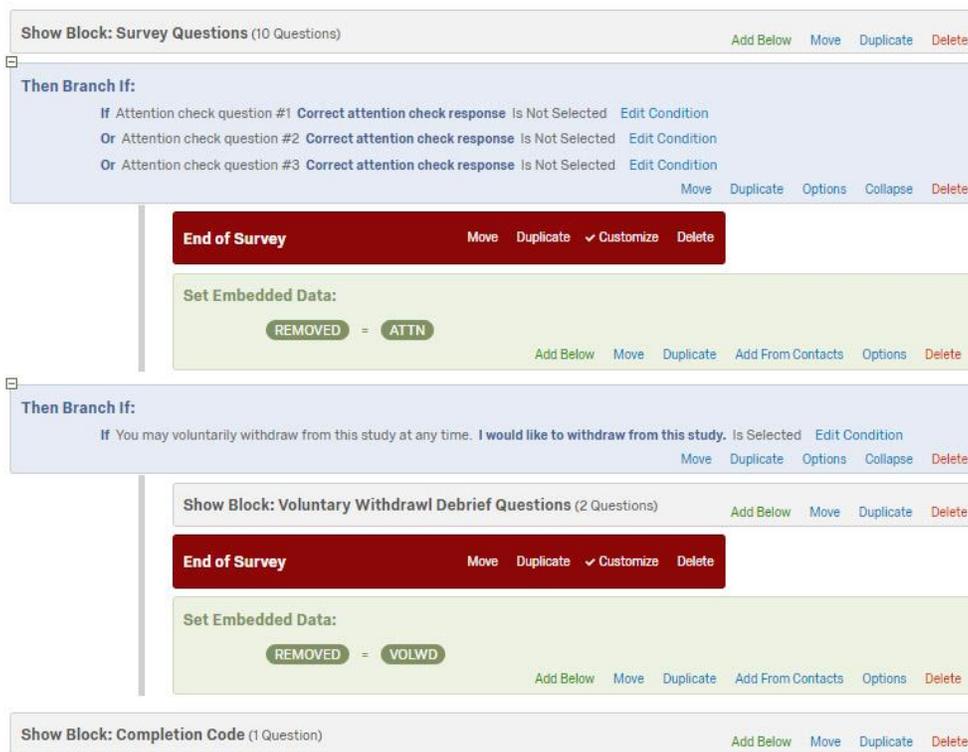


Figure 6. Example of Flow Logic in Qualtrics for Removing Participants

5.5. Exclude Repeat and Ineligible Participants

If researchers use MTurk to recruit their sample but collect the study data outside of MTurk, a Worker can accept a HIT, partially complete the study instrument, and then attempt to restart using the same link. Even if researchers inform

Workers that subsequent attempts to complete the HIT will not be accepted, a determined few will likely still try to participate. Since MTurk can only prevent Workers from accepting a HIT more than once, the researcher might find that they have multiple attempts from the same Worker ID despite only seeing them accept the HIT once. Most online data collection platforms attempt to prevent “ballot stuffing” (e.g., restricting participation to one response per IP address) (Lowry et al., 2016). However, these measures are not always reliable, especially if participants employ proxies, use multiple Internet browsers, or clear browser cookies.

Also, if researchers follow the suggestion to collect data in batches, previous participants must be prevented from participating in the same study again (Cheung et al., 2017). Workers who failed attention or manipulation checks in a prior attempt should be excluded from future batches of the same HIT. Failing to remove inattentive participants or allowing multiple attempts would likely invalidate their responses due to priming. Since they have been previously exposed to the HIT, researchers are no longer able to capture their true and unbiased response. This issue is especially critical for those conducting experiments. Once a Worker has been exposed to a treatment, the study would suffer from poor experimental control if he or she is given an opportunity to participate in the study a second time. Paolacci et al. (2010) also recommend tracking participants to ensure independent responses when publishing multiple HITs for the same or related studies. Additional steps must be taken to ensure that each observation collected on MTurk is unique and unbiased.

Researchers should employ multiple approaches when excluding Workers. First, the HIT should be limited to one attempt per Worker. Second, researchers should employ the method suggested by Peer et al. (2012) and use JavaScript to append the MTurk Worker ID to the link to the study instrument, which is incorporated into the code we provided in a supplementary file. Automatically checking a Worker ID against a list of previous participants is highly effective for excluding Workers when using Qualtrics. A similar approach can be adapted to other platforms using Unique Turker (<http://uniqueturker.myleott.com>). Lastly, researchers can completely block Workers from a HIT using MTurk’s web interface or command line tools (Cheung et al., 2017).

6. Best Practices After Collection

The practices suggested in this section, summarized in Table 7, assist researchers in assessing the quality of the data collected. Researchers should perform the steps in best practices 6.1 and 6.2 immediately following the completion of each batch of data collected so that the work approval process can be completed in a timely manner.

Number	Best Practice	How to Implement
6.1	Promptly Review Submitted Work	<ul style="list-style-type: none"> • Check for repeat attempts based on Worker ID • Verify completion codes match each Worker ID • Review completion times for outliers • Evaluate and approve work using predetermined rubric in accordance with approval matrix • Automate steps using MTurk Developer Tools
6.2	Backup and Secure Data	<ul style="list-style-type: none"> • Backup all MTurk data and study responses • Disassociate Worker IDs from responses after work has been reviewed
6.3	Assess Overall Data Quality	<ul style="list-style-type: none"> • Check reverse coded items • Assess participant drop-out rates across treatments of an online experiment • Look for patterns in the responses • Ensure data is representative of population

Table 7. Best Practices After Collection

6.1. Promptly Review Submitted Work

We suggest researchers actively monitor and review submissions as they are completed. This allows for speedy approval and rejection and ensures that poor work is not automatically approved once the time set for auto-approval has expired. Prompt approval of work is well received by the Worker community and will be reflected in the Turkopticon reviews for the Requester, further improving the researcher’s reputation. While more detailed data analysis should be

reserved until the full data collection has ended, we recommend the following steps be completed in sequential order following each batch.

First, assuming that priming is a concern for the study, we recommend that researchers double check their study responses for duplicate Worker IDs. Again, best practices 5.5 and 6.1 will only prevent known Worker IDs from reattempting the study. Therefore, it is possible for Workers to accept a HIT and access the external instrument multiple times during the same batch. If multiples of the same Worker ID are present, we recommend rejecting all work associated with the Worker ID and flagging their responses to be removed from the final analysis. The prohibition of reattempts should be made clear in the study expectations (see Appendix A).

Second, we recommend that researchers check the randomized completion codes to ensure that the correct Worker ID is associated with a single, complete response. Incorrect completion codes are grounds for rejection. Completion codes entered on MTurk can be quickly matched with the Worker IDs associated with each response using a spreadsheet application, like Microsoft Excel. There are multiple functions available in Excel to assist in completing this step, such as VLOOKUP, MATCH, or INDEX.

Third, we recommend evaluating complete responses in accordance with the quality standards developed when following Best Practice 3.4. One of the most telling metrics for data quality, especially when collecting online data, is the completion time per observation (Lowry et al., 2016). If the study instrument is delivered using Qualtrics, timing questions can be embedded in each page to provide even more detail (Qualtrics, n.d.). Some respondents might be exceptionally quick readers, but the unsupervised nature of online sampling does allow for unrealistic completion times. The use of attention and manipulation check questions should catch a large majority of participants who are not reading carefully and fail to provide thoughtful responses, but a review of extreme outliers with unrealistic completion times is always a good practice. However, the decision to reject such data is far more challenging, especially if the participant successfully navigated through the attention and manipulation checks. In these select cases approving the work is probably best, but researchers might consider marking the observations as potential candidates for removal during the final data analysis. It would also be helpful to the research community, but certainly not expected, if researchers would take the time to message such Workers to encourage them to slow down when participating in future studies.

Once the quality of each response has been categorized, researchers should follow the work approval matrix from Table 3 when deciding to accept work, issue bonus payments, and communicate with Workers. The execution of this step can be automated if researchers take advantage of the MTurk Developer Tools, as discussed in best practice 4.1.

6.2. Backup and Secure Data

Researchers should be aware that MTurk data will only be available for 120 days after collection. Because of this, we encourage researchers to immediately download and backup their qualification test data and batch results from MTurk. Researchers should also save a copy of their HIT properties and content for future reference or reuse and made available to reviewers upon request. If responses are collected using an external platform, such as Qualtrics, we advise creating a backup of that data as well.

Although the collection of personally identifiable information on MTurk is prohibited by Amazon's terms of service, we encourage researchers to treat the responses of their participants with the utmost care. While general demographic information about each Worker can be retained to qualify participants for future studies, there is no need to store the Worker ID with their individualized responses. Therefore, once researchers have completed their review of work and processed payments, it would be prudent to disassociate the Worker ID from their submission. Doing so protects participants should Amazon's user data ever be breached, or the Worker ID is ever found to be identifiable, as was the case in the early days of MTurk (Lease et al., 2013).

6.3. Assess Overall Data Quality

While following the suggested best practices provided in this paper is likely to produce a higher level of data quality when using MTurk, no amount of vigilance can eliminate the need for additional analysis. The chances are that some of the accepted work, upon closer examination, will not be suitable for inclusion in the final analysis. Employing traditional statistical and experimental controls should not be overlooked (Kerlinger & Lee, 2000; Pedhazur & Schmelkin, 1991; Shadish et al., 2002). Researchers should still perform commonly accepted assessments for checking the quality of data (Lowry et al., 2016). For example, researchers should still check any reverse coded items and assess participant drop-out rates across treatments of an online experiment (Rand, 2012). Researchers should also look for patterns in the answer choices that possibly indicate poor quality responses (Mason & Suri, 2012) and use known population demographics (e.g., census data) or other demographic information from prior research that draws from similar populations to make

sure that the data collected is representative of the target population (Cheung et al., 2017). Further, if a qualification survey was conducted to establish MTurk Qualifications, it would be wise to compare the demographics reported in both samples for each respondent to be sure consistent and reliable responses were obtained. This will help verify that the participant recruitment methods employed did, in fact, yield the desired sample.

7. Discussion

Although MTurk can be a quick, convenient, and cost-effective, yet powerful data collection method for academic research, authors often receive negative feedback from reviewers and editors about the quality of such data. Additional scrutiny is warranted if proper measures were not taken to ensure data quality, although common criticisms often have nothing to do with the actual methods employed but rather with the use of MTurk in general. Therefore, we attempt to address these concerns in the following sections.

7.1. Recommendations for Authors

Authors should adopt as many of the suggested best practices as possible to improve the quality of data collected on MTurk. Although page limits often require authors to shorten or remove insightful explanations of the data collection procedures, we believe that providing this information is extremely valuable to assessing data quality and should, therefore, be included. Following the practices outlined in this paper would also allow authors to simply provide a citation to concisely communicate the data collection methods employed. However, authors are still encouraged to explain study-specific criteria, such as qualification questions, to provide additional insight on the methods employed to sample the desired target population.

7.2. Recommendations for Reviewers

Regardless of the platform used, reviewers should require that authors disclose their data collection procedures to better assess data quality rather than making an assessment based solely upon the platform being used. In fact, we argue that the use of MTurk affords researchers greater control and understanding of the data collection process, especially when compared to paid online panel providers that promise to deliver samples of the desired populations yet fail to provide any real method of verification. Therefore, reviewers should carefully critique the methods used for participant recruitment, qualification, and compensation for all research. It should also be noted that, unlike MTurk, the amount paid to online research companies (e.g., Qualtrics and SurveyMonkey) for online panels is not directly paid to those who participate. Considering such a rate as participant compensation or gauging the perceived “quality” of data collected based upon such a figure is inaccurate.

7.3. Recommendations for Editors

Poor practices can certainly lead to poor data, but MTurk provides researchers far more control and insight into their sample than paying other firms to recruit participants for their study. Editors should be sure that any issues raised by reviewers pertaining to the use of MTurk are based upon the methods employed by the authors rather than MTurk in general. Encouraging reviewers to critique participant recruitment, qualification, and compensation, rather than simply disregarding MTurk as a research tool, will yield constructive feedback and improve the quality of all research. While we understand the difficulty of staying under page limitations, we encourage editors to request that a detailed description of the sampling methodology be reported for every study to improve the assessment of data quality for all published research.

8. Conclusion

Although we only focused our paper on survey and experimental research, the wide range of research applications for MTurk is exciting. Regardless of how MTurk is used, researchers must make sure that proper measures are taken to maintain academic rigor. Researchers might find themselves overwhelmed with having total control of the subject recruitment and qualification process, so we have provided a practical tutorial to follow before, during, and after conducting research using MTurk. We discussed specific options and settings available in MTurk as well as included images, websites, and scripts so that researchers new to MTurk will be able to successfully create their own HITs. Following our recommended best practices should ease the burden of using MTurk and ultimately enhance the quality of data collected. We also provide arguments for the acceptance of MTurk as a quality research platform and discuss significant advantages of MTurk over existing online methods currently accepted. Finally, we argue that reviewers and editors of academic research must ensure that criticism of the data collection methods employed in any study is rooted in the procedures followed, not the platform itself.

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Appendix A: Recommended Language for HIT Expectations

In this appendix, we provide researchers with recommended language to use when communicating expectations to Workers in the HIT description on MTurk. Please note that the elements in brackets should be edited to fit the context of the study in question. Be sure to use high-level language to avoid priming participants.

Expected Time	Based upon average completion time from a pilot study, completing this HIT will take approximately [X] to [Y] minutes . The time allotted to complete this HIT is [Y x 2] minutes .
Compensation	The reward for accepted work is [Recommended minimum: \$7.25 x completion time for the 75th percentile from pilot study/60 minutes] for this HIT.
Importance	This scientific study will impact [broadly stated research area]. Your attentive and honest responses are appreciated.
Environment	Prior to accepting this HIT, please ensure that you are in a distraction-free environment that is conducive to deep thought.
Acceptance	We will review work within [X] hours . Honest, attentive, and complete responses will be accepted.
Rejection	Your work will be rejected if it does not satisfy our quality standards. If your work is rejected, you will be compensated for your time through a bonus payment.
Communication	The researcher(s) may be contacted via email at any time. You will be provided with contact email addresses at the beginning of the study. However, please ensure that you use an email address that will not identify you and only refer to your work by providing your Mechanical Turk Worker ID.
Affirmation	By accepting this HIT, you affirm that you have read and understand the expectations of participating in this study.

Table 8. Example HIT Expectations

Appendix B: Recommended Language for Study Instrument

In this appendix, we provide researchers with recommended language to use on the study instrument. We recommend including Table 9 after your institution's IRB human consent form.

Contact Information	If you have any questions or concerns about the study, you may contact the researchers via email. However, please ensure that you use an email address that will not identify you and only refer to your work by providing your Mechanical Turk Worker ID. [Researcher 1] [researcher1@example.edu] [Researcher 2] [researcher2@example.edu]
Repeated Attempts	Be sure that you only click on the study link once. If you experience technical issues, please contact us immediately before reattempting the study. Unauthorized repeat attempts will be rejected without compensation.
Quality Controls	Your work will be rejected if it does not satisfy our quality standards. If your work is rejected, you will still be compensated for your time through a bonus payment. Reattempts will be rejected without additional payment.
Research Purposes	The data collected for this study will be used for academic research purposes. We intend to publish the results of this study in academic outlets, such as conferences and journals.
Anonymity	Your anonymity is important to us. We have made every effort to avoid the collection of any personally identifiable information. Unless you have indicated that you would like to be considered for future studies, the use of your Worker ID is strictly for HIT approval and payment purposes. However, if you inadvertently disclose personally identifiable information, we promise not to disclose your identity to any third-party.
Confidentiality	The responses you provide while participating in this study will be kept strictly confidential. Data analysis will be reported in aggregate form. Written responses will be anonymized, with no reference to your Worker ID.
Non-Disclosure	The content of this study is confidential and should not be shared with other potential participants (forums, social media, etc.). Doing so will jeopardize the integrity of the research project.
Feedback	You will have an opportunity to provide feedback at the end of the study. Please report any questions, concerns, and/or difficulties experienced. Your feedback will help us ensure that we provide a positive experience for other Workers on MTurk.
Affirmation	By continuing, you affirm that you have read and understand the instructions for this study.

Table 9. Example Study Overview

We recommend including **Table 10** as the last screen of the study instrument.

Confidentiality	Thank you for participating in our study! Remember, to preserve the integrity of the study, you may not share anything about the experiment with other potential participants (forums, social media, etc.).
Completion Code	To receive compensation, please ensure that you copy and paste the following six-digit survey code into the Human Intelligence Task for this study on Mechanical Turk. [Randomized Completion Code]

Table 10. Example End of Survey Screen

Appendix C: Code for HIT Expectations

Peer, Paolacci, Chandler, & Mueller (2012) provided a script to append Worker IDs to the study URL that was later extended by Shawn Zamechek (2015). We build upon their work by incorporating our suggested HIT Expectations language from Table 8 into the code we provide as a supplementary file. Replacing the default code in the Design Layout with our code will create the HIT Expectations shown in Figure 7.

HIT EXPECTATIONS	
Study Description	REPLACE WITH BROADLY STATED STUDY DESCRIPTION.
Expected Time	Based upon average completion time from a pilot study, completing this HIT will take approximately ____ to ____ minutes. The time allotted to complete this HIT is ____ minutes.
Compensation	The reward for accepted work is \$____ for this HIT.
Importance	This scientific study will impact [REPLACE WITH BROADLY STATED RESEARCH AREA]. Your attentive and honest responses are appreciated.
Environment	Prior to accepting this HIT, please ensure that you are in a distraction-free environment that is conducive to deep thought.
Acceptance	We will review work within ____ hours. Honest, attentive, and complete responses will be accepted.
Rejection	Your work will be rejected if it does not satisfy our quality standards. If your work is rejected, you will be compensated for your time through a bonus payment.
Communication	The researcher(s) may be contacted via email at any time. You will be provided with contact email addresses at the beginning of the study. However, please ensure that you use an email address that will not identify you and only refer to your work by providing your Mechanical Turk Worker ID.
Completion Code	Make sure to leave this window open as you complete the survey. When you are finished, you will return to this page to paste the code into the box.
Affirmation	By accepting this HIT, you affirm that you have read and understand the expectations of participating in this study.

Survey link: The link will appear here only if you accept this HIT.

Provide the survey code here:

Figure 7. HIT Instructions on MTurk When Using Provided Code

Author Biographies



Jacob A. Young is an assistant professor of management information systems and the director of the Center for Cybersecurity at Bradley University. He earned his doctorate from Louisiana Tech University and received his Bachelor of Science and Master of Business Administration from Henderson State University. He focuses his research on privacy, security and anonymity issues related to information systems. His work has been published in *AIS Transactions on Human-Computer Interaction* and the *DePaul Business & Commercial Law Journal*.



Kristie M. Young is an assistant professor of accounting at Illinois State University. She earned her Bachelor of Science in Accounting and Master of Business Administration from Eastern Illinois University and her doctorate at Louisiana Tech University. Dr. Young's research interests include mergers and acquisitions and measuring the impact on psychological contracts and employee outcomes. Her work has been published in *Management Accounting Quarterly* and the *IMA Educational Case Journal*.

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Building Trust in Wearables for Health Behavior

Madhav Sharma

Oklahoma State University, madhav.sharma@okstate.edu

David Biros

Oklahoma State University, david.biros@okstate.edu

Abstract

Advances in Internet of Things (IoT) have given users the ability to monitor heart rate, calories burned, steps walked, time spent exercising, and the electrical activity of the heartbeat. Although major players in the wearable industry have marketed their wearables using the health and activity tracking features, a noteworthy health behavior change has not been observed at individual or societal level. A prominent barrier to adoption of healthcare features in these devices is lack of user trust. This research conceptualizes the formation of user's initial trust in wearables. Here, wearable systems are proposed as three-dimensional framework constituting the device, the organization (manufacturer or app-maker), and the Internet. Understanding the formation of initial trust on wearable systems' healthcare features can lead to improvement in user's health-related behaviors, which in turn has the potential to cause a societal change in primary healthcare delivery.

Keywords: Healthcare, IoT, trust, technology use, smart watch, conceptual.

Please note: A prior version of this article received a best paper award at the 2019 Midwest Association for Information Systems (MWAIS) in Oshkosh, Wisconsin. The article has been expanded and subject to a second round of reviews. We congratulate the authors.

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1. Introduction

Rapid advancements in electronics and connectivity have enabled users to connect everyday ‘things’ such as home appliances, vehicles, and watches to each other. Connectivity among these ‘things’ help users better monitor themselves (wearable technologies) and their environments (thermostats and motion sensors), increase convenience in everyday tasks (smart speakers, baby monitors), and automate a plethora of other activities such as storefronts, smart locks, smart beds, and vacuum cleaners. The Internet of Things (IoT) is defined as ‘*connectivity of physical objects equipped with sensors and actuators to the internet via data communication technologies*’ (Oberländer et al. 2018). Wearables are a subset of IoT that includes ‘things’ that can be incorporated into clothing or worn on the body as accessories. Smart Watches such as Apple watch and Fitbit have emerged as the most popular form of wearables. The number of wearable units is projected to grow to 378.8 million in the USA by 2021 (Statista 2019). Total shipments of wearable devices is projected to increase by 25.8% worldwide by end of 2019 and by over 153% in 2022 (Gartner 2018).

In recent years, wearables have become technologically advanced with features that are capable of monitoring heart rate, calories burned, steps walked, blood pressure, time spent exercising, and the electrical activity of the heartbeat. Wearable-makers have marketed these devices as tools to improve health behaviors. With features such as steps tracker, calories tracker, and exercise tracker, wearables have been in forefront of the quantified self-movement. Quantified self refers to the engagement of individuals in self-tracking of their biological and physical behaviors (Swan 2013). Capabilities such heart rate monitoring tend to make these devices a secondary personal diagnostic tool. Recently, numerous reports have surfaced where wearables alerted their users of previously undiagnosed and potentially fatal heart conditions (Reisinger 2018). These capabilities put wearables in the position to be a monitor of health behavior and instigator of health behavior change. Health behavior refers to individual’s belief and action regarding their health and well-being.

For all the perceived health benefits, wearables face barriers in their adoption. Recent news reports of major data breach in fitness-tracking apps (Dickey 2018) and wearable devices data compromising the location of secret military bases (Taylor 2018) underscore the security consequences and instigate a lack of trust. Both IS and medical literature have outlined various barriers to wearable systems such as affordability, inconsistent accuracy, and ability of feedback to motivate health and activity related actions (Benbunan-Fich 2018; Hamel et al. 2014; Piwek et al. 2016). Other barriers to adoption are related to the maturity of the technology regarding their perceived ease of use and perceived usefulness (Davis et al. 1989b). These barriers were faced by many pervasive information systems in the past such as e-commerce and mobile banking during this phase of their diffusion (Awad and Ragowsky 2008; Rogers 2010). Formation of user’s trust on information systems has played an imperative role in user’s acceptance of these technologies (Kim et al. 2009; McKnight et al. 2002).

Wearables have the potential to be the information system that can bring about a significant change in user’s lifestyle and healthcare behavior. Barriers faced by wearables have been investigated by IS and medical literature but the factors that influence the formation of trust have not been explored by present literature (Patel et al. 2015; Piwek et al. 2016). For research, we identify wearable system as a multidimensional information system constituting the device, the organizations associated responsible to collect and provide health-related data (manufacturer or app-maker), and the internet. This paper draws on existing trust literature in IS and proposes a theoretical model for the formation of user’s initial trust on wearable systems and their health monitoring features. We add to the cumulative research by differentiating wearable systems from other information systems and positing specific additional factors that can affect formation of trust in wearable systems: source expertise, tech-savviness, and automation bias. For practice, we expect that this research allows practitioners to design and market wearable systems that instigate positive health behavior changes.

The rest of the paper is organized as follows. In section 2, we briefly review the literature on trust and how it applies to wearables context. We further introduce wearable systems as a three dimensional information system and explain constructs that are used in initial trust formation model. In section 3, we discuss theoretical and practical implications of this research, and possible challenges and limitations of this work.

2. Theoretical Background

Scholars of various disciplines have attempted to study, define, and measure trust. Trust has diverse underlying assumptions across various disciplines. For example, economists view trust as calculus based or institution based while psychologists view trust in terms of attributes of trustor and trustee (Williamson 1975; Zucker 1986). However, there are

commonalities that exist in trust related literature across disciplines. For example, most scholars agree that trust is not static, it has phases of formation, stability and dissolution (Rousseau et al. 1998). The presence of trust indicates that parties involved in exchange have confident positive expectations from each other, and show willingness to be vulnerable. Mayer et al. (1995) defines trust as ‘willingness of a party (trustor) to be vulnerable to the actions of another party (trustee) based on expectations that the other will perform a particular action important to the trustor, irrespective of the ability to monitor or control that other party’. Meyer et al. (1995)’s model of trust has been used in various IS research to understand the proliferation of e-commerce (Dwyer et al. 2007; Gefen et al. 2003; Malhotra et al. 2004; McKnight et al. 2002). This model describes trust as a unidirectional relationship between trustee and trustor based on trustor’s disposition to trust and their perception about the trustee’s trustworthiness. The trustor’s perception of trustworthiness is formed by their perceptions about trustee’s ability, credibility, and benevolence. Here, *ability* is defined as the group of skills, competencies, and characteristics that enable a party to have influence in specific domain. *Benevolence* is the extent to which a trustee is believed to want to do good to the trustor, aside from an egocentric profit motive. *Integrity* is trustor’s perception that trustee adheres to a set of principles that trustor finds acceptable (Mayer et al. 1995).

Due to the novelty of wearable devices and the introduction of health information, users who adopt these devices form their perceptions about the wearable’s trustworthiness. Information acceptance in context of wearables heavily depends on the formation of *initial trust* between users and the wearable system. Formation of initial trust has been studied for e-commerce and social media (Pavlou and Fygenson 2006; Ridings et al. 2002). Initial trust is defined as trust in an unfamiliar trustee (McKnight et al. 1998). Trust formation in web-based information systems such as e-commerce and social media hinged on user’s perceptions at two levels: trustworthiness of specific e-commerce enabler or social media websites and trustworthiness of internet as an institution. Wearable information systems constitute three dimensions: the device, the organization, and Internet as an institution (as shown in Figure 1). For user to trust a wearable device to provide reliable and actionable information about their health, the user must have a positive perception of the device’s ease to use, accuracy, and quality of feedback (Piwek et al. 2016; Spil et al. 2019).



Figure 1. Wearable Information System

First, the design of the device should appeal to the users, i.e. the wearable must be easy to set-up and use. Benbunan-Fich (2018) investigated the relationship between simplicity of design and complexity of use using affordances lens. Wearable devices, which are currently in the market have a high variability in design. Devices like Fitbit Flex and smart rings have minimalistic design with limited feedback. In contrast, smart watches such as Apple watch and Fitbit Versa have interactive displays and larger portfolios of applications and functionalities. Users found simple and minimalistic designs of wearables complex to use. Conversely, wearables with interactive displays and shared platform with smart

phones (Apple watch, Galaxy watch, Fitbit) have found more appreciation and acceptance. Becker et al. (2017) further showed that limited functionality, support devices, and comfort form insufficiencies in user's tendency to use wearables. Wearable devices have had incremental changes in quality of design and ease of use. Thus, users' competence to use technologies factor into the formation of trust in wearable devices. Second, the users must trust the feedback or information provided by the wearable device (i.e. they should be able to accept the data provided by their wearable as accurate to a degree to which it can influence an action) (Jung et al. 2016).

The capabilities of these devices such as heart rate tracker and breathing volume monitor, can be used as a personal secondary diagnostic tool to detect sleep apnea, anxiety, obesity, asthma, panic disorders, and more (Piwek et al. 2016). However, the accuracy of activity-tracking and health-monitoring features of wearables vary across devices. Wang et al. (2017) conducted lab experiments with to test the accuracy of wearables in detecting heart rate. Devices such as Apple watch and Fitbit Charge were included in the study and it was found that, no device achieved the accuracy of chest-strap based monitor. Hamel et al. (2014) categorized wearable devices as a part of mobile health and proposed recommendations for regulations that legitimizes the mobile health systems without inhibiting innovation. Industry and the government has responded to recommendations such as these, and as a result, Apple Watch Series 4 along with numerous other wearables have been cleared or approved by the U.S. Food and Drug Administration. Lastly, the feedback of the device must motivate the user to take action. These actions can cause a positive health behavior change only if the feedback the user gets is convincing. For example: if a user gets notified by their device to incorporate more standing, the user must see value in that feedback to actually stand up. Research dealing with e-commerce has showed that perception of information quality, system quality and information presentation drives decision making satisfaction (Bharati and Chaudhury 2004; DeLone and McLean 1992). Here, system quality refers to the ease of use of the design of the device and information quality refers to the perceived accuracy of information provided by the device. Information presentation has been measured based on characteristics of the interface that make the information easier to process (Bharati and Chaudhury 2004). In context of wearables, actions related to health and activity behavior are taken by the users when information presented to them is able to motivate them.

These factors differentiate wearables from technologies such as e-commerce and social media and thus, warrants a study on formation of user's initial trust in wearables. McKnight et al. (1998) proposed an integrative model for formation of initial trust. This model used the theoretical framework from the theory of reasoned action (TRA) which states that beliefs lead to attitudes which leads to behavioral intentions which, in turn, leads to behaviors. Applying TRA to the formation of trust, they theorized that trusting beliefs lead to trusting intentions which in turn, leads to trusting behavior. Individual's disposition to trust and institution based trust were explained as antecedents of trusting beliefs. McKnight et al. (2002) developed and validated measures for testing the formation of initial trust of users on e-commerce. This paper uses McKnight et al. (2002)'s model to understand the formation of initial trust between users and wearables. The model proposed in this paper seeks to adapt McKnight et al. (2002)'s model in the wearable context. The core constructs studied in McKnight et al. (2002): personal disposition to trust, institution based trust, trusting beliefs, trusting intentions, and trusting behaviors are explained in the context of wearables in the following subsections. Additionally, we posit three additional factors that affect the formation of trusting that are specific to wearable and health monitoring features.

2.1. Trust Related Behaviors

Trust-related behaviors are user's actions that demonstrate dependence on a wearable. These actions may make one vulnerable to the device and organization associated with it or increase one's risk (Mayer et al. 1995). In the current context, trust related health behaviors are individual's actions regarding their health and well-being. Common trust related behaviors with respect to wearables include sharing personal information, purchasing health monitoring and advising subscriptions, and acting on information provided by wearables. Sharing personal health information on a wearable device and app-maker or manufacturer shows that a users' trusts the wearable system with the privacy and security of their information. Purchasing a monitoring and advising subscription shows that user sees value in the information generated by wearables and trusts that the information will be reliable and actionable.

2.2. Trusting Intentions

Trusting intentions means the trustor is willing to depend, or intends to depend, on the trustee. McKnight, et al., (2002) defined two sub-constructs of trusting intentions: *willingness to depend* and *subjective probability of depending*. Willingness to depend is defined as one's tendency to make oneself vulnerable to others. A user shows willingness to depend on a wearable if they regularly check their blood pressure or heart rate on it. The subjective probability of depending is defined as the perceived likelihood that trustor will depend on the trustee. A user has higher subjective

probability of depending on their wearable if they share their personal information on their device (with the organization associated). Based on our definitions of trusting intentions and trusting behaviors, TRA, and findings from McKnight et al.'s (2002) model, we posit the following proposition:

Proposition 1: Users' trusting intentions are positively associated with trust related behaviors.

2.3. Trusting Beliefs

Trusting beliefs refers to the confident trustor perception that the trustee—in this context, a specific wearable system (comprising of device and manufacturer or app maker) —has attributes that are beneficial to the trustor. Information provided by wearables such as heart rate and suggestions regarding activities are supposed to instigate positive health behavior change. Hence, it is imperative that users believe that the system is providing them with reliable information. Here, the user is the trustor and the wearable system is the trustee. The wearable system collects personal information and provides measured health information, diagnostics, and activity prompts and thus, is seen as a source of risk. Trustor's judgement of trustworthiness is seen as a cornerstone for formation of trust beliefs. Users project the attributes (competence, integrity, and benevolence) of manufacturer or application makers to the wearable devices. McKnight et al. (2002) posited that the valence and intensity of trusting beliefs lead to trusting intentions. Based on findings from McKnight et al. (2002) and consistent with TRA, we posit the following proposition:

Proposition 2: Users' trusting beliefs are positively associated with trusting intentions.

2.4. Institution Based Trust

Institution-based trust is the belief that needed structural conditions are present (i.e., for IoT) to enhance the probability of achieving a successful outcome in an endeavor like health monitoring. This is the sociological dimension of trust and deals with structures that make an environment trustworthy. Factors that may contribute in institution based trust in health IoT may range from reputation of manufacturers, institutions involved, and general sentiment towards giving health data to apps. Institution based trust has two dimensions: *structural assurance* and *situational normality*.

Structural assurance refers to 'one's belief that structures like guarantees, regulations, promises, legal recourse, or other procedures are in place to promote success' (Zucker 1986). For example, an individual may be more inclined to use a wearable system for health monitoring purposes if it was FDA approved. The regulations such as FDA approval or clearance are structural assurances for the wearable system. These structural assurances strengthens trust of users in wearable systems and institutions associated (such as manufacturer, app-makers, etc.).

Situational normality refers to 'one's belief that the environment is in proper order and success is likely because the situation is normal or favorable' (Baier 1986). Individuals are more inclined to use wearables if they can perceive them to be trustworthy enough to have a normal outcome. The perception of organization's (manufacturer, app-maker, etc.) trustworthiness can be measured as individual's perception of their competence, integrity, and benevolence. McKnight et al (2002) posited that institution based trust has a positive effect on trusting beliefs and trusting intentions. Based on findings from McKnight et al. (2002) and consistent with TRA, we posit the following propositions:

Proposition 3: Users' institution-based trust is positively associated with trusting beliefs.

Proposition 4: Users' institution-based trust is positively associated with trusting intentions.

2.5. Disposition to Trust

Disposition to trust is extent to which a person displays a tendency to be willing to depend on others across a broad spectrum of situations and persons. Early theories of trust defined it as '*an expectancy held by an individual or a group that the word, promise, verbal or written statement of another individual or group can be relied upon*' (Rotter 1967). From this definition and various anecdotes and prior conceptualizations, it was inferred that some parties are more likely to trust other parties (Conlon and Mayer 1994; Williams et al. 1988). McKnight et al (2002) used two sub-constructs to measure an individual's disposition to trust: *faith in others* and *trusting stance*. Individual's faith in others refers to one's assumption that people and organizations are usually upright and well meaning. Trusting stance means that, regardless of what one believes about people's attributes, one assumes better outcomes result from dealing with people as though they are well meaning and reliable.

Disposition to trust has significant impact on trust building strategies, which lead to initial trust. Individual's choice of wearable in many instances driven by disposition of trust. Companies such as Apple, Samsung, and Google have dominated digital mobile and computer applications market for a long time (Gawer and Cusumano 2008). These companies have played a pivotal role in diffusion of wearable systems and have emerged as market leaders in this domain (Metcalf et al. 2016). Thus, if an individual has high disposition to trust, they may have more affinity towards wearables sold by these established companies, while individuals with low disposition to trust may be skeptical of any trust building attempts. McKnight et al (2002) stated that disposition to trust has a positive effect on institution based trust, trusting beliefs, and trusting intentions. Based on findings from McKnight et al. (2002) and consistent with TRA, we posit the following propositions:

Proposition 5: Users' disposition to trust is positively associated with institution-based trust.

Proposition 6: Users' disposition to trust is positively associated with trusting beliefs.

Proposition 7: Users' disposition to trust is positively associated with trusting intentions.

2.6. User Technology Interaction Factors

User-technology interaction has been extensively studied in IS literature using perceived usefulness and perceived ease of use (Davis et al. 1989a). Wearable systems are a relatively new technology with limited but rapidly increasing market share (Gartner 2018). *Tech-savviness* is defined as user's competence in usage of technology (Davis et al. 2009). Users' competence to use the wearable systems has an effect on trusting beliefs as first users of these technologies are tech-savvy early adopters (Rogers 2010). Thus, if a user is more tech savvy, the more he or she will tend to form trusting beliefs for wearable systems. Also, the relationship between disposition to trust and trusting beliefs and institution based trust and trusting beliefs will be moderated by users' tech savviness. Based on these conclusions, we posit the following propositions:

Proposition 8a: Users' tech savviness is positively associated with trusting beliefs.

Proposition 9a: Users' tech savviness has a moderating effect on relationship between users' disposition to trust and trusting beliefs; i.e. presence of higher levels of tech savviness strengthens the relationship between disposition to trust and trusting beliefs.

Proposition 10a: Users' tech savviness has a moderating effect on relationship between users' institution-based trust and trusting beliefs; i.e. presence of higher levels of tech savviness strengthens the relationship between institution-based trust and trusting beliefs.

Trust in healthcare-related information provided by variables can lead to critical decisions. For example, a user may incorrectly decide to not visit a doctor based on the vital diagnostics check from their device. *Automation bias* is defined as 'tendency to use automation as a heuristic replacement for vigilant information seeking and processing' (Skitka et al. 1999). Thus, users may believe that wearable system is trustworthy, when they have a higher automation bias. Also, the relationship between disposition to trust and trusting beliefs and institution based trust and trusting beliefs will be moderated by users' automation bias. Based on these conclusions, we posit the following propositions:

Proposition 8b: Users' automation bias is positively associated with trusting beliefs.

Proposition 9b: Users' automation bias has a moderating effect on relationship between users' disposition to trust and trusting beliefs; i.e. presence of higher levels of automation bias strengthens the relationship between disposition to trust and trusting beliefs.

Proposition 10b: Users' automation bias has a moderating effect on relationship between users' institution based trust and trusting beliefs; i.e. presence of higher levels of automation bias strengthens the relationship between institution-based trust and trusting beliefs.

Lastly, the availability of healthcare information is an important aspect of wearables. However, the sensitivity and criticality of healthcare-related readings vary among users. *Source expertise* refers to the extent that user is aware of the context of information provided by the wearables. Source expertise can have a positive effect on trusting beliefs. For example, a healthcare professional may find the feature to measure heart rate more useful than users who have limited knowledge of the field. Source expertise, in select cases of wearables, can adversely affect the formation of trusting beliefs as users may be aware about the variability in accuracy of wearable devices, compared to medical equipment (Wang et al. 2017). The awareness of users about the benefits and shortcomings of wearables' ability to monitor and provide health and activity-related information affects the formation of trusting beliefs. Also, the relationship between disposition to trust and trusting beliefs and institution based trust and trusting beliefs will be moderated by users' source

expertise. Based on these conclusions, we posit the following propositions:

Proposition 8c: Users' source expertise is negatively associated with trusting beliefs.

Proposition 9c: Users' source expertise has a moderating effect on relationship between users' disposition to trust and trusting beliefs; i.e. presence of higher levels of source expertise weakens the relationship between disposition to trust and trusting beliefs.

Proposition 10c: Users' source expertise has a moderating effect on relationship between users' institution based trust and trusting beliefs; i.e. presence of higher levels of source expertise weakens the relationship between institution-based trust and trusting beliefs.

2.7. Initial Trust Formation for Wearables

Based on the constructs discussed above and their relationships according to the theory of reasoned action, we propose initial trust formation model for wearables (Figure 2). This model takes into account the characteristics of the user, the user's perception about the device and organizations associated with them, and their overall perception of wearable systems. According to characteristics of users, their disposition to trust should have a positive relationship with user's institution based trust, user's trusting beliefs, and user's trusting intent to engage in trust related behaviors with wearables. User's institution based trust should have a positive relationship with user's trusting beliefs and trusting intentions. According to TRA, trusting beliefs should lead to trusting intentions, and finally, trusting intentions should lead to trust related behaviors.

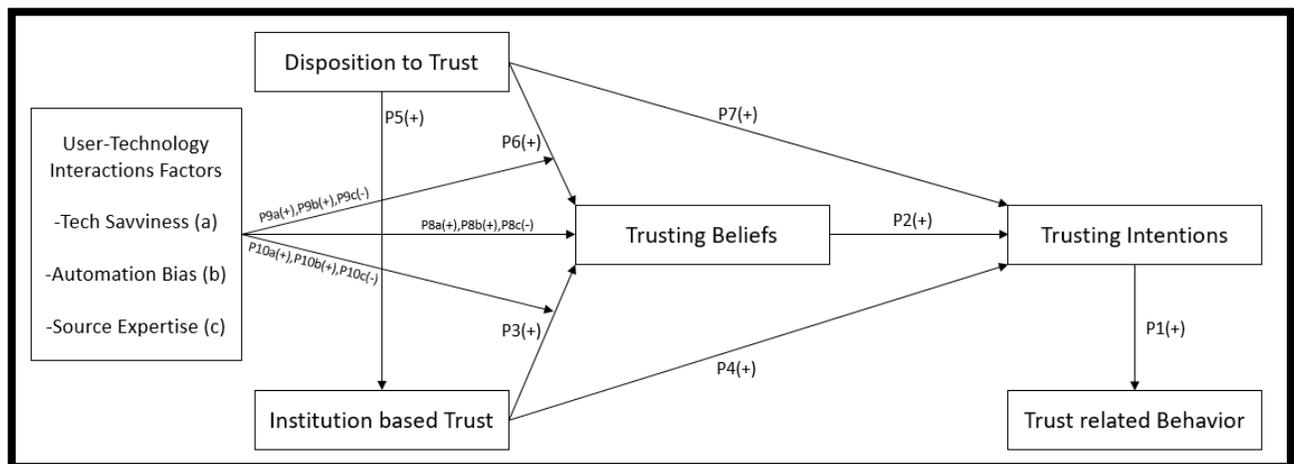


Figure 2. Proposed Theoretical Model: Initial Trust Formation in Wearables

3. Discussion

Wearables are becoming increasingly advanced and robust in healthcare-monitoring. The adoption and consequences of wearable technologies have not been studied in IS or medical literature to any noteworthy extent. Research in both disciplines have shown that wearable technologies have the potential to bring about a change in healthcare behavior at individual as well as society level (Hamel et al. 2014). Wearable technologies have also been identified as a system different from web based platforms such as social media and e-commerce. Thus, the underlying assumptions of research in those contexts may not apply to wearable context. This research summarizes the factors that affect the relationship between use of wearables and health behavior change, identified by IS and medical literature. This research posits that formation of user's initial trust can overcome these barriers. Future research can experimentally test and extend the proposed model. The constructs of disposition to trust, institution based trust, trusting beliefs, and trusting intentions have been measured and the relationships between them have been tested in numerous studies before (Kim et al. 2009; Li et al. 2008; Zhou 2012). We have identified three measureable user-technology factors that can influence the formation for trust. With suitable adjustments, scales used in previous studies can be adapted to test the proposed model to create a better understanding of formation of trusting intentions on health monitoring features of wearable systems using surveys. Controlled experiments can be used to test effect of trusting intentions formed by the various factors described in the model on health behaviors.

This research is expected to contribute to the growing literature dealing with trust in IS and use of ubiquitous technologies and IoT. This research can also generate insights and actionable recommendations to practitioners (wearable developers and marketers) to make wearables more acceptable and trustworthy for the uses. The user tech-enabled healthcare market is projected to grow remarkably in the coming years (Darie 2019). There have been attempts to overcome barriers to wearable adoption and use. Many insurance companies have attempted to release interactive insurance plans that either subsidizes wearable devices or incentivizes consumers to use wearables and share data (Paluch and Tuzovic 2017). However, these plans are still in infancy and their effect on affordability of wearables cannot be measured at this stage. Similarly, FDA regulations are aimed to increase user confidence in the wearables for health purposes. Future research can also measure the effectiveness of these attempts in wearable use and health behavior change. There are a few challenges associated with this research strand. In research on wearables thus far, the issue of endogeneity has emerged when researchers have attempted to quantify the motivational ability of wearables to cause healthy behavior. Piwek et al. (2016) has also noted that analysis of healthy behavior among wearable users faces validity concerns since, consumers with healthy lifestyle are more prone to adopt wearables. Future research must also look at research design to overcome endogeneity.

4. Conclusion

With sustained market growth and rapid advancements in design, wearables have the potential to be an information system that can bring about a significant change in user's lifestyle and healthcare behaviors. Yet, there are factors that influence this change. Our research summarizes posits that formation of initial trust will be able to overcome barriers to wearable use for health behavior change. We proposed a theoretical model that can be tested and extended by future research. This research contributes to the growing literature dealing with trust in IS and use of ubiquitous technologies and IoT.

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Author Biographies



Mr. **Madhav Sharma** is a PhD Student, studying Management Science and Information Systems at Oklahoma State University. His research interests included Diffusion of Innovation, Use and Implication of Artificial Intelligence, Machine Learning, and Internet of Things.



Dr. David Biros is an Associate Professor of Management Science and Information Systems and Fleming Chair of Information Technology Management at Oklahoma State University. A retired Lieutenant Colonel of the United States Air Force, Dr. Biros' last assignment was as Chief, Information Assurance Officer for the AF-CIO. His research interests included deception detection, insider threat, information system trust and ethics in information technology. He has been published *MIS Quarterly*, *the Journal of Management Information Systems*, *Decision Support Systems*, *Group Decision and Negotiation*, *MISQ Executive*, *the Journal of Digital Forensics Security and Law* and other journals and conference proceedings.

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Trust Violation and Rebuilding After a Data Breach: Role of Environmental Stewardship and Underlying Motives

Gaurav Bansal

University of Wisconsin – Green Bay, bansalg@uwgb.edu

Noah Redfearn

University of Wisconsin – Green Bay, redfnp05@uwgb.edu

Abstract

The study examined the role of different Corporate Social Responsibility (CSR) initiatives on a decline in trust and its restoration following a data breach and a subsequent CEO apology. The study uses four scenarios: a website with recognition of a genuine environmental CSR initiative (W1), a website with an environmental CSR initiative with a profit-motive (W2), a website with an ethical CSR initiative (W3), and a control website with no specific CSR initiative (W4). The data was collected from 500 Amazon MTurk workers and analyzed using ordinary least squares regression and multivariate tests. The findings confirm the role of a CSR initiative (vs. no CSR) and also the impact of underlying motives (profit-motive vs. genuine environmental CSR) on a trust decline and restoration. The results indicate the role of privacy concerns is moderated by the underlying CSR context. The article concludes with a discussion of the managerial and theoretical implications.

Keywords: Data breach, trust violation, trust rebuilding, corporate social responsibility (CSR)

Please note: A prior version of this article received a best paper award at the 2018 Midwest Association for Information Systems (MW AIS) in Oshkosh, Wisconsin, Springfield, IL. The article has been expanded and subject to a second round of reviews. We congratulate the authors.

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1. Introduction

Data breaches are increasing, and there is limited research on how to contain the negative impact of trust violations and how to repair trust following a data breach (Bansal 2017). In this research study, we examine the factors that may help in containing the harm to trust and then aid in trust restoration after the breach and a subsequent apology from an online business. Prior research has looked at various factors such as the role of timing in acknowledging the breach, CEO gender, mode of breach – unauthorized sharing or hacking, type of response – denial or an apology for a trust violation among others (Bansal 2019). We examine the role of perceived engagement in environmental corporate social responsibility (CSR) in cushioning the negative impact on trust and restoring the violated trust. Environmental awareness is on the rise, and increasingly businesses witness customers expecting them to devote resources towards environmental CSR. In this research study, we were particularly interested in the following two research questions: (a) Can CSR be used as a shield to cushion trust violation and aid in trust repair following a data breach; (b) does “other-centered” CSR provide significant advantage over “self-centered” CSR in trust violation and repair process.

This article has three major sections: a review of the theory and research model, a summary of the research methodology and results, and finally a discussion of the findings.

2. Theory and Research Model

CSR has been defined in multiple different ways. For the purpose of this research study we relied on the following definition from the Commission on the European Communities (2001): *A concept whereby companies integrate social and environmental concerns in their business operations and in their interaction with their stakeholders voluntarily* (Dahlsrud 2008). Prior research suggests that companies engaged in CSR are perceived as more trustworthy (Choi and La 2013). Thus, it is no surprise that many corporations are actively engaged in CSR out of genuine need (other-centered) and/or to gain financial rewards (self-centered). However, research also suggests that “other-centered” CSR is rewarded highly as compared to “self-centered” CSR (Sen et al. 2006). Research suggests that negative CSR or self-centered motives can have a detrimental effect on product evaluations whereas positive CSR can enhance product evaluations (Brown and Dacin 1997). Based on the literature review we argue that CSR leads to trust due to three factors: genuine attribution (De Roeck and Delobbe 2012), identification (Sen et al. 2006) and insurance policy (Godfrey et al. 2009) effect. Self-centered CSR businesses would encounter higher attribution (the perception that the website is using CSR to promote self-interest, and is opposite to *genuine attribution*), lower identification, and lower insurance policy effect.

Research has noted that CSR initiatives could backfire when consumers are skeptical about the Organization’s motives – genuine and “other-centered,” as opposed to profit-oriented and “self-centered” (De Roeck and Delobbe 2012). Such skeptical motives would have a three-fold effect. First, they would increase the degree of negative attribution regarding consumer exploitation (attribution). Second, they would lower the degree to which the consumers identify their values with the company’s (identification). Third, they would decrease the degree of perceived benevolence towards “others” (insurance policy) effect of any CSR (Iglesias et al. 2018, Godfrey 2009). So, when there is a negative event such as a data breach, the higher identification associated with the “other-centered” websites would lower the attribution and also provide greater “insurance policy” effect whereas, the lower identification associated with “self-centered” websites would increase the attribution and thus the “insurance policy” effect as well.

Hypothesis 1: Following an insider data breach, there is a greater trust drop in the “self-centered” website (W2) as opposed to (a) “other-centered” websites such as environment (W1), and (b) ethics (W3), and the neutral website (c) control (W4).

Hypothesis 2: Following an insider data breach and subsequent apology from the website, there will be a greater trust restoration for (a) W1 as compared to W2 and, also (b) W1 as compared to W4.

Privacy concern (PC) is argued to be associated with the degree of control and fairness on how one’s information is used and protected (Bansal and Zahedi 2015). A data breach could lessen the users’ trust in the organization’s ability to properly safeguard one’s information by signaling failure on the part of the management to prevent the breach. We argue that such a breach would be associated with higher trust drop especially for the users with high PC as opposed to users with low PC. An apology is associated with a promise to “mend” the relationship. However, it also signals an admittance of guilt (Schweitzer et al. 2015; Walfisch et al. 2013). Thus, it could be argued that high PC users (as opposed to low PC

users) would find their trust restoration hampered following an apology after a data breach.

Hypothesis 3a: Privacy concern will be positively associated with trust drop after the breach, and negatively associated with trust restoration after a subsequent apology.

CSR reflects an organization’s moral character as well as a commitment to improving economic, social and environmental wellbeing. Organizations engaged in CSR activities generate higher trust in the users and lower their perceived risks in doing business with them – as they help lower attribution (De Roeck and Delobbe 2012), increase identification (Sen et al. 2006) and provide “insurance policy” effect (Iglesias et al. 2018, Godfrey 2009). Thus, we argue any CSR (as opposed to no CSR) would help allay the fears of high PC users regarding the safeguarding of their data controlled and managed by the online business.

Hypothesis 3b: Privacy concern will be positively associated with trust drop after the breach, and negatively associated with trust restoration after a subsequent apology more so for non-CSR websites (W4) than for CSR websites (W1, W2, and W3).

CSR initiatives that are perceived to be profit-oriented and “self-centered” lower the identification (Sen et al. 2006) increase the attribution (De Roeck and Delobbe 2012) thus lowering any “insurance policy” (Godfrey et al. 2009) effect associated with CSR.

Hypothesis 3c: Privacy concern will be positively associated with trust drop after the breach, and negatively associated with trust restoration after a subsequent apology more so for self-centered CSR websites (W2) than for other-centered CSR websites (W1, and W3).

3. Research Methodology and Findings

The study was examined using four scenarios – W1, W2, W3, and W4 (as shown in Table 1). Since CSR activities have an ethical component as well (Choi and La 2013), thus we created two different control groups – one with ethical-centered orientation (W3), and one neutral – with no CSR initiative (W4). We used Qualtrics for data collection. The respondents were recruited through Amazon Mechanical Turk from all over the US. Data were analyzed using SPSS. We used existing items in our experimental design to ensure reliability and validity. The experiment flow chart is explained in Figure 1.

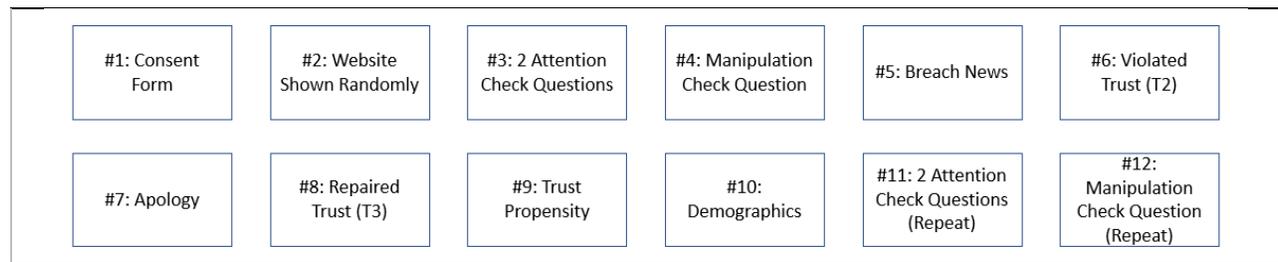


Figure 1. Experiment Flow Chart

Website #	Context	Description
W1	A website with recognition for genuine environmental CSR	You are planning to buy furniture for your family. You came across Warehouse E-mart online. You were able to find this site by searching on Google. You learn from the website that in order to save the environment the company uses recycled wood to manufacture its furniture. It has also been awarded and recognized for its contributions and efforts towards maintaining sustainable forests, by planting new trees as the old trees are felled.
W2	A website with environmental CSR for profit-	You are planning to buy furniture for your family. You came across Warehouse E-mart online. You were able to find this site by searching on Google. You learn from the website that the company is helping the environmental cause by using recycled

	motive	furniture to manufacture some of its products.
W3	A website with ethical CSR	You are planning to buy furniture for your family. You came across Warehouse E-mart online. You were able to find this site by searching on Google. You learn from the website that the company puts extra emphasis on ensuring that it follows ethically correct business operations and engages with only those organizations that follow fair labor practices.
W4	A website with no specific CSR initiative (Control)	You are planning to buy furniture for your family. You came across Warehouse E-mart online. You were able to find this site by searching on Google.

Table 1. Vignettes Used

3.1. Data Collection

We collected data from 500 MTurk workers. Only those respondents who correctly answered the attention check and scenario manipulation questions were retained for further analysis. We had 146 male respondents and 159 female respondents. Six respondents chose not to disclose or associate themselves with male or female options. Thus, we had 311 individuals in our final sample size. The dependent variables trust drop and trust restoration were computed by differencing the average of violated trust from the average of initial trust, and the average of restored trust from the average of violated trust respectively.

	#N	#Males	#Females	Age Range	Age Mean	Age Std dev
W1	72	32	39	24-83	41.17	13.403
W2	92	48	44	21-91	36.50	11.858
W3	88	47	38	20-73	37.98	11.818
W4	59	19	38	19-68	39.20	12.857

Table 2. Demographics

3.2. Data Analysis and Results

The analysis in Figures 2 and 3 show that our manipulation check was successful. Univariate analysis in Figure 2 shows that in terms of CSR – people associated W1 with the highest level of CSR, as compared to W2 next, and W3 being third best, and W4 the last. The differences were significant at $p \leq 0.004$. Also, Univariate analysis in Figure 3 shows that attribution (using CSR for a selfish motive) was significantly lower for W1 both as compared to W2 ($p = 0.018$), and W3 ($p = 0.041$). We then analyzed the data using multivariate and regression analysis. The results are shown in Table 3 also in Figure 4 and summarized in Table 4.

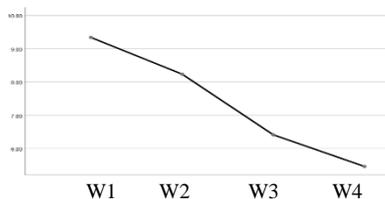


Figure 2. Univariate Analysis for CSR (no covariates)

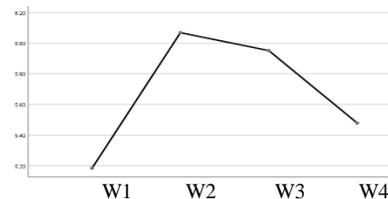


Figure 3. Univariate Analysis for CSR Attribution (no covariates)

	Combined Multivariate Analysis	Regression Analysis for 4 groups
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Construct	Dependent Variable	df	F	P value	Overall Direction*	(p values)			
						W1	W2	W3	W4
(R Square)						.539	.311	.353	.340
PC	Trust Drop	1	0.251						.006
	Trust Restoration	1	0.849				-.014		
CSR Attribution	Trust Drop	1	8.762	0.003	-			-.048	
	Trust Gain	1	0.386			-.004			
News Seriousness	Trust Drop	1	56.776	0.000	+	.000	.009	.004	
	Trust Gain	1	0.208						
Age	Trust Drop	1	2.479						
	Trust Gain	1	0.354						
Moral Beliefs	Trust Drop	1	8.562	0.004	-	-.030			
	Trust Gain	1	2.816	0.094	-	-.001			
Environmental Consciousness	Trust Drop	1	2.145						
	Trust Gain	1	7.419	0.007	+	.006			
CSR	Trust Drop	1	0.061						
	Trust Gain	1	0.000				-.015		
Initial Trust	Trust Drop	1	23.15	0.000	+	.009	.010		
	Trust Gain	1	1.731				.002		
Trust Propensity	Trust Drop	1	1.483						
	Trust Gain	1	2.844	0.093	+	.004		.011	
Scenario Shown	Trust Drop	3	1.234			-	-	-	-
	Trust Gain	3	1.535			-	-	-	-

Table 3. Multivariate and Regression Analysis (with covariates)

* Direction is reported where p values were less than .10; only the significant p values (less than .10) are shown.

Trust Drop and Rebuilding analysis (no covariates)

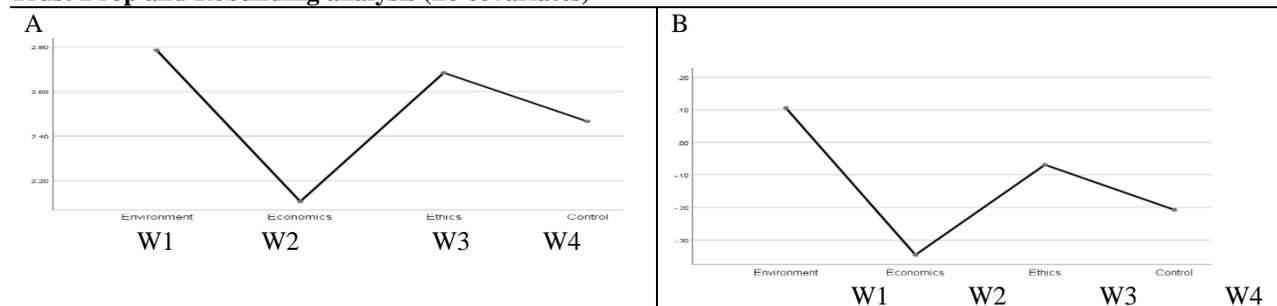


Figure 4. Overall Trust Drop (A) and Trust Restoration (B)

Hyp#	Hypotheses Argument	Test Results	Remarks
H1a	Trust drop: W2 > W1	Posthoc multi variate test: p .071 (Figure 4iA)	Reverse supported at .10 level
H1b	Trust drop: W2 > W3	Posthoc multi variate test: ns (Figure 4iA)	Not supported

H1c	Trust drop: W2 > W4	Posthoc multi variate test: ns (Figure 4iA)	Not supported
H2a	Trust restoration: W1 > W2	Posthoc multi variate test: p .031 (Figure 4iB)	Supported
H2b	Trust restoration: W1 > W4	Posthoc multi variate test: ns (Figure 4iB)	Not supported
H3a	(i) PC increases Trust drop	Combined multivariate analysis: ns (Table 3)	Not supported
	(ii) PC lowers Trust restoration	Combined multivariate analysis: ns (Table 3)	Not supported
H3b	(i) PC increases Trust drop when there is no CSR	Regression analysis: p .006 (Table 3)	Supported
	(ii) PC lowers Trust restoration when there is no CSR	Regression analysis: ns (Table 3)	Not supported
H3c	(i) PC increases Trust drop for self-centered than for other-centered	Regression analysis: ns (Table 3)	Not supported
	(ii) PC lowers Trust restoration for self-centered than for other-centered	Regression analysis: p .014 (Table 3)	Supported

Table 4. Result Summary

Table 4 shows that H1a is reverse supported at $p < .10$ level and H2a, H3b(i) and H3c(ii) are supported at $p < .05$ level.

4. Discussion

The research provides with several interesting findings. Contrary to the hypothesized argument we found that trust drop is higher for *other-centered* W1 than for *self-centered* W2. The effect is weak and is significant only at .10 level; however, it does indicate that at times we get hurt more by the ones' we love or expect more from (Miller 1997). The fact that W2 experienced lower trust drop is surprising in light of the fact that respondents associated W2 with higher attribution (Figure 3), and lower CSR (Figure 2) as compared to W1. One reason could be that users have low expectations from W2 (self-centered); hence it experienced a low drop, but then W2 was punished by low trust restoration after an apology. We argue that since W2 was doubted at first place for its motives, and the apology confirmed the guilt, and therefore W2 experienced lower trust restoration. Trust restoration after a breach and apology is higher for W1 than for W2. This shows that website with recognition for genuine environmental CSR provides higher genuine "attribution," higher "identification," and "insurance policy" as compared to the website with environmental CSR for the profit motive. The role of privacy concern is moderated by the underlying CSR context. Privacy concern increases the trust drop if the website is not associated with a CSR initiative, and lowers the trust restoration for *self-centered* CSR websites. The study thus adds to the trust violation and repair literature and also provides practical guidance to managers of websites indulged in CSR activities. Results show that perceived CSR levels were high for W1 and also for W2, as compared to W3 (refer to Figure 2). This is an important finding suggesting that even profit motive environmental engagement is perceived at a higher CSR level than ethics governance.

4.1. Limitations and Extensions

Even though we used a scenario-based study to control for extraneous variables, it will be helpful to replicate the findings using longitudinal field studies. Another limitation is that third-party recognition as in W1 versus the self-claim in W2 and W3 could have impacted the degree of attribution and CSR levels (Kim 2019) for the website W1. All the items were self-reported including the initial, violated and repaired trust.

There is limited research on examining broken trust and trust repair process after a data breach. As the number of data breaches increases and people get more environmentally aware, a deeper understanding of how CSR initiatives could cushion the trust drop and aid in trust restoration is needed. Our work makes a contribution in this direction. Furthermore, our work shows that there is merit in examining the role of privacy concern and CSR motives in trust violation and repair process.

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Author Biographies



Dr. Gaurav Bansal is Frederick E. Baer Professor in Business and full Professor MIS/Statistics at the Austin E. Cofrin School of Business at UW-Green Bay. He earned his Ph.D. in Management Information Systems (MIS) from University of Wisconsin - Milwaukee in 2008, and M.B.A. from Kent State University, Ohio in 2002. Dr. Bansal has published in several premier MIS journals such as *Journal of Management Information Systems (JMIS)*, *European Journal of Information Systems (EJIS)*, *Decision Support Systems (DSS)*, *Information & Management (I&M)* and *Journal of Computer Information Systems*, among others. He is the Past President of the Midwest Association for Information Systems and is now serving as an at-large director for the association. He is the founding director of the Collaborative Master of Science in Data Science at UW-Green Bay. His current research interests are in the areas of information systems security and privacy, trust violation and rebuilding, and ethical issues in IS including big data.



Noah Redfearn is a third-year student at the Austin E. Cofrin School of Business at UW-Green Bay. He is currently studying in the business administration program and majoring in entrepreneurship and finance with a minor in international business. He is perusing a career path in business ownership and corporate business management. He currently serves as senior vice president for Society for Information Systems Management and Business Analytics (SISMBA). He also is a participating member in the student finance association (SFA) along with the Collegiate Entrepreneurs Organization (CEO).