ABSTRACT

STOUGHTON, JACK WILLIAM. Organizational Opinions Untethered: Mobile Technologies in Survey Deployment. (Under the direction of Lori Foster Thompson).

The advancement of the organizational sciences relies on self-report survey data. The effort, attention, and affective reactions of employees taking organizational surveys are critical to the success of organizational survey initiatives, many of which are conducted online. Recently, smartphone and tablet use has increased, providing a new means for employees to access surveys. The present study examines whether mobile devices affect: (a) the quality of data produced by the survey respondents, (b) the affective reactions of survey respondents to an employee opinion survey, and (c) whether or not level of mobile optimization influences the degree to which the survey device utilized affects these outcomes. Participants (*N* = 292) were randomly assigned to one of three survey device conditions: (a) smartphone, (b) tablet, and (c) computer – with the level of website optimization manipulated for mobile respondents. Results indicated that for both closed-and open-ended items, the device utilized for survey completion did not significantly affect data quality. However, as expected, survey respondents on smartphones and tablets took significantly longer to complete the survey, with smartphone respondents exhibiting a higher rate of attrition than any other survey group. Additionally, results indicated that smartphone respondents were significantly less satisfied with the survey modality compared to tablet and computer respondents. Finally, the level of mobile-optimization increased satisfaction with the survey for both smartphone and tablet respondents. Taken together, the results provide useful information for researchers and practitioners deploying surveys for organizational analysis.

Organizational Opinions Untethered: Mobile Technologies in Survey Deployment

by
Jack William Stoughton

A dissertation submitted to the Graduate Faculty of
North Carolina State University
in partial fulfillment of the
requirements for the degree of
Doctor of Philosophy

Psychology

Raleigh, North Carolina

2014

APPROVED BY:

Dr. Lori Foster Thompson Committee Chair	Dr. Adam W. Meade
Dr. Mark A. Wilson	Dr. S. Bartholomew Craig

BIOGRAPHY

Will Stoughton was born in Pasadena, CA and grew up in Glendora, CA. After graduating Damien High School in La Verne, CA he attended the University of Southern California. At USC, Will received a B.S. in Business Administration (International Relations) and completed a minor in Psychology. Upon graduation in 2006 Will moved to Raleigh, NC to attend North Carolina State University.

In 2011 Will was awarded an M.S. in Psychology, his thesis was titled, *Examining Applicant Reactions to the Use of Social Networking Websites in Pre-Employment Screening*, which was completed under the direction of Dr. Lori Foster Thompson. Will married this same year.

From 2009 through 2014 Will worked for Horizon Performance, LLC, a consulting firm in Cary, NC that specializes in assessment and selection, while continuing his studies. Will acted as a Subject Matter Expert in an assessment center setting helping to select America's elite warriors, embracing the scientist/practitioner heritage of I/O Psychology. Early in 2014 Will moved to Minneapolis, MN with his wife, Hannah. He transitioned to a pre-sales consulting role at CEB | SHL Talent Measurement explaining the science and practice of I/O to a diverse commercial audience. He will maintain this job after graduation while continuing to pursue various academic endeavors.

ACKNOWLEDGEMENTS

I started my thesis acknowledgements with, “First, and foremost, I would like to thank my advisor Dr. Lori Foster Thompson.” After three years this statement still rings true. While she is undoubtedly the most tireless individual I have encountered in my short life, I am truly indebted to her for the genuine care and interest she took in both my life and work. Through my time at State I have seen her increasingly take on responsibility, no doubt, raising the prestige of the field we share and working to ensure its relevance in the years to come, while continually maintaining the attention she has paid toward all of her students during her tenure. Thank you Lori.

I would also like to thank the members of my committee Drs. Adam W. Meade, S. Bartholomew Craig, and Mark A. Wilson. You have all been sounding boards at various points in my time at State. In particular I want to thank Dr. Meade, the effort that he has put in mentoring me through various academic pursuits has been instructive and invaluable in my young career. As frustrated as I got, he helped me maintain perspective and encouraged me to continue submitting manuscripts, I’m now well aware that 100 percent of the manuscripts not submitted are not published.

I would like to thank Drs. Clara E. Hess and Amy M. DuVernet, in addition to Mr. Tom Whelan for adopting me in their cohort. While I often fell through the cracks of the departmental curriculum, the three of them were always there to assist me academically and socially. They created a support system when graduate school could have otherwise been a solitary existence.

Finally, I would like to thank my wife. Her rapid progress in her own doctoral program was inspirational in the waning years of my time at State. I am so thankful for her encouragement and candor as I struggled to balance degree completion and my job. She constantly pushes me to better myself and I am continually excited at the prospect of spending my life with her.

TABLE OF CONTENTS

LIST OF FIGURES

LIST OF TABLES

Introduction

The advancement of the organizational and psychological sciences relies on self-report survey data, asking people to rate their perceptions, attitudes, and personality, among other topics. The effort, attention, and affective reactions of employees are critical to the success of organizational survey initiatives, which rely on engaged participants attending to and completing the measures of interest (Meade & Craig, 2012; Rogelberg, Luong, Sederburg, & Cristol, 2000; Thompson, Surface, Martin, & Sanders, 2003). Over the past decades, surveys have undergone a transformation, evolving from paper-and-pencil formats to emailed hyperlinks and web-hosted solutions that participants can fill out on their own devices, at their convenience (Granello & Wheaton, 2004; Kraut, 2006). The transition to Internet surveys created the opportunity to more easily gather large samples quickly, lowering the cost of data collection, and easing data entry, while producing a potentially user-friendly experience (Macey, 1996; Naus, Philipp, & Samsi, 2009; Weigold, Weigold, & Russell, 2013). Moreover, the shift to online surveys led to an increase in the administration of employee opinion surveys, a common means of gauging employee attitudes and perceptions on a range of issues (Kraut, 2006; Rogelberg et al., 2000; Thompson & Surface, 2009). Paralleling this shift to online surveys was the growth of smartphone and tablet usage. Although the psychological and organizational sciences were quick to recognize the side effects of mobile device Internet capability for job applicants, where online access permits job candidates to take selection tests via smartphones or tablets (e.g., Doverspike, Arthur, Taylor, & Carr, 2012; Illingworth, Morelli, Scott, Moon, & Boyd, 2013; Lawrence, Wasko, Delgado, Kinney, & Wolf, 2013; Morelli, Illingworth, Scott, & Lance, 2012), less attention has been paid to the phenomenon in employee opinion survey research. Accordingly, the current study will redress this gap in the literature by examining the differences between smartphones, tablets, and personal computers with respect to: (a) the quality of data produced by the survey respondents, (b) the affective reactions of survey respondents to an employee opinion survey, and (c) whether or not level of mobile optimization influences the degree to which the survey device utilized affects these outcomes. This phenomenon will be examined in a U.S. context.

Mobile Devices and Organizational Surveys

By 2010, smartphones, defined as "programmable mobile phones with relatively sophisticated sensing capabilities, increasing storage capacity, and built-in networking," outpaced shipments of the personal computer (PC) (Goldman, 2011; Raento, Oulasvirta, & Eagle, 2009, p. 427). By early 2012, nearly 90% of the United States population, or 276 million people, used mobile phones (Gahran, 2012). By 2013, market research demonstrated that smartphones were used by 65% of the United States population, up from 18% in 2009 (Fingas, 2014; Roberts, 2012). Additionally, nearly 70% of new phones purchased, are "smart" (Roberts, 2012). Similarly, the use of tablet computers, general-purpose computers contained in a single panel that utilize touch screens for input, is rapidly expanding (PCMag, n.d.). First introduced by Microsoft at an industry tradeshow in late 2000, the tablet computer gained popularity quickly after the introduction of the iPad in 2010 (Ranger, 2013). Early estimates of tablet sales predicted more tablets sold than PCs by 2016 (DisplaySearch, 2012). However, in a short time that figure was pushed forward one year and estimates have tablets outselling PCs in 2015 (Petronzio, 2014). Moreover, this is not just an American trend. Smartphones and tablets are increasingly making worldwide access to the Internet ubiquitous, helping to bridge the so-called "digital divide," a theoretical division between "those who have" and "those who do not" with respect to internet access (Chong & de Mendoza, 2012; Joshi & Avasthi, 2007).

The capacity to access the Internet, inherent to both smartphones and tablets, provides employees the opportunity to complete employee opinion surveys via a mobile device. In the case of employee opinion surveys, smartphones and tablets provide an option for the mobile workforce frequently away from the office on travel, or those who do not have the time or resources to complete the survey at work. Mobile devices are often available, providing ample opportunity to work on a survey from a location of one's choosing. For example, employees with mobile devices could work on a survey from: an airport, while waiting for an appointment, in a coffee shop, or while watching TV (Perlow, 2012). Mobile devices also provide another option for those who would prefer to complete the survey away from the office; for example, those working in public spaces where there is some concern about others seeing their computer screen during survey completion or those who are concerned about the anonymity of kiosks or other measures taken by an organization to promote survey response anonymity (Whelan, 2008).

However, the ability of employees to access opinion surveys via mobile devices is not without potential drawbacks. For instance, using a smartphone or tablet to complete an opinion survey operates in opposition to one of the touted advantages of online instruments, increased consistency of administration. Consistency, with respect to Internet surveys, refers to the delivery of an instrument with identical instructions, precise timing, and uniform item and page presentation for all participants (Tippins et al., 2006). When employees access opinion surveys on their mobile device, organizations forfeit the consistency of administration because of constraints inherent to smartphones and tablets. For instance, smartphones and tablets generally have smaller screens than desktop and laptop computers, causing users to scroll more to read text, such as survey items or instructions (Sanchez & Branaghan, 2011). Smartphones typically display only fifteen lines of thirty to forty characters on the screen compared to a desktop screen with approximately forty lines of one hundred characters (Lee & Rethemeyer, 2012). Additionally, smartphones and tablets generally include a standard QWERTY keyboard on a small touchscreen or possibly a tactile keyboard with very small buttons placed below the screen (Morgan & Thompson, 2013). Users could connect a mouse or keyboard via the Bluetooth capability of the device in order to remedy some of these deficiencies. However, it is presently not "the norm" for most users to sacrifice the portability and convenience of the device by committing time and resources to connecting an external mouse or keyboard. As such, users often do not have the ability to type with two hands while completing a survey. As a result, mobile devices can be more difficult to use than desktop and laptop computers, making input relatively cumbersome.

As smartphones and tablet computers become the most common means of accessing information on the Internet, examining the effects on organizational survey efforts grows critical (Doverspike et al., 2012; Joshi & Avasthi, 2007; Morelli et al., 2012; Sanchez & Branaghan, 2011). Internet surveys have received considerable attention, with researchers investigating a range of topics: attrition, psychometric properties, and satisfaction, to name just a few (Rogelberg et al., 2003; Stoughton, Gissel, Clark, & Whelan, 2011; Thompson & Surface, 2007; respectively). Similar attention is warranted for the transition to smartphones and tablet use in the employee opinion survey literature, a point reinforced by the differing user experiences on the mobile Internet.

By mid-2013, smartphones and tablets accounted for more Internet browsing time than PCs in the United States (Goodman, 2013). However, a mobile user's experience can vary dramatically from website-to-website, and best practices are rapidly changing. Mobile-optimized (MO) websites are the current industry standard for a satisfactory mobile user experience. A MO-website is built for smartphones and tablets or auto-detects mobile devices and reformats, acknowledging the smaller screen, streamlining navigation with bigger text and buttons, with less requirement to scroll or zoom (Gallizzi, 2013; Technologies, 2013). Often, MO-websites take advantage of "touch" options, with push-to-call or email, used throughout the page (Technologies, 2013). Conversely, non-mobile-optimized (NMO) websites are designed to display on a smartphone or tablet just as they would on a computer, only smaller (Gallizzi, 2013; Technologies, 2013). For smartphone and tablet users, this means that they are often required to scroll left and right to view text cut off by the smaller screen, referred to as web-clipping, as well as zoom to better display smaller text (Albers & Kim, 2002; Sanchez & Goolsbee, 2010). In the popular press and marketing literature, NMO sites are referred to as “mobile-friendly;” however, this format for web-display is less than ideal and arguably not friendly. Accordingly, mobile-friendly websites are referred to hereafter as non-mobile-optimized throughout this text.

Effect of Mobile Use on Employee Opinion Survey Data Quality

In short, smartphones and tablet computers are changing the way people use the Internet. As mentioned above, the relatively small existing body of literature concerning smartphones and tablets for work tends to concern applicants using the devices for pre-employment tests (e.g., Illingworth et al., 2013; Impelman, 2013; Morelli et al., 2012). Past studies have not addressed the implications for data quality on employee opinion surveys. To examine this issue thoroughly, the quality of both closed-ended and open-ended survey responses needs to be considered.

Close-ended items. The quality of closed-ended rating data can be studied by examining what the scientific literature refers to as “careless responding” indices. Inattentive or careless responding, a subset of content nonresponsivity, is defined as responding without concern for the item content (Meade & Craig, 2012; Nichols, Greene, & Schmolck, 1989). This responding can manifest itself in a variety of data patterns. For instance, an employee could choose to respond at random to all closed-ended items; or, a nonrandom pattern could be employed where all “agree” responses are input, or a “strongly disagree, disagree, neither agree/disagree, agree, strongly agree,” pattern of item response could be exhibited. The common theme of careless responding is a failure to respond to the *content* of the items regardless of the motivation of the survey taker (Nichols et al., 1989).

Careless responding can result in: skipped items, instrument non-completion, non-normal data, and other problems as response patterns exhibit carelessness. Whatever the mechanism, this data loss or carelessness is important because it results in exclusion of cases from the dataset, which affects overall sample size (Hardre, Crowson, & Xie, 2012). In the case of careless responding that exhibits a pattern, the resultant data can be decidedly nonrandom, impacting the quality of data, especially the internal consistency of instruments or item equivalence between subjects (Meade & Craig, 2012). Said differently, the raw data provided by a respondent may not accurately reflect his or her true level on the measured construct. Due to the inherent decrease in data quality and to draw clear linkages with open-ended comments, careless responding indices will be referred to as closed-ended data quality measures throughout the rest of the manuscript.

Previous examinations of close-ended data quality in an employee hiring/selection setting (where an applicant is likely to be motivated to provide high quality data) revealed the phenomenon to be as high as five percent (Ehlers, Zajack, Weekley, & Greene-Shortridge, 2009). In another study of employees' propensity to provide inferior data, Curran, Kotrba, and Denison (2010) found the base-rate to range from 7%-50% depending on the indicator of data quality used. Even in a setting that should engender conscientious survey completion (i.e., organizational surveys) it seems that many participants will provide low quality data, necessitating investigations of the factors that contribute to the inattention to survey item content. Increased survey time-to-completion and increased cognitive load created by using mobile devices to complete surveys may be two such factors that contribute to decreased data quality for close-ended items.

Previous research demonstrated that using small electronic devices rather than computers to complete reasoning tasks increases the time-to-completion (Illingworth, Morelli, Scott, & Boyd, 2014; Sanchez & Branaghan, 2011). It is possible that these findings would be similar for survey completion on smartphones and tablets. While it is generally accepted that participant interest in a psychological survey decreases the likelihood of inattention to item content, longer instruments likely increase fatigue and cause participant attention to wane, even with highly motivated samples such as employees (Berry et al., 1992; Ehlers et al., 2009; Meade & Craig, 2012; Schwarz, 1999; Tourangeau, Rips, & Rasinski, 2000). Additionally, initial investigations of cross-sectional survey completion have linked increased time-to-completion with greater respondent attrition (Meade & Pappalardo, 2013). Therefore, even if the content of the survey is kept shorter to avoid decreased data quality, the constraints presented by smartphones and tablets, such as smaller screens, may contribute to workload, inattention, and attrition.

The smaller screens of smartphones and tablets compared to computers likely increases cognitive load for survey takers by requiring them to remember information not in their visual field when text is cut off due to screen size. Whereas long term memory is unlimited, working memory is limited (Thorndike et al., 2009). This is fundamental to the four maxims of cognitive load theory: (1) humans have a limited working memory, which can only process a limited number of elements at any given time, (2) individuals have unlimited long term memory that can be used to overcome deficits in working memory, (3) the mind creates schemas in long term memory that assimilate information in order to reduce the burden on working memory, and (4) the mind then processes this information automatically, as opposed to consciously, further reducing the burden on working memory (Pollock, Chandler, & Sweller, 2002; Thorndike et al., 2009). On smartphones, much of a user's time is spent scrolling to read textual information clipped due to the size of the screen when on NMO websites (Sanchez & Branaghan, 2011). Previous research demonstrated increased scrolling results in increased cognitive load (MacIsaac, Cole, Cole, McCullough, & Maxka, 2002). This should affect close-ended data quality, as increased cognitive load serves to fatigue survey takers. Owing to the effect of the device itself on survey time-to-completion and participant cognitive load, survey takers may be more likely to provide lower quality data. In light of the possible increase in survey time-to-completion and cognitive load of survey takers, I propose the following hypotheses:

> *Hypothesis 1**:*** Smartphones (*H1a*) will affect time-to-completion such that those who complete a survey on a smartphone will take longer, followed by those completing a survey on a tablet (*H1b*), while those completing a survey on a computer are expected to take the least amount of time to complete a survey.
>
> *Hypothesis 2**:*** Smartphones (*H2a*) will affect attrition such that those who complete a survey on a smartphone will demonstrate the most attrition,

followed by those completing a survey on a tablet (*H2b*), while those completing a survey on a computer are expected to attrit the least.

*Hypothesis 3**:*** Smartphones (*H3a*) will decrease close-ended data quality such that those who complete a survey on a smartphone will exhibit the lowest quality data, followed by those completing a survey on a tablet (*H3b*), while those completing a survey on a computer are expected to provide the highest quality data.

*Hypothesis 4**:*** There will be an interaction between mobile device and presence of mobile-optimization, such that the degree to which smartphones (*H4a*) and tablets (*H4b*) decrease close-ended data quality depends on presence or absence of mobile-optimization.

For the hypotheses above, inattention to survey content will be tested across several different indices of closed-ended data quality, as decreases in the quality of closed-ended item data can manifest in several distinct ways.

Open-ended comments. The move to Internet surveys renewed interest in open-ended comments (i.e., questions with no pre-determined response options), which are now generally included on organizational surveys (Kraut, 2006; Poncheri, Lindberg, Thompson, & Surface, 2007). The quality of open-ended comments can be critical to a survey effort as managers and key organizational decision makers often pay particular attention to open-ended responses, especially in instances where open- and close-ended questions differ in results (Poncheri et al., 2007). The increased use of mobile devices for survey completion however may have implications for the collection of open-ended responses.

For open-ended comments, the quality of data may be determined in part by the length of response (Denscombe, 2007; Hardre et al., 2012; Mehta & Sivadas, 1995). Longer responses are often more refined, containing more vivid descriptions, rich with information (Hardre et al., 2012). For employees, it is hypothesized that the renewed interest in open-ended responses has been tolerated by respondents because often-times individuals type faster than they write (Thompson et al., 2003). Indeed, the assertion that employees may not mind open-ended comments for Internet surveys is supported by the increase in length of open-ended comments on online surveys compared to paper-and-pencil alternatives (Kraut, 2006). However, smartphones and tablets may make open-ended comments cumbersome. The difficulty of input is apparent when comparing speed; smartphone users' typical input speed is approximately 20 words per minute, compared to 60 words per minute on the computer (Bao, Pierce, Whittaker, & Zhai, 2011). If Thompson and colleagues (2003) are correct about survey respondents accepting open-ended comments because of ease of entry on a computer, the move to smartphones and tablets while continuing to include open-ended questions on surveys may negatively affect quality of employee open-ended comments. Accordingly I propose the following hypothesis:

> *Hypothesis 5**:*** Smartphones (*H5a*) will affect length of open-ended comments such that those who complete a survey on a smartphone will have shorter open-ended comments, followed by those completing a survey on a tablet

(*H5b*), while those completing a survey on a computer are expected to have the longest open-ended comments.

In addition, open-ended comments can lead to skipped items, also referred to as item nonresponse. Past examinations of open-ended responses versus closed-ended responses revealed more item nonresponse for open-ended questions (Reja, Manfreda, Hlebec, & Vehovar, 2003). This is hypothesized to occur because of the increased burden of providing open-ended written comments (Reja et al., 2003). As mentioned above, smartphones and tablets generally make open-ended responses more cumbersome because of the technical limitations of the devices. Accordingly, I propose the following hypothesis:

Hypothesis 6: Smartphones (*H6a*) will affect nonresponse to open-ended items such that those who complete a survey on a smartphone will skip the greatest number of open-ended questions, followed by those completing the survey on a tablet (*H6b*), while those completing the survey on a computer are expected to skip the fewest open-ended questions.

Satisfaction with Mobile Surveys

In addition to data quality, considering participant reactions to organizational survey efforts is important (Hardre et al., 2012; Thompson & Surface, 2009). Satisfaction is meaningful to contemplate as Thompson and Surface (2007) suggested that employees' like or dislike with a particular survey medium (e.g., mobile device or computer) could influence response behavior, such as attrition before completely filling out the instrument, on an organizational survey if respondents have a negative affective reaction to the instrument.

Given the importance of reactions to a survey, there is a need to consider how device may influence user acceptance of a survey initiative (Thompson et al., 2003). Currently no data exist for researchers or practitioners to answer the question of whether employees are more satisfied taking surveys on their computer or a mobile device.

The visual presentation of survey items has been shown to influence the affective impression of a user (Cho, Park, Han, & Kang, 2011). As noted above, NMO- and MO-websites offer different visual mobile user experiences. Survey items on NMO-websites require participants to scroll left and right to view item content cutoff by the smaller screen (Gallizzi, 2013). This is perceived to be a poor user experience, which could affect survey respondents' satisfaction. MO-websites, on the other hand, are intentionally designed to be viewed on a smartphone or tablet, with streamlined navigation to decrease scrolling and zooming (Gallizzi, 2013).

Counteracting the potential negative effects caused by characteristics of mobile devices, the convenience of using a smartphone or tablet may alleviate concerns or increase approval. For instance, members of an organization's mobile workforce may prefer the option of easy access to organizational surveys while away from the workplace. For this segment of an organization's workforce, a smartphone or tablet is more likely to have Internet access than a computer, permitting people to take a survey without the added effort of finding an Internet access point when away from office connectivity. It is therefore possible that the ability to immediately respond to a survey when a link is emailed, rather than waiting until access to a connected computer is available, may increase the acceptance of surveys taken on a smartphone or tablet. In 2001, Church posed the following question about paper-and-pencil vs. computer surveys, “Given the choice which method of response do employees prefer?” (p. 938). Following this line of inquiry, I propose the following research questions:

Research Question 1: Which survey device (i.e., smartphone, tablet, or computer) promotes the greatest satisfaction with the survey?

Research Question 2: Does level of mobile optimization (i.e., NMO vs. MO) affect survey taker satisfaction for mobile device users?

Method

Participants

Participants (*N* = 292) were U.S.-based adults utilizing Amazon’s Mechanical Turk (MTurk) crowdsourcing website. MTurk is an online marketplace that connects requesters (e.g., researchers) with individuals willing to do tasks unable to be completed by a computer, such as those requiring human intelligence. Previous investigations found MTurk users to be more demographically diverse than university subject pools and produce data that met or exceeded the psychometric standards of published research (Buhrmester, Kwang, & Gosling, 2011). Moreover, peer-reviewed research not specifically investigating the efficacy of MTurk and instead examining psychological and organizational research questions has started to appear in the literature (e.g., Giacopelli, Simpson, Dalal, Randolph, & Holland, 2013; Stoughton, Thompson, & Meade, 2013). For a more detailed explanation of using MTurk in psychological research see Barger, Behrend, Sharek, and Sinar (2011) and

Behrend, Sharek, Meade, and Wiebe (2011). The mean age of the sample was 30.42 years (*SD* = 11.53). With respect to ethnicity, 76% of the sample was Caucasian, 9% was African American, 6% was Asian American, and approximately 9% reported another ethnicity. The sample was nearly split with respect to gender; 51% female, 49% male. To qualify for this study, participants were required to have a computer, a smartphone, and a tablet and work 30 or more hours a week (see Table 1 for participant occupations). Participants were paid U.S. $0.50 for their participation in the *human intelligence task* (HIT), outlined below. The level of compensation was comparable to the median pay rate for research studies requiring a similar time and resource commitment.

Design

This study used a between-groups design with random assignment to conditions. There were two independent variables of interest: (1) survey device and (2) website optimization. However, these two variables could not be fully-crossed as survey takers utilizing a computer cannot experience a NMO website. Thus, participants were randomly assigned to one of five conditions: (1) smartphone-NMO, (2) smartphone-MO, (3) tablet-NMO, (4) tablet-MO, and (5) computer. As smartphones continue to grow larger, the distinction between smartphone and tablet becomes blurred. In general, tablets range from 7- to 13-inches (Radar, 2013); this rule of thumb was used to classify devices into the appropriate condition, with devices below 7 inches categorized as smartphones and devices above 7 inches categorized as tablets. There were two dependent variables of interest: (1)

data quality and (2) satisfaction with the survey. Data quality was examined with respect to both closed- and open-ended items, and was assessed in a variety of ways, described below.

Procedure

An advertisement was created on MTurk that contained a brief description of the study and a link to an informed consent form. The description indicated that the study entailed completing an employee opinion survey, and that in order to qualify for the study participants must own a smartphone, tablet, and a computer and work 30 or more hours each week. Additionally, the informed consent explained to participants that their payment was contingent on completing the questionnaire on the appropriate device. After checking a box to electronically transmit their informed consent, participants were asked to complete a survey. Participants were randomly assigned to one of the five possible conditions via a JavaScript application embedded in the online study materials. At this point, participants followed a link to their appropriate survey, which may have required them to change devices to complete the questionnaire if they initiated the study on a computer and were assigned to a mobile condition or vice versa. Participants were prompted, "Please navigate to [survey link] on your [device type] to complete the survey. I remind you that you must complete the survey on your [device type] to receive payment." Additionally, steps were taken to ensure that the switch from computer to mobile device was made for survey completion. An item was embedded in the survey content that limited survey completion to a specific device type, mobile or computer based on the condition assigned.

Mobile-optimization was prevented for the NMO conditions by utilizing an iframe. An iframe is an inline frame used to embed another document (i.e., the survey) in another website, in this case one that does not permit mobile-optimization. Most survey software does not permit the option to “turn-off” mobile-optimization when the capability exists. Because the study required mobile-optimization for two of the conditions, the use of an iframe in a website that did not permit mobile-optimization allowed the same survey software (i.e., Qualtrics) to be employed across all study conditions increasing the standardization between conditions. See Figure 1 for an example of NMO vs. MO survey presentation. The survey was five pages in length with 20 close-ended items per page, the response scale presented at the top of the page, prompt and radio buttons presented in matrix format, and one open-ended question at the end of each page. All of these questions permitted skipping. Participants were asked to imagine they were responding to the survey for the organization they work 30 or more hours at each week. After the questionnaire was completed, participants filled out the outcome variables of interest (i.e., a survey satisfaction instrument) and manipulation check items. Participants were then debriefed. See Figure 2 for the flow of respondents through the survey.

Measures

Employee Opinion Survey (100 items). Table 2 summarizes the measures used to simulate the employee opinion survey. The items administered on the employee opinion survey were chosen to represent the types of questions commonly used across a number of roles and industries. Moreover, the breadth of content is reflective of many yearly organization “engagement” or “opinion” survey initiatives (Kraut, 2006; Thompson & Surface, 2009).

Manipulations Checks. There were two manipulations that required assessment: mobile-optimization and survey device. Accordingly, two different types of checks were devised to ensure that participants had the intended experience on the right device.

MO Manipulation Checks (5 items, $\alpha = 0.80$). The mobile optimization manipulation was assessed with five items utilizing a five point Likert-scale, with responses ranging from 1 (*never*) to 5 (*always*). An example item is, “Did you enlarge the text (zoom in) at any point to better read or answer questions?”

Survey Device Check (2 items). One item was administered to assess the survey device utilized by the mobile condition participants. Participants selected the device they were using from a list of options. Sales data from 2013 were utilized to populate the survey device list prior to administering the survey. Additionally, an “other” category was included to account for devices that may not have been on the list as it was not intended to be exhaustive, but instead to pick out the “most likely” utilized devices for ease of coding. As mentioned above, an item was also embedded in the survey content of the mobile conditions to exclude all but mobile devices from taking the survey and vice versa for the computer condition, while returning both operating system and screen resolution with each respondent’s data. As such, only mobile users were able to take the mobile survey conditions and computer users the computer condition.

Dependent Variables.

Time-to-completion. Time-to-completion was measured using an embedded marker in the survey content. This was collected by the survey software; survey participants were not required to make an entry for start and end times. Time was measured continuously in seconds and converted to minutes for ease of interpretation.

Attrition. Survey completion was collected by the survey software; attrition was coded a *0* for those that did not complete the survey and a *1* for those who completed the survey.

Close-Ended Indices of Data Quality. There are three types of post hoc methods for identifying lower quality close-ended item data: consistency indices, outlier indices, and study response time (Meade & Craig, 2012). Consistency indices refer to methods of identifying decreased data quality by matching similar items together, based on either the underlying construct or historical correlation, and examining whether there is a lack of consistent responding. Outlier indices look at a series of responses and the relative distances for these items to identify outliers. Finally, study response time often identifies a time threshold for low data quality, such that those respondents who take less time than the threshold are identified as producing decreased quality data.

Examining the relative merits of the different close-ended item data quality indicators, Meade and Craig (2012) made a number of practical recommendations. For cases in which robust correlations are of interest (e.g., employment surveys), they recommend using instructed response items (e.g., “Respond with ‘strongly agree’ for this item.”) and three post hoc data quality indices: the Even-Odd Consistency Index (Jackson, 1976), the

Maximum LongString Index (Johnson, 2005), and the Mahalanobis D (Mahalanobis, 1936). In line with the recommendations of Meade and Craig (2012), each of these indices was utilized to investigate data quality in the current study and scored so that higher values represented decreased levels of data quality.

Instructed Response Items (5 items). On each of the five pages of the survey, a single item was included to assess participant response attention. These quality check items, recommended by Meade and Craig (2012) (e.g., “Respond with ‘strongly agree’ for this item.”), were used as a continuous measure of respondent carelessness. Items were scored 0 for a correct response and 1 for an incorrect response summed across the five items, thus scores ranged from 0 to 5 such that those exhibiting lower quality data to the items had a higher score.

Even-Odd Consistency Index. The Even-Odd Consistency Index is a consistency indicator of closed-ended data quality predicated on the idea that items from the same scale should correlate with each other for a particular individual (Huang, Curran, Keeney, Poposki, & DeShon, 2011). Huang and colleagues (2011) identified Even-Odd Consistency as one of the more discriminating indices of data quality, with the power to identify inattention in survey research while refraining from misspecifying normal patterns of response. Even-Odd Consistency was computed by dividing the items from all of the scales on the employee opinion survey into two groups based on the order in which the items appeared, even and odd (Jackson, 1976). Subscale scores were computed for each grouping of items (i.e., 14) based on the average value of each response for the group of items. A within person correlation was then calculated for the matching even and odd subscale scores to generate the final value for the Even-Odd Consistency Index. The item groups were corrected for length using the Spearman-Brown formula, as recommended by Jackson (1976). Lower individual internal consistencies are indicative of lower data quality. For ease of interpretation these values were transposed after scoring; accordingly, for all indicators of closed-ended data quality higher values equate with lower quality response.

Maximum LongString Index. The Maximum LongString Index is a consistency index for close-ended data quality referring to the consecutive string of a particular response option for any given survey page (e.g., “strongly agree”). Costa and McCrae (2008) recommend LongString calculations for detecting low quality data, citing that none of their compliant study participants demonstrated particularly long strings of continuous responses for a particular response option. A response set consisting of the same response option for a given survey page is unlikely, especially given reverse worded options (Johnson, 2005). The Maximum LongString was computed for each survey page using a Microsoft Excel array formula. An array formula can return multiple calculations on one or more of the items in an array, in this case values in a row of participant data. Like Meade and Craig (2012), I only investigated the longest single string of response options; accordingly, the array calculated the longest string for all survey pages, and then returned the greatest value from the five pages. Again, higher scores are more likely to represent low quality data (Johnson, 2005).

Mahalanobis D. Mahalanobis distance, or Mahalanobis D, is an outlier index for identifying decreased data quality. Mahalanobis distance is a multivariate vector of a respondent's item response distances from the vector of response means (Meade & Craig, 2012). Ehlers et al. (2009) found Mahalanobis D to be an effective index for identifying inattentive responding to a job application, a setting where participants are likely highly motivated to respond attentively. Mahalanobis distance measures were calculated for all study scales. Following the procedures of Meade and Craig (2012), separate distance measures were calculated for each scale and averaged into a single Mahalanobis distance value to reduce the computational burden of using the raw, item-level data across all items. Higher values for Mahalanobis D indicate decreased levels of data quality.

Open-ended Comment Data Quality. Open-ended item comment quality was measured two ways. First, length of open-ended comments completed was measured using a word-count software option to determine the total number of words generated across all open-ended items. Additionally, open-ended item comment completion was recorded, where number of open-ended comments skipped was scored continuously with scores ranging from 0 to 5; higher scores were indicative of more items skipped.

Survey Satisfaction (7 items, $\alpha = 0.93$). Respondent satisfaction with the survey device and format were assessed using items adapted from Thompson and colleagues (2003). Items were presented using a Likert-type scale, with responses ranging from 1 (*strongly disagree*) to 5 (*strongly agree*). An example item is, "This online format is a useful way to complete organizational surveys."

Results

Background Analysis

Prior to data collection, an a priori power analysis was conducted using G*Power 3 (Faul, Erdfelder, Lang, & Buchner, 2007). The results suggested that for analyses utilizing an *F* statistic with five conditions, a minimum sample size of $N = 200$ was needed to produce sufficient statistical power at a value of 0.80 for $\alpha = .05$ to detect a medium effect size of 0.25 (see Cohen, 1988). Thus, the final sample size of $N = 292$ was deemed adequate to detect a medium or large effect. Though similar, sample sizes were not identical across conditions due to small differences in response rates and the number of eligible participants per condition. As noted earlier, participants were randomly assigned to condition via a JavaScript application embedded in the online study materials. The application was set so that each condition had the same statistical likelihood of having a participant assigned. At the time data collection was terminated, the number of participants assigned to each condition was slightly uneven due to random chance (see Figure 2).

Table 3 provides descriptive means, standard deviations, and correlations among the study variables. Next, experimental manipulations were checked. The data were inspected to ensure respondents accessed the survey on the appropriate device and removed where appropriate. Figure 2 demonstrates the efficacy of the embedded item that limited a large number of noncompliant respondents to the appropriate device. Subsequently, the data were examined to determine the extent to which participants perceived the mobile-optimization. A 2 (optimized/non-optimized) × 2 (smartphone/tablet) Analysis of Variance (ANOVA) conducted on the mobile-optimization manipulation check items across the four mobile conditions was significant, $F(3, 180) = 12.91$, $p = .001$, $\eta^2 = 0.18$. As expected, there was a main effect for mobile optimization, $F(1, 180) = 10.87$, $p = .001$, $\eta^2 = 0.05$. Survey respondents on smartphones ($d = 1.06$) and tablets ($d = 0.25$) perceived differences between conditions such that those in NMO-conditions had to zoom, scroll, turn to view landscape, et cetera more than those in MO-conditions. Table 4 shows mean responses per condition for the mobile optimization manipulation items.

Hypothesis Tests

Table 4 provides the means and standard deviations per condition for the eight primary outcome variables of interest. For directional hypotheses, one-tailed tests are appropriate and are indicated where applicable in table or text. *H1a* and *H1b* predicted that mobile devices would affect time-to-completion on online surveys. The initial test of this hypothesis required a one-way ANOVA comparing the five conditions (collapsed across optimization) with respect to time-to-completion on the survey. The overall ANOVA was significant (see Table 5). Planned comparisons indicated survey respondents on mobile devices took significantly longer than computers, however respondents on smartphones did not take significantly longer than those on tablets. Taken together these findings provide partial support for hypothesis 1 in that mobile devices increase time-to-completion on surveys, but the effect does not increase in magnitude based on the screen size of the device; see Table 5 for means by device utilized.

Hypothesis 2 predicted smartphones (*H2a*) would affect attrition such that those completing a survey on a smartphone would demonstrate the most attrition, followed by those completing the survey on a tablet (*H2b*), while those completing the survey on a computer were expected to attrit the least. The results of a one-way ANOVA comparing the five conditions (collapsed across optimization) with respect to attrition on the survey were significant (see Table 5). Planned comparisons indicated that survey takers utilizing mobile devices did not attrit significantly more than those on a computer, but the comparisons did demonstrate survey participants on smartphones attrit more than those on tablets; Table 5 provides attrition percentages by device. Taken together these findings provide partial support for hypothesis 2 in that smartphones demonstrate increased attrition over tablets and computers (*H2a*), however tablets did not demonstrate more attrition than computers (*H2b*).

To test *H3a* and *H3b*, that mobile devices would decrease data quality compared to computers for online surveys, a multivariate analysis of variance (MANOVA) was utilized. The results of the MANOVA revealed no multivariate differences in respondent carelessness by device, Wilk's $\lambda = 0.96$, $F(8, 486) = 1.31$, $p = 0.236$, $\eta^2_{partial} = 0.02$. Therefore, hypothesis 3a and 3b were not supported.

Hypothesis 4 stated there would be an interaction between mobile device and level of mobile-optimization, such that the degree to which smartphones (*H4a*) and tablets (*H4b*) affect data quality depends on level of mobile-optimization and was tested via MANOVA. The MANOVA results revealed a significant multivariate difference between the conditions and quality of survey respondent data, Wilk's $\lambda = 0.79$, $F(12, 463.30) = 3.60$, $p < 0.001$,

$\eta^2_{partial} = 0.08$. Four univariate ANOVAs and discriminant function analyses (see Table 6) were conducted to investigate the nature of these differences. Results revealed significant univariate differences for the *Instructed Response* indicators; the Tukey Post Hoc tests revealed significant differences within device conditions for smartphones, but not in the expected direction. Thus, hypothesis 4a and 4b were also not supported. See Table 7 for correlations among data quality indices.

Hypothesis 5 predicted that smartphones (*H5a*) and tablets (*H5b*) would decrease the length of open-ended comments by survey takers versus those on a computer. Because hypothesis 6 investigates skipped items only completed comments were analyzed. A one-way ANOVA comparing all conditions (collapsed across mobile devices) was not significant (see Table 5). Planned comparisons indicated that survey takers utilizing mobile devices did not write significantly less those on a computer and survey participants on smartphones did not write significantly less than those on tablets. These findings do not provide support for *H5a* or *H5b.*

Hypothesis 6 predicted that smartphones (*H6a*) and tablets (*H6b*) would affect open-ended responses such that the use of mobile devices for survey completion would decrease completion of open-ended questions. A one-way ANOVA was not significant. Planned comparisons indicated that survey takers utilizing mobile devices did not skip significantly more open-ended comments than computer users. Additionally, participants on smartphones did not skip significantly more comments than those on tablets. Therefore, *H6a* and *H6b* were not supported.

In order to address research question 1 [Which survey device (i.e., smartphone, tablet, or computer) promotes the greatest satisfaction with the survey?], a one-way ANOVA was conducted comparing the five conditions for satisfaction with the survey $F(4, 172.67) = 8.41$, $p = .000$, $\eta^2 = 0.13$. Tukey post hoc tests revealed that the mean score for the smartphone-NMO ($M = 3.10$, $SD = 1.15$) and smartphone-MO ($M = 3.39$, $SD = 1.02$) conditions were significantly lower than the score for both the tablet-MO ($M = 4.11$, $SD = 0.86$, $d = -0.99$, $d = -0.76$) and computer ($M = 4.09$, $SD = 0.68$, $d = -1.05$, $d = -0.81$) conditions.

In order to address research question 2, whether level of mobile optimization (i.e., NMO vs. MO) affects survey taker satisfaction for mobile device users, a 2 (optimized/non-optimized) × 2 (smartphone/tablet) ANOVA was conducted revealing a significant main effect for level of optimization on the amount of satisfaction with the survey, $F(1, 180) = 6.74$, $p = .010$, $\eta^2 = 0.03$. Participants taking a non-optimized survey ($M = 3.33$, $SD = 1.31$) experienced significantly less satisfaction than those taking an optimized survey ($M = 3.70$, $SD = 1.01$, $d = -0.32$). Consistent with results of research question 1, there was a main effect for the survey device used on level of survey satisfaction, $F(1, 180) = 11.84$, $p = .001$, $\eta^2 = 0.06$. Smartphone users ($M = 3.27$, $SD = 1.08$) experienced significantly less satisfaction than participants taking the survey on a tablet ($M = 3.82$, $SD = 1.21$, $d = -0.48$). The interaction between survey device used and optimization was not significant, $F(1, 180) = 0.71$, $p = 0.113$, $\eta^2 = 0.00$, indicating the degree to which non-mobile-optimization reduced survey satisfaction did not vary across device conditions.

Discussion

This investigation provides an initial examination of the effects of smartphones and tablets on survey data quality and respondent satisfaction, providing a useful step forward to answering questions about organizational opinions untethered by empirically demonstrating the effect of smartphone and tablet use for current organizational surveys initiatives. Results indicated survey respondents utilizing smartphones and tablets did not produce data of significantly lower quality for closed-ended items or open-end comments, although respondents on smartphones and tablets took significantly longer to complete the survey, with the former demonstrating a greater rate of attrition than any other survey respondent group. While the ease of access to survey content permitted by smartphones and tablets was thought to potentially mitigate the inherent limitations of the devices with respect to respondent reactions, results indicated that respondents completing the survey on a smartphone were significantly less satisfied with the survey modality compared with tablet and computer respondents. Finally, the level of mobile-optimization was found to increase satisfaction with the survey format for mobile device respondents on both device types. Taken together, the results of this investigation provide useful information for researchers and practitioners deploying surveys for organizational analysis.

Study Limitations and Future Research

While this study makes a notable contribution to the extant literature, it has several limitations that should be acknowledged. First, the requirement of owning a smartphone, tablet, and computer for survey participation could be perceived to limit the generalizability of the study and represent a uniquely tech savvy population. However, as of 2013, 30% of smartphone owners also owned a tablet, a percentage that reflects how generalizable the sample was even when requiring a multitude of devices to be owned (Fingas, 2014). Additionally, the requirement of owning all three devices facilitated random assignment to condition and thus allowed the study to truly test cause and effect for mobile devices and outcomes of interest. Studies initially examining employment testing on mobile devices (e.g., Illingworth et al., 2014) state that the decision of survey respondents to take an assessment on a smartphone or tablet may stem from the unfounded perception that their ability to appropriately respond to the content presented is as great as on a computer without acknowledging the technical limitations (i.e., screen size, virtual keyboard, etc.) of the mobile devices. Thus, this study provided a true test of respondent response quality and affective reaction across devices by experimentally manipulating survey modality.

The nature of the survey and the context under which it was conducted may also serve as boundary conditions. The survey was relatively short in nature (M = 14.42 minutes, SD = 7.68 minutes) when compared to other research studies on survey data quality (e.g., Meade & Craig, 2012; Meade & Pappalardo, 2013) where longer surveys are utilized to induce variance in the sample by creating conditions conducive to lowering data quality. However, in an effort to increase the face-validity of the study, the survey was kept to a length more closely resembling organizational survey efforts. Additionally, the use of Mechanical Turk and the payment received by study participants may have served to increase participant diligence and attentiveness on the survey task. Individuals participating in an employee opinion survey though have a vested interest in informing their organization with respect to the issues at hand. Thus, the interest and conscientiousness of survey participants is likely to extend to individuals engaged in organizational survey initiatives.

Additionally, the added effort required to utilize the device prescribed by the study randomization may have attenuated the correlations between the survey device utilized and data quality indicators. As stated in the method, individuals that initiated the survey on a computer could have been required to switch to a mobile device after reading the informed consent if assigned to a mobile condition and vice versa for mobile device users assigned to a computer condition (see Figure 2). The additional effort to switch devices after starting on one may have led to a particularly diligent sample that attended to close-ended items and open-ended questions on the survey to a greater extent than those choosing not to continue when required to switch to a different device. Thus, what remains to be seen is the magnitude of the effect of mobile device use when participants self-select device type.

The study was a first step in exploring how mobile devices are changing organizational survey efforts. Future research should investigate whether these findings generalize to both older and younger generations. Younger generations may be more apt to take surveys in areas filled with distractions. First, they are cited as more likely to multi-task (e.g., Carrier, Cheever, Rosen, Benitez, & Chang, 2009), which can include: listening to music, watching television, or playing online games while engaging in another activity. While every attempt may be made to attend to the task at hand, involuntary shifts of attention are indeed possible (Cowan, 1988). In addition, the portability of smartphones and tablets creates a situation where the barriers to completing a survey in a less than desirable location are removed. Future researchers should examine the effect of smartphones and tablets on where surveys are taken and the implications this has on attention and data quality.

Related to the physical context in which the survey is filled out are respondent perceptions of anonymity. Web-based surveys are considered among the more private modes of survey administration (Couper, 2011). This tends to engender higher perceptions of anonymity in participants (Whelan, 2008). Unlike computers, which are perceived as less private in public, mobile phones engender a sense of privacy with researchers previously describing smartphone use with a “bubble” of private space (Lee & Rethemeyer, 2012; Puro, 2002). Future research should investigate participant perceptions of privacy and anonymity on different devices to help identify conditions that induce survey respondent candor especially when sensitive organizational information is at issue.

The literature on data quality indicates that cognitive load is one of the likely mechanisms affecting survey outcome variables of interest. As noted above, researchers demonstrated increased cognitive load results in survey respondent carelessness and attrition (MacIsaac et al., 2002; Sanchez & Branaghan, 2011). However, the current investigation did not directly measure cognitive load and thus could not link survey device utilized to increases in load. Future researchers would benefit from the direct linking of survey device and increases in load in order to more fully understand the nature of the relationships among the variables of interest.

Moreover, MO-manipulation check items in the current study confirmed that survey respondents utilizing mobile devices zoomed and scrolled more than computer respondents, which has been hypothesized to increase cognitive load (Sanchez & Branaghan, 2011). Researchers suggest presenting information in pieces as opposed to all at once to limit the effect of scrolling, which can be accomplished in surveys by limiting the number of items presented per page (Pollock et al., 2002). However, at times this is taken to the extreme and only one item is presented per page for mobile respondents. Each page change therefore represents a state change taxing users' cognitive systems, where mobile respondents are forced to assimilate complex information across multiple pages. Previous research showed the perception of continuity (i.e., gradual state changes) helped to reduce cognitive load (Joshi & Avasthi, 2007). Future research should further examine best practices with respect to item presentation for mobile surveys beyond the MO findings in the present investigation.

Theoretical and Practical Implications

The study was the first known investigation of smartphones' and tablets' effects on organizational survey efforts. Integrating survey, cognitive load, and mobile communication literature to create a framework for the evaluation of survey respondent data quality to new survey modalities. The current effort serves as a useful contribution to researchers' understanding of the both data quality and satisfaction with different survey modalities for survey respondents utilizing mobile devices.

The significant results with respect to attrition for smartphones is particularly interesting as it creates a unique situation where the actual time-to-completion for smartphones may be underestimated. That is, individuals on smartphones who took the longest were likely to have been the individuals who attrited; thus, the relationship between smartphones and time-to-completion is possibly attenuated. The likelihood of this supposition is bolstered by the survey satisfaction results. Survey respondents utilizing smartphones rated the experience most poorly, which Thompson and Surface (2007) identified as a likely contributor to nonresponse for cross-sectional survey research. When attrition is occurring due to device type, the possibility exists that the nature of the relationships between the outcomes of interest (e.g., closed-ended data quality) is not accurate, that is to say nonresponse bias may be at play. Thus, it is likely that the magnitude of the effects remain to be seen.

Additionally, the effects of device differences, specifically attrition and the suboptimal experience reported by smartphone users, could have far reaching implications when additional factors such as the socioeconomic status of the respondents are considered. Individuals in lower socioeconomic groups are more likely than higher income, more highly educated individuals to use their smartphone as their primary point of access to the Internet (Madden, Lenhart, Duggan, Cortesi, & Gasser, 2013). As such, differences by device (e.g., survey attrition) could manifest in nonresponse bias for the lower socioeconomic groups of an organization's workforce. For example, line workers in a manufacturing organization may be more likely to take an organizational survey on their smartphone. Accommodations could be made for these workers, such as kiosks to complete a survey, however anonymity concerns may prevent would-be respondents from utilizing such survey adjustments

(Whelan, 2008). Therefore, even if efforts are made to combat nonresponse bias for certain groups, the possibility of bias is very real. The implications of smartphone deficits for disparate groups within organizations cannot be understated, according to the Bureau of Labor Statistics (2014) the manufacturing industry represents one in six jobs in the US with nearly 12 million Americans employed directly in manufacturing, a number that demonstrates the far reaching implication of the current example.

Furthermore, the results and demographics characteristics of smartphone users suggest that the aforementioned digital divide has not been bridged; rather, it has transformed and may be subtler and less apparent than it once was. Smartphone users do not have the same Internet experience as tablet or computer users and thus in some ways are still “those who have not” with respect to Internet access, disadvantaged by their suboptimal user experience. Smartphone users’ satisfaction with the survey and mobile-optimization may generalize to similar settings (e.g., high stakes employment testing) if not beyond. What remains unknown is the degree to which this study’s findings extend to other situations where individuals may be apt to utilize a smartphone in lieu of a tablet or computer.

The results also indicate that mobile versus non-mobile is not the appropriate distinction to be made. Instead researchers should more appropriately conceptualize differences by device group and examine differences accordingly (see Illingworth et al., 2014 for an additional discussion of device level analysis). The extent to which previous studies conceptualized as devices into mobile and non-mobile (e.g., Arthur, Doverspike, Muñoz, Taylor, & Carr, 2014) and not by specific device (i.e., smartphone, tablet, and/or computer) may have inadvertently prevented significant differences from being revealed. Future researchers may benefit from increased specificity of analysis by device type and have justification for categorizing devices in this way.

For practitioners in organizations, this study has very concrete implications. First, organizational stakeholders need to understand whether or not their survey collection software permits mobile devices to access survey content. When organizational systems permit mobile access to surveys several considerations need to be made. Practitioners should consider the length of the survey request. Knowing that smartphone users will take longer to complete the survey, organizational researchers should keep survey lengths to a minimum in order to facilitate increased attention to the items at hand to and ensure that participant attention does not wane throughout the duration of the survey. Shorter surveys should also help to prevent smartphone respondent attrition before the survey is completed, helping to produce more useable data for evaluation.

Next, organizational researchers need to be aware that they cannot make distinctions between smartphones and tablets with their survey software. Android devices do not distinguish between smartphone and tablet when reporting their operating system to websites or survey software, so practitioners cannot limit the decision to “go mobile” exclusively to tablets. Moreover, Android tablets and smartphones occupy a market share of greater than 50%, so a decision by organizational researchers to include or exclude mobile devices from accessing organizational systems mean this limitation of Android devices affects more than half of all possible mobile respondents (Rivera & van der Meulen, 2014; Whitney, 2014).

Effectively this means practitioners cannot make decisions about smartphones and tablets in a vacuum, considerations of the possible effects of each device must be contemplated when deciding whether to allow the use of mobile devices for employee surveys.

Finally, practitioners would do best to ensure the highest level of mobile-optimization possible is delivered to survey respondents when mobile access to survey content is permitted. Mobile optimization increased satisfaction with the survey format for both survey modalities (i.e., smartphones and tablets). As mentioned previously, increased satisfaction with a particular survey format helps to ensure the overall success of the organizational survey initiative.

References

Albers, M., & Kim, L. (2002). Information design for the small-screen interface: An overview of Web design issues for personal digital assistants. *Technical Communication*, *49*(1), 45–60.

Arthur, W., Doverspike, D., Muñoz, G. J., Taylor, J. E., & Carr, A. E. (2014). The Use of Mobile Devices in High-stakes Remotely Delivered Assessments and Testing. *International Journal of Selection and Assessment*, *22*(2), 113–123. doi:10.1111/ijsa.12062

Bao, P., Pierce, J., Whittaker, S., & Zhai, S. (2011). *Smart phone use by non-mobile business users.* Proceedings of the 13th International Conference on Human Computer Interaction with Mobile Devices and Services - MobileHCI '11, New York, New York. doi:10.1145/2037373.2037440

Barger, T., Behrend, T. S., Sharek, D. J., & Sinar, E. F. (2011). I-O and the crowd: Frequently asked questions about using Mechanical Turk for research. *The Industrial-Organizational Psychologist*, *49*(2), 11–18.

Bauer, T. N., Maertz, C. P., Dolen, M. R., & Campion, M. A. (1998). Longitudinal assessment of applicant reactions to employment testing and test outcome feedback. *Journal of Applied Psychology*, *83*(6), 892–903. doi:10.1037/0021-9010.83.6.892

Behrend, T. S., Sharek, D. J., Meade, A. W., & Wiebe, E. N. (2011). The viability of crowdsourcing for survey research. *Behavior Research Methods*, *43*(3), 800–13. doi:10.3758/s13428-011-0081-0

Berry, D. T. R., Wetter, M. W., Baer, R. A., Larsen, L., Clark, C., & Monroe, K. (1992). MMPI-2 random responding indices: Validation using a self-report methodology. *Psychological Assessment*, *4*(3), 340–345. doi:10.1037/1040-3590.4.3.340

Bretz, R. D., & Judge, T. A. (1994). Person–Organization Fit and the Theory of Work Adjustment: Implications for Satisfaction, Tenure, and Career Success. *Journal of Vocational Behavior*, *44*(1), 32–54. doi:10.1006/jvbe.1994.1003

Buhrmester, M., Kwang, T., & Gosling, S. D. (2011). Amazon's Mechanical Turk: A new source of inexpensive, yet high-quality, data? *Perspectives on Psychological Science*, *6*(1), 3–5. doi:10.1177/1745691610393980

Carrier, L. M., Cheever, N. A., Rosen, L. D., Benitez, S., & Chang, J. (2009). Multitasking across generations: Multitasking choices and difficulty ratings in three generations of

Americans. *Computers in Human Behavior*, *25*(2), 483–489. doi:10.1016/j.chb.2008.10.012

Cho, Y., Park, J., Han, S. H., & Kang, S. (2011). Development of a web-based survey system for evaluating affective satisfaction. *International Journal of Industrial Ergonomics*, *41*(3), 247–254. doi:10.1016/j.ergon.2011.01.009

Chong, A., & de Mendoza, C. (2012, March 31). Cyber-behaviors and development impacts in Latin America. In (Z. Yan, Ed.) *Encyclopedia of Cyber Behavior*. Hershey, PA: IGI Global. doi:10.4018/978-1-4666-0315-8

Church, A. H. (2001). Is there a method to our madness? The impact of data collection methodology on organizational survey results. *Personnel Psychology*, *54*(4), 937–969. doi:10.1111/j.1744-6570.2001.tb00238.x

Cohen, J. (1988). *Statistical power analysis for behavioral sciences* (2nd ed.). Hillsdale, N.J.: Lawrence Erlbaum Associates.

Costa Jr., P. T., & McCrae, R. R. (2008). The Revised NEO Personality Inventory (NEO-PI-R). In G. J. Boyle, G. Matthews, & D. H. Saklofske (Eds.), *The Sage handbook of personality theory and assessment: Personality measurement and testing* (pp. 179–198). London: SAGE Publications, Inc.

Couper, M. P. (2011). The Future of Modes of Data Collection. *Public Opinion Quarterly*, *75*(5), 889–908. doi:10.1093/poq/nfr046

Cowan, N. (1988). Evolving conceptions of memory storage, selective attention, and their mutual constraints within the human information-processing system. *Psychological Bulletin*, *104*(2), 163–191. doi:10.1037/0033-2909.104.2.163

Curran, P. G., Kotrba, L., & Denison, D. (2010). *Careless responding in surveys: Applying traditional techniques to organizational settings.* Paper presented at the 25th annual conference of the Society for Industrial and Organizational Psychology, Atlanta, GA.

Denscombe, M. (2007). The length of responses to open-ended questions: A comparison of online and paper questionnaires in terms of a mode effect. *Social Science Computer Review*, *26*(3), 359–368. doi:10.1177/0894439307309671

DisplaySearch. (2012). Tablet Shipments to Surpass Notebook Shipments in 2016. *NPD*. Retrieved February 06, 2013, from http://www.displaysearch.com/cps/rde/xchg/displaysearch/hs.xsl/120703_tablet_shipments_to_surpass_notebook_shipments_in_2016.asp

Doverspike, D., Arthur, W., Taylor, J. E., & Carr, A. E. (2012). *Mobile Mania: Impact of Device Type on Remotely Delivered Assessments.* Paper presented at the 27th annual meeting of the Society for Industrial and Organizational Psychology, San Diego, CA.

Ehlers, C., Zajack, M. D., Weekley, J. A., & Greene-Shortridge, T. M. (2009). *The exploration of statistical methods in detecting random responding.* Poster presented at the 24th annual conference of the Society for Industrial and Organizational Psychology, New Orleans, LA.

Eisenberger, R., Huntington, R., Hutchison, S., & Sowa, D. (1986). Perceived organizational support. *Journal of Applied Psychology*, *71*(3), 500–507. doi:10.1037/0021-9010.71.3.500

Engel, L. (2013). The mobile candidate experience — It's already too late. *ere.net*. Retrieved October 10, 2013, from http://www.ere.net/2013/07/10/the-mobile-candidate-experience-its-already-too-late/

Faul, F., Erdfelder, E., Lang, A.-G., & Buchner, A. (2007). G*Power 3: A flexible statistical power analysis program for the social, behavioral, and biomedical sciences. *Behavior Research Methods*, *39*(2), 175–191. doi:10.3758/BF03193146

Field, A. (2005). *Discovering statistics using SPSS*. (D. B. Wright, Ed.) (Second Edi.). Thousand Oaks, CA: SAGE Publications, Inc.

Fingas, J. (2014). Two-thirds of Americans now have smartphones. *Engadget*. Retrieved March 01, 2014, from http://www.engadget.com/2014/02/11/two-thirds-of-americans-now-have-smartphones/

Gahran, A. (2012). Survey says most U.S. cell phone owners have smartphones; so what? *CNN.com*. Retrieved November 27, 2012, from http://www.cnn.com/2012/03/02/tech/mobile/smartphones-majority-pew-gahran/index.html

Gallizzi, M. (2013). Mobile-friendly or mobile-optimized websites. *Moire Marketing Blog*. Retrieved October 10, 2013, from http://www.moiremarketing.com/blog/mobile-friendly-or-mobile-optimized-websites

Gesenhues, A. (2013). Only 6% of top 100 Fortune 500 companies have sites that comply with Google's mobile requirements. *Search Engine Land*. Retrieved October 10, 2013, from http://searchengineland.com/only-6-of-top-100-fortune-500-companies-have-sites-that-comply-with-googles-mobile-requirements-164748

Giacopelli, N. M., Simpson, K. M., Dalal, R. S., Randolph, K. L., & Holland, S. J. (2013). Maximizing as a predictor of job satisfaction and performance: A tale of three scales. *Judgment and Decision Making*, *8*(4), 448–469.

Goldman, D. (2011). Smartphones have conquered PCs. *CNN.com*. Retrieved November 27, 2012, from http://money.cnn.com/2011/02/09/technology/smartphones_eclipse_pcs/index.htm

Goodman, E. (2013). There's a $20 billion pot of gold at the end of the mobile advertising rainbow. *ComScore*. Retrieved October 10, 2013, from http://www.comscore.com/Insights/Blog/Theres_a_20_Billion_Pot_of_Gold_at_the_End_of_the_Mobile_Advertising_Rainbow

Google. (2013). Changes in rankings of smartphone search results. *Google Webmaster Central Blog*. Retrieved October 10, 2013, from http://googlewebmastercentral.blogspot.com/2013/06/changes-in-rankings-of-smartphone_11.html

Granello, D. H., & Wheaton, J. E. (2004). Online Data Collection: Strategies for Research. *Journal of Counseling & Development*, *82*(4), 387–393. doi:10.1002/j.1556-6678.2004.tb00325.x

Hackman, J. R., & Oldham, G. R. (1975). Development of the Job Diagnostic Survey. *Journal of Applied Psychology*, *60*(2), 159–170. doi:10.1037/h0076546

Hardre, P. L., Crowson, H. M., & Xie, K. (2012). Examining Contexts-of-Use for Web-Based and Paper-Based Questionnaires. *Educational and Psychological Measurement*, *72*(6), 1015–1038. doi:10.1177/0013164412451977

Harman, R. P., Thompson, L. F., & Surface, E. A. (2009). *Understanding survey comment nonresponse and the characteristics of nonresponders.* Poster presented at the 24th annual meeting of the Society for Industrial and Organizational Psychology, New Orleans, LA.

Huang, J. L., Curran, P. G., Keeney, J., Poposki, E. M., & DeShon, R. P. (2011). Detecting and deterring insufficient effort responding to surveys. *Journal of Business and Psychology*, *27*(1), 99–114. doi:10.1007/s10869-011-9231-8

Illingworth, A. J., Morelli, N. A., Scott, J. C., & Boyd, S. L. (2014). Internet-based, unproctored assessments on mobile and non-mobile devices: Usage, measurement equivalence, and outcomes. *Journal of Business and Psychology*. doi:10.1007/s10869-014-9363-8

Illingworth, A. J., Morelli, N. A., Scott, J. C., Moon, S., & Boyd, S. (2013). *Equivalence of assessments on mobile devices: Impact of device software.* Paper presented at the 28th annual conference of the Society for Industrial and Organizational Psychology, Houston, TX.

Impelman, K. (2013). *Mobile assessment: Who's doing it and how it impacts selection.* Paper presented at the 28th annual conference of the Society for Industrial and Organizational Psychology, Houston, TX.

Jackson, D. N. (1976). *The appraisal of personal reliability.* Paper presented at the meetings of the Society of Multivariate Experimental Psychology, University Park, PA.

Johnson, J. A. (2005). Ascertaining the validity of individual protocols from Web-based personality inventories. *Journal of Research in Personality*, *39*(1), 103–129. doi:10.1016/j.jrp.2004.09.009

Joshi, D., & Avasthi, V. (2007). *Mobile Internet UX for Developing Countries.* Poster presented at Mobile HCI 07, Singapore.

Kelloway, E. K., Gottlieb, B. H., & Barham, L. (1999). The source, nature, and direction of work and family conflict: A longitudinal investigation. *Journal of Occupational Health Psychology*, *4*(4), 337–346. doi:10.1037/1076-8998.4.4.337

Kraut, A. I. (2006). Moving the needle: Getting action after a survey. In A. I. Kraut (Ed.), *Getting action from organizational surveys: New concepts, technologies, and applications* (pp. 1–30). San Francisco, CA: Jossey-Bass.

Lawrence, A., Wasko, L., Delgado, K., Kinney, T., & Wolf, D. (2013). *Does mobile assessment administration impact psychological measurement?* Paper presented at the 28th annual conference of the Society for Industrial and Organizational Psychology, Houston, TX.

Lee, J., & Rethemeyer, R. K. (2012). Virtual Interactions via Smartphones. In *Encyclopedia of Cyber Behavior*. IGI Global. doi:10.4018/978-1-4666-0315-8.ch016

Macey, W. H. (1996). Dealing with the data: Collection, processing, and analysis. In A. I. Kraut (Ed.), *Organizational surveys: Tools for assessment and change* (pp. 204–232). San Francisco, CA: Jossey-Bass.

MacIsaac, D., Cole, R. P., Cole, D. M., McCullough, L., & Maxka, J. (2002). Standardized Testing in Physics via the World Wide Web. *Electronic Journal of Science Education*, *6*(3). Retrieved from http://ejse.southwestern.edu/article/view/7681/5448

Madden, M., Lenhart, A., Duggan, M., Cortesi, S., & Gasser, U. (2013). *Teens and technology 2013*. Washington, DC. Retrieved from http://www.pewinternet.org/files/old-media//Files/Reports/2013/PIP_TeensandTechnology2013.pdf

Mahalanobis, P. C. (1936). *On the generalised distance in statistics.* Paper presented to National Institute of Sciences of India (pp. 49–55). Bengal, India.

McCarthy, J. M., Van Iddekinge, C. H., Lievens, F., Kung, M., Sinar, E. F., & Campion, M. A. (2013). Do candidate reactions relate to job performance or affect criterion-related validity? A multistudy investigation of relations among reactions, selection test scores, and job performance. *Journal of Applied Psychology*, *98*(5), 701–19. doi:10.1037/a0034089

Meade, A. W., & Craig, S. B. (2012). Identifying careless responses in survey data. *Psychological Methods*, *17*(3), 437–55. doi:10.1037/a0028085

Meade, A. W., & Pappalardo, G. (2013). *Predicting careless responses and attrition in survey data with personality.* Poster presented at the 28th Annual Meeting of the Society for Industrial and Organizational Psychology, Houston, TX.

Mehta, R., & Sivadas, E. (1995). Direct marketing on the Internet: An empirical assessment of consumer attitudes. *Journal of Direct Marketing*, *9*(3), 21–32. doi:10.1002/dir.4000090305

Moorman, R. H. (1991). Relationship between organizational justice and organizational citizenship behaviors: Do fairness perceptions influence employee citizenship? *Journal of Applied Psychology*, *76*(6), 845–855. doi:10.1037/0021-9010.76.6.845

Morelli, N. A., Illingworth, A. J., Scott, J. C., & Lance, C. E. (2012). *Are Internet-Based, Unproctored Assessments on Mobile and Non-Mobile Devices Equivalent?* Paper presented at the 27th annual meeting of the Society for Industrial and Organizational Psychology, San Diego, CA.

Morgan, K. M., & Thompson, L. F. (2013). *Attributions in mobile computer-mediated communication.* Poster presented at the 28th annual meeting of the Society for Industrial and Organizational Psychology, Houston, TX.

Naus, M. J., Philipp, L. M., & Samsi, M. (2009). From paper to pixels: A comparison of paper and computer formats in psychological assessment. *Computers in Human Behavior*, *25*(1), 1–7. doi:10.1016/j.chb.2008.05.012

Nichols, D. S., Greene, R. L., & Schmolck, P. (1989). Criteria for assessing inconsistent patterns of item endorsement on the MMPI: Rationale, development, and empirical trials. *Journal of Clinical Psychology*, *45*(2), 239–250. doi:10.1002/1097-4679(198903)45:2<239::AID-JCLP2270450210>3.0.CO;2-1

PCMag. (n.d.). Definition of:tablet computer. *PC Magazine*. Retrieved May 15, 2013, from http://www.pcmag.com/encyclopedia/term/52520/tablet-computer

Perlow, L. A. (2012). *Sleeping with your smartphone: How to break the 24/7 habit and change the way you work*. Boston, MA: Harvard Business Review Press.

Petronzio, M. (2014). Tablets expected to outsell PCs by 2015. *Mashable*. Retrieved October 11, 2014, from http://mashable.com/2014/03/07/tablet-pc-chart/

Pollock, E., Chandler, P., & Sweller, J. (2002). Assimilating complex information. *Learning and Instruction*, *12*(1), 61–86. doi:10.1016/S0959-4752(01)00016-0

Poncheri, R. M., Lindberg, J. T., Thompson, L. F., & Surface, E. A. (2007). A comment on employee surveys: Negativity bias in open-ended responses. *Organizational Research Methods*, *11*(3), 614–630. doi:10.1177/1094428106295504

Puro, J.-P. (2002). Mobile Communication, Private Talk, Public Performance. In J. E. Katz & M. A. Aakhus (Eds.), *Finland: a mobile culture* (pp. 19–29). Cambridge, UK: Cambridge University Press. doi:10.1017/CBO9780511489471.004

Qualtrics. (2014). Qualtrics. Provo, UT: Qualtrics. Retrieved from qualtrics.com

Radar, T. (2013). Best tablets 2013: our top 10 ranking. *Tech Radar*. Retrieved November 23, 2013, from http://www.techradar.com/us/news/mobile-computing/tablets/10-best-tablet-pcs-in-the-world-today-1079603

Raento, M., Oulasvirta, A., & Eagle, N. (2009). Smartphones: An Emerging Tool for Social Scientists. *Sociological Methods & Research*, *37*(3), 426–454. doi:10.1177/0049124108330005

Ranger, S. (2013). Surface tension: The long, strange history of the Windows tablet. *ZDNet*. Retrieved February 06, 2013, from http://www.zdnet.com/surface-tension-the-long-strange-history-of-the-windows-tablet-7000009947/

Reja, U., Manfreda, L. K., Hlebec, V., & Vehovar, V. (2003). Open-ended vs. close-ended questions in web questionnaires. *Advances in Methodology and Statistics (Metodološki Zvezki), 19*, 159–177.

Rivera, J., & van der Meulen, R. (2014). Gartner says worldwide tablet sales grew 68 percent in 2013, with Android capturing 62 percent of the market. *Gartner*. Retrieved October 12, 2014, from http://www.gartner.com/newsroom/id/2674215

Roberts, C. (2012, August 15). Smartphones rule half the U.S. market. *NY Daily News*. New York, NY. Retrieved from http://articles.nydailynews.com/2012-08-15/news/33220716_1_smartphone-market-t-mobile-usa-mobile-phones

Rogelberg, S. G., Conway, J. M., Sederburg, M. E., Spitzmuller, C., Aziz, S., & Knight, W. E. (2003). Profiling active and passive nonrespondents to an organizational survey. *Journal of Applied Psychology*, *88*(6), 1104–14. doi:10.1037/0021-9010.88.6.1104

Rogelberg, S. G., Luong, A., Sederburg, M. E., & Cristol, D. S. (2000). Employee attitudes surveys: Examining the attitudes of noncompliant employees. *Journal of Applied Psychology*, *85*(2), 284–293. doi:10.1037//0021-9010.85.2.284

Sanchez, C. A., & Branaghan, R. J. (2011). Turning to learn: Screen orientation and reasoning with small devices. *Computers in Human Behavior*, *27*(2), 793–797. doi:10.1016/j.chb.2010.11.004

Sanchez, C. A., & Goolsbee, J. Z. (2010). Character size and reading to remember from small displays. *Computers & Education*, *55*(3), 1056–1062. doi:10.1016/j.compedu.2010.05.001

Scarpello, V., & Jones, F. F. (1996). Why justice matters in compensation decision making. *Journal of Organizational Behavior*, *17*(3), 285–299. doi:10.1002/(SICI)1099-1379(199605)17:3<285::AID-JOB750>3.0.CO;2-0

Schwarz, N. (1999). Self-reports: How the questions shape the answers. *American Psychologist*, *54*(2), 93–105. doi:10.1037/0003-066X.54.2.93

Bureau of Labor Statistics (2014). *Current employment statistics*. Washington, DC. Retrieved from http://www.bls.gov/iag/tgs/iag31-33.htm#workforce

Stoughton, J. W., Gissel, A., Clark, A. P., & Whelan, T. J. (2011). Measurement invariance in training evaluation: Old question, new context. *Computers in Human Behavior*, *27*(5), 2005–2010. doi:10.1016/j.chb.2011.05.007

Stoughton, J. W., Thompson, L. F., & Meade, A. W. (2013). Examining applicant reactions to the use of social networking websites in pre-employment screening. *Journal of Business and Psychology*. doi:10.1007/s10869-013-9333-6

Technologies, 4C. (2013). Mobile friendly vs. mobile optimized vs. responsive design. *4C Blog*. Retrieved October 10, 2013, from http://blog.cccctech.com/mobile-friendly-vs-mobile-optimized-vs-responsive-design/

Thompson, L. F., & Surface, E. A. (2007). Employee surveys administered online: Attitudes toward the medium, nonresponse, and data representativeness. *Organizational Research Methods, 10*(2), 241–261. doi:10.1177/1094428106/294696

Thompson, L. F., & Surface, E. A. (2009). Promoting favorable attitudes toward personnel surveys: The role of follow-up. *Military Psychology*, *21*(2), 139–161. doi:10.1080/08995600902768693

Thompson, L. F., Surface, E. A., Martin, D. L., & Sanders, M. G. (2003). From paper to pixels: Moving personnel surveys to the web. *Personnel Psychology*, *56*(1), 197–227. doi:10.1111/j.1744-6570.2003.tb00149.x

Thorndike, F. P., Carlbring, P., Smyth, F. L., Magee, J. C., Gonder-Frederick, L., Ost, L.-G., & Ritterband, L. M. (2009). Web-based measurement: Effect of completing single or multiple items per webpage. *Computers in Human Behavior*, *25*(2), 393–401. doi:10.1016/j.chb.2008.05.006

Tippins, N. T., Beaty, J., Drasgow, F., Gibson, W. M., Pearlman, K., Segall, D. O., & Shepherd, W. (2006). Unproctored Internet testing in employment settings. *Personnel Psychology*, *59*(1), 189–225. doi:10.1111/j.1744-6570.2006.00909.x

Tourangeau, R. L., Rips, L. J., & Rasinski, K. A. (2000). *The Psychology of Survey Response*. Cambridge, UK: Cambridge University Press.

Weigold, A., Weigold, I. K., & Russell, E. J. (2013). Examination of the equivalence of self-report survey-based paper-and-pencil and internet data collection methods. *Psychological Methods*, *18*(1), 53–70. doi:10.1037/a0031607

Whelan, T. J. (2008). *Antecedents of anonymity perceptions in web-based surveys.* Poster presented at the 23rd annual meeting of the Society for Industrial and Organizational Psychology, San Francisco, CA.

Whitney, L. (2014). Android loses some US market share but remains top dog. *C-Net*. Retrieved October 12, 2014, from http://www.cnet.com/news/android-loses-some-us-market-share-but-remains-top-dog/

Wilhelm, A. (2014). At current pace, Tablets will outsell PCs by Q2 2014. *Techcrunch.com*. Retrieved from http://techcrunch.com/2013/07/29/at-current-pace-tablets-will-outsell-pcs-by-q2-2014/

Table 1

Occupational Background of Study Respondents by Condition

Occupation	SP-NMO (*N* = 56)	SP-MO (*N* = 67)	T-NMO (*N* = 50)	T-MO (*N* = 44)	Computer (*N* = 75)	Total %*
Computer and mathematical	7	8	11	4	8	13.0
Sales and related	6	9	4	4	9	11.0
Office and administrative support	6	6	3	4	11	10.3
Education, training, and library	8	5	4	6	5	9.6
Business and financial operations	4	3	4	7	8	8.9
Management	5	3	3	2	6	6.5
Arts, design, entertainment, sports, and media	3	0	3	5	5	5.5
Production	2	6	1	1	3	4.5
Life, physical, and social science	1	4	5	1	1	4.1
Health practitioners and technical	1	3	3	1	3	3.8
Food preparation and serving related	3	1	1	3	3	3.8
Community and social services	2	3	0	1	1	2.4
Transportation and material moving	0	3	1	0	3	2.4
Healthcare support	1	1	2	2	1	1.7
Protective services	2	0	1	0	2	1.7
Legal	2	1	0	0	1	1.4
Personal care and service	0	2	1	1	0	1.4
Farming, fishing, and forestry	0	3	0	0	1	1.4
Architecture and engineering	0	0	1	0	2	1.0
Construction and extraction	0	1	1	0	1	1.0
Installation, maintenance, and repair	0	0	1	2	0	1.0
Military specific	1	1	0	0	1	1.0
Building grounds cleaning and maintenance	0	2	0	0	0	0.7

Note. *N* = 292, includes participants that attrited, SP = Smartphone, T = Tablet, respondents were asked to select their occupation from the list of O*NET Occupational Taxonomy Standard Occupational Classifications, O*NET was developed under the sponsorship of the U.S. Department of Labor and is the primary source of occupation information in the United States, * total % does not equal 100 due to rounding and 4 participants electing not to disclose occupation

Table 2

Summary of Scales Used for Employee Opinion Survey

Scale	No. items	Example item	Response scale	α	Source
1. Perceived Organizational Support	17	"The organization values my contribution to its well-being."	1 (*strongly disagree*) to 5 (*strongly agree*)	0.96	Eisenberger, Huntington, Hutchison, and Sowa (1986)
2. Job Satisfaction	5	"Generally speaking, I am very satisfied with this job."	1 (*strongly disagree*) to 5 (*strongly agree*)	0.89	Hackman and Oldham (1975)
3. Turnover Intentions	4	"I am thinking about leaving this organization."	1 (*strongly disagree*) to 5 (*strongly agree*)	0.95	Kelloway, Gottlieb, and Barham (1999)
4. Person-Organization Fit	30	"This organization encourages and rewards loyalty."	1 (*strongly disagree*) to 5 (*strongly agree*)	0.87	Bretz and Judge (1994)
5. Intrinsic Work Motivation	6	"My opinion of myself goes up when I do this job well."	1 (*strongly disagree*) to 5 (*strongly agree*)	0.71	Hackman and Oldham (1975)
6. Organizational Justice	18	"Your supervisor considers your viewpoint."	1 (*strongly disagree*) to 5 (*strongly agree*)	0.95	Moorman (1991)
7. Pay Fairness	15	"Determining the pay for my job."	1 (*very dissatisfied*) to 5 (*very satisfied*)	0.96	Scarpello and Jones (1996)
8. Open-ended Comment Questions	5	"Please use the space below to provide additional information or to make comments about your satisfaction with your job that has not been covered to this point."			Adapted from Harman, Thompson, and Surface (2009)

Table 3

Descriptive Statistics and Correlations among the Study Variables

Variable	*M*	*SD*	1	2	3	4	5	6	7	8	9
1. Time-to-completion	14.42	7.68	–								
2. Attrition	14%	0.35	0.19**	–							
3. Instructed Response Items	0.61	0.98	-0.16*	-0.10	–						
4. Even-odd Consistency Index	-3.10	21.88	-0.07	-0.04	0.01	–					
5. Maximum LongString Index	8.31	4.38	-0.01	0.40**	-0.04	-0.02	–				
6. Mahalanobis D	14.14	6.85	0.05	0.17**	0.25**	-0.14*	-0.33**	–			
7. Open-ended Comment Length	13.11	15.87	0.36**	0.05	-0.45	0.01	0.02	-0.13	–		
8. Open-ended Comment Skips	4.04	1.67	-0.17**	-0.16**	0.02	0.02	0.06	-0.12	-0.28**	–	
9. Survey Satisfaction	3.68	1.09	-0.02	0.69**	-0.11	-0.03	-0.06	-0.08	0.15	-0.03	(0.94)

N = 251, **p* < .05, ***p* < .01, coefficient alpha reliabilities on diagonal, *N* = 292 for correlations with attrition

Table 4

Criterion Means, Standard Deviations, and 95% Confidence Intervals by Condition

	Smartphone-NMO (N = 40)				Smartphone-MO (N = 57)				Tablet-NMO (N = 44)				Tablet-MO (N = 43)				Computer (N = 67)			
Condition	*M*	*(SD)*	CI_L	CI_U	*M*	*(SD)*	CI_L	CI_U	*M*	*(SD)*	CI_L	CI_U	*M*	*(SD)*	CI_L	CI_U	*M*	*(SD)*	CI_L	CI_U
Mobile-optimization Manipulation Check	2.71	(1.09)	2.36	3.06	2.10	(0.54)	1.95	2.24	1.84	(0.92)	1.55	2.12	1.62	(0.81)	1.37	1.87	–	–	–	–
Time-to-completion	15.83	(8.62)	13.07	18.59	15.28	(8.67)	12.98	17.58	15.35	(9.18)	12.56	18.15	13.47	(5.00)	11.93	15.01	12.83	(6.28)	11.30	14.36
Attrition	29%	(0.46)	0.59	0.84	15%	(0.36)	0.76	0.94	12%	(0.33)	0.46	0.79	2%	(0.15)	0.93	1.00	11%	(0.31)	0.82	0.96
IR Items	0.32	(0.92)	0.03	0.62	1.11	(0.70)	0.92	1.29	0.41	(0.79)	0.17	0.65	0.35	(0.87)	0.08	0.62	0.66	(1.21)	0.36	0.95
Even-Odd Cons.	-1.79	(7.01)	-4.04	0.45	-3.11	(21.16)	-8.77	2.56	-1.18	(5.90)	-2.98	0.62	-7.96	(43.77)	-21.60	5.68	-2.07	(12.82)	-5.20	1.05
Max LongString	8.03	(4.18)	6.69	9.36	8.11	(4.31)	6.96	9.25	9.25	(4.61)	7.85	10.65	7.35	(4.13)	6.08	8.62	8.64	(4.54)	7.53	9.75
Mahalanobis D	15.06	(6.81)	12.88	17.24	15.11	(7.29)	13.18	17.05	13.90	(8.63)	11.28	16.53	12.59	(5.97)	10.75	14.43	13.92	(5.54)	12.57	15.27
OE Comment Length	8.88	(7.50)	4.35	13.41	14.48	(10.17)	9.43	19.54	11.06	(10.74)	5.54	16.58	10.52	(6.65)	7.22	13.83	16.53	(25.16)	6.78	26.29
OE Comment Skips	4.15	(1.73)	3.60	4.70	4.18	(1.53)	3.77	4.58	4.02	(1.65)	3.52	4.52	3.84	(1.77)	3.29	4.38	3.99	(1.72)	3.57	4.40
Survey Satisfaction	3.10	(1.15)	2.73	3.47	3.39	(1.02)	3.12	3.66	3.54	(1.43)	3.10	3.97	4.11	(0.86)	3.84	4.37	4.09	(0.68)	3.92	4.25

Note. N = 251, N = 292 for attrition, N = 94 for open-ended comment length, IR = Instructed Response, Cons. = Consistency, OE = Open-ended

Table 5

Univariate ANOVA and Planned Comparison Results for Time-to-completion, Attrition, and Open-Ended Comment Quality

	M (SD)												Contrast *d*s	
Dependent Variable	Smartphone		Tablet		Mobile[a]		Computer		*F*	*df* (between, within)	*p*	η^2	1	2
1. Time-to-completion	15.51	(8.61)	14.42	(7.43)	15.00	(8.07)	12.83	(6.28)	2.44	2, 248	0.015	0.02	0.30‡	0.14
2. Attrition	21%		7%		15%		11%		5.15	2, 273†	0.001	0.03	-0.12	-0.41‡
3. OE Comment Length	12.13	(9.43)	10.78	(8.75)	11.42	(9.03)	16.53	(25.16)	1.11	2, 91	0.056	0.02	-0.27	0.15
4. OE Comment Skips	4.16	(1.60)	3.93	(1.70)	4.05	(1.65)	3.99	(1.72)	0.49	2, 248	0.102	<0.01	0.04	0.14

Note. *N* = 251, *N* = 292 for attrition analysis, *N* = 94 for respondents completing open-ended comments, hypotheses are directional thus all *p* values one-tailed, † *df* rounded when homogeneity assumption violated and robust test used, ANOVA = Analysis of Variance, OE = Open Ended, [a] Mobile is a combination of both smartphone and tablet conditions, For all planned comparisons mobile compared with computer first (contrast 1), followed by smartphone to tablet (contrast 2), ‡ indicates significant planned comparison

Table 6

Univariate Analysis of Variance, Standardized Discriminant Function Coefficients, and Tukey Post Hoc Pairwise Tests for Close-ended Data Quality Indices by Mobile Condition

				M				
Dependent Variable	*F(3, 178)*	*p*	η^2	SP-NMO	SP-MO	T-NMO	T-MO	Std. Discriminant *f(x)* Coefficients
1. Instructed Response	10.08	0.000	0.10	0.33[a]	1.07[abc]	0.41[b]	0.36[c]	-0.79
2. Even-Odd Consistency	0.67	0.574	0.01	-1.79	-3.11	-1.18	-7.96	0.43
3. Maximum LongString	2.09	0.104	0.01	8.03	7.89	9.25	7.04	0.54
4. Mahalanobis Distance	1.17	0.324	0.00	15.06	15.37	13.90	12.87	0.81

Note. $N = 249$, $^{**}p < .01$, SP = Smartphone, T = Tablet, Standardized Discriminant Function Coefficient, Superscripts indicate significant Tukey comparisons

Table 7

Correlations among Close-ended Data Quality Indices

Variable	*M*	*SD*	1	2	3	4
1. Instructed Response	0.61	0.98	–			
2. Even-Odd Consistency	-3.10	21.88	0.01	–		
3. Maximum LongString	8.30	4.38	-0.04	-0.02	–	
4. Mahalanobis Distance	14.14	6.85	0.25**	-0.14**	-0.33**	–

N = 251, *$p < .05$ **$p < .01$

Smartphone-NMO Survey

Smartphone-MO Survey

Figure 1. Example of differences between survey presentation by level of mobile-optimization.

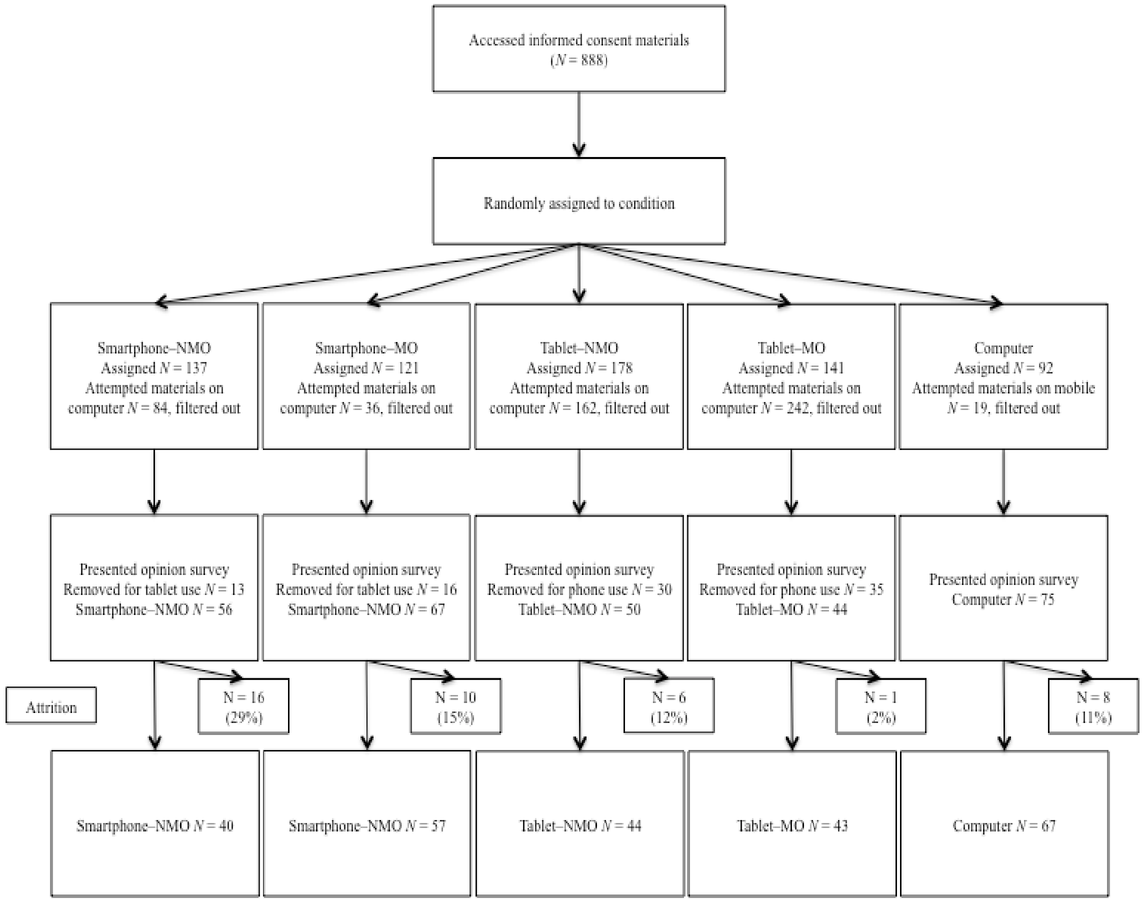

Figure 2. Flow of participants through each stage of the experiment.

APPENDIX

Appendix A.

Proposal Document

Organizational Opinions Untethered: Mobile technologies in survey deployment

The advancement of the organizational and psychological sciences relies on self-report survey data, asking people to rate their perceptions, attitudes, and personality, among other topics. The effort, attention, and affective reactions of employees is critical to the success of organizational survey initiatives, which rely on engaged participants attending to and completing the measures of interest (Meade & Craig, 2012; Rogelberg et al., 2000; Thompson et al., 2003). Over the past decades, surveys have undergone a transformation, evolving from paper-and-pencil formats to emailed hyperlinks and web-hosted solutions that participants can fill out on their own devices, at their convenience (Granello & Wheaton, 2004; Kraut, 2006). The transition to Internet surveys created the opportunity to more easily gather larger samples quickly, lowering the cost of data collection, and easing data entry, while producing a potentially user-friendly experience (Macey, 1996; Naus et al., 2009; Weigold et al., 2013). Moreover, the shift to online surveys has led to an increase in the administration of employee opinion surveys, a common means of gauging employee attitudes and perceptions on a range of issues (Kraut, 2006; Rogelberg et al., 2000; Thompson & Surface, 2009).

Paralleling this shift to online surveys is the growth of smartphone and tablet usage. By 2010, smartphones, defined as “programmable mobile phones with relatively sophisticated sensing capabilities, increasing storage capacity, and built-in networking,” outpaced shipments of the personal computer (PC) (Goldman, 2011; Raento, Oulasvirta, & Eagle, 2009, p. 427). By early 2012, nearly 90% of the United States population, or 276 million people, used mobile phones (Gahran, 2012). By 2013, market research demonstrated that smartphones were used by 65% of the United States population, up from 18% in 2009 (Fingas, 2014; Roberts, 2012). Additionally, nearly 70% of new phones purchased, are "smart" (Roberts, 2012). Similarly, the use of tablet computers, general-purpose computers contained in a single panel that utilize touch screens for input, is rapidly expanding (PCMag, n.d.). First introduced by Microsoft at an industry tradeshow in late 2000, the tablet computer gained popularity quickly after the introduction of the iPad in 2010 (Ranger, 2013). Early estimates of tablet sales predicted more tablets sold than PCs by 2016 (DisplaySearch, 2012). However, in short time that figure was pushed forward two years and estimates have tablets outselling PCs the second quarter of 2014 (Wilhelm, 2014). Moreover, this is not just an American trend, smartphones and tablets are increasingly making worldwide access to the Internet ubiquitous, helping to bridge the so-called "digital divide," a theoretical division between "those who have" and "those who do not" with respect to internet access (Chong & de Mendoza, 2012; Joshi & Avasthi, 2007).

The capacity to access the Internet, inherent to both smartphones and tablets, provides employees the opportunity to complete employee opinion surveys via a mobile device. In the case of employee opinion surveys, smartphones and tablets provide an option for the mobile workforce frequently away from the office on travel, or those who do not have the time or resources to complete the survey at work. Mobile devices are often available, providing ample opportunity to work on a survey from a location of one's choosing. For example, employees with mobile devices could work on a survey from: an airport, while waiting for an appointment, in a coffee shop, or while watching TV (Perlow, 2012). Mobile devices provide another option for those who would prefer to complete the survey away from the office; for example, those working in public spaces where there is some concern about others seeing their computer screen during survey completion or those who are concerned about the anonymity of kiosks or other measures taken by an organization to promote survey response anonymity (Whelan, 2008).

However, the ability of employees to access opinion surveys via mobile devices is not without potential drawbacks. For instance, using a smartphone or tablet to complete an opinion survey operates in opposition to one of the touted advantages of online instruments, increased consistency of administration. Consistency, with respect to Internet surveys, refers to the delivery of an instrument with identical instructions, precise timing, and uniform item and page presentation for all participants (Tippins et al., 2006). When employees access opinion surveys on their mobile device, organizations forfeit the consistency of administration because of constraints inherent to smartphones and tablets. For instance, smartphones and tablets generally have smaller screens than desktop and laptop computers, causing users to scroll more to read text, such as survey items or instructions (Sanchez & Branaghan, 2011). Smartphones typically display only fifteen lines of thirty to forty characters on the screen compared to a desktop screen with approximately forty lines of one hundred characters (Lee & Rethemeyer, 2012). Additionally, smartphones and tablets generally include a standard QWERTY keyboard on a small touchscreen or possibly a tactile keyboard with very small buttons placed below the screen (Morgan & Thompson, 2013). Users could connect a mouse or keyboard via the Bluetooth capability of the device in order to remedy some of these deficiencies. However, it is presently not “the norm” for most users to sacrifice the portability and convenience of the device by committing time and resources to connecting an external mouse or keyboard. As such, users often do not have the ability to type with two hands while completing a survey. As a result, mobile devices can be more difficult to use than desktop and laptop computers, making input relatively cumbersome.

As smartphones and tablet computers become the most common means of accessing information on the Internet, examining the effects on organizational survey efforts grows critical (Doverspike et al., 2012; Joshi & Avasthi, 2007; Morelli et al., 2012; Sanchez & Branaghan, 2011). Internet surveys have received considerable attention, with researchers investigating a range of topics: attrition, psychometric properties, and satisfaction, to name just a few (Rogelberg et al., 2003; Stoughton et al., 2011; Thompson & Surface, 2007; respectively). Although the psychological and organizational sciences were quick to recognize the side effects of mobile device Internet capability for job applicants, where online access permits them the ability to take screening/selection tests via smartphones or tablets (e.g., Doverspike et al., 2012; Illingworth et al., 2013; Lawrence et al., 2013; Morelli et al., 2012), less attention has been paid to the phenomenon in the employee opinion survey literature. Accordingly, this study will address this gap in the literature by examining the differences between smartphones, tablets, and personal computers with respect to: (a) the quality of data produced by the survey-takers, (b) the affective reactions of the survey participants to an employee opinion survey, and (c) whether or not level of mobile optimization influences the degree to which the survey device utilized affects these outcomes. This phenomenon will be examined in a U.S. context.

The Mobile Internet

By mid-2013, smartphones and tablets accounted for more Internet browsing time than PCs in the United States (Goodman, 2013). However, the mobile user experience can vary dramatically from website-to-website, and best practices are rapidly changing. Mobile-optimized (MO) websites are the current industry standard for a satisfactory mobile user experience. An MO-website is built for smartphones and tablets or auto-detects mobile devices and reformats, acknowledging the smaller screen, streamlining navigation with bigger text and buttons, with less requirement to scroll or zoom (Gallizzi, 2013; Technologies, 2013). Often, MO-websites take advantage of “touch” options, with push-to-call or email, used throughout the page (Technologies, 2013). Conversely, non-mobile-optimized (NMO) websites are designed to display on a smartphone or tablet just as they would on a PC, only smaller (Gallizzi, 2013; Technologies, 2013). For smartphone and tablet users, this means that they are often required to scroll left and right to view text cut off by the smaller screen, referred to as web-clipping, as well as zoom to better display smaller text (Albers & Kim, 2002; Sanchez & Goolsbee, 2010). In the popular press and marketing literature, NMO sites are referred to as “mobile-friendly;” however, this format for web-display is less than ideal and arguably not friendly. Accordingly, mobile-friendly websites are referred to hereafter as non-mobile-optimized throughout the text.

Effect of Mobile Use on Employee Opinion Survey Data Quality

In short, smartphones and tablet computers are changing the way people use the Internet. As mentioned above, the relatively small existing body of literature concerning smartphones and tablets for work tends to concern applicants using the devices for pre-employment tests (e.g., Illingworth et al., 2013; Impelman, 2013; Morelli et al., 2012), past studies have not addressed the implications for data quality on employee opinion surveys. To examine this issue thoroughly, the quality of both closed-ended and open-ended survey responses needs to be considered.

Careless Responding. The quality of closed-ended rating data can be studied by examining what the scientific literature refers to as "careless responding" indices. Inattentive or careless responding, a subset of content nonresponsivity, is defined as responding without concern for the item content (Meade & Craig, 2012; Nichols et al., 1989). This responding can manifest itself in a variety of data patterns. For instance, an employee could choose to respond at random to all closed-ended items; or, a nonrandom pattern could be employed where all "agree" responses are input, or a "strongly disagree, disagree, neither agree/disagree, agree, strongly agree," pattern of item response could be exhibited. The common theme of careless responding is a failure to respond to the *content* of the items regardless of the motivation of the survey taker (Nichols et al., 1989).

Careless responding can result in: skipped items, instrument non-completion, non-normal data, and other problems as response patterns exhibit carelessness. Whatever the mechanism, this data loss or carelessness is significant because it results in exclusion of cases from the dataset, which affects overall sample size (Hardre et al., 2012). In the case of careless responding that exhibits a pattern, the resultant data can be decidedly nonrandom, impacting the quality of data, especially the internal consistency of instruments or item equivalence between subjects (Meade & Craig, 2012). Said differently, the raw data provided by a respondent may not accurately reflect his or her true level on the measured construct. Moreover, previous examinations of careless responding in an employee hiring/selection setting (where an applicant is likely to be motivated to provide high quality data) revealed the phenomenon to be as high as five percent (Ehlers et al., 2009). In another study of employees' propensity to carelessly respond, Curran, Kotrba, and Denison (2010) found the base-rate to range from 7%-50% depending on the indicator of careless response used. Even in a setting that should engender conscientious survey completion (i.e., organizational surveys) it seems that many participants will respond carelessly, necessitating investigations of the factors that contribute to the inattention to survey item content. Increased survey time-to-completion and increased cognitive load created by using mobile devices to complete surveys may be two such factors that contribute to careless responding.

In brief, employees' use of mobile devices to complete surveys is a possible antecedent of careless responding. Previous research has demonstrated that using small electronic devices rather than computers to complete reasoning tasks increases the time-to-completion (Sanchez & Branaghan, 2011). It is possible that these findings would be similar for survey completion on smartphones and tablets. While it is generally accepted that participant interest in a psychological survey decreases the likelihood of careless responding, longer instruments likely increase fatigue and cause participant attention to wane, even with highly motivated samples such as employees (Berry et al., 1992; Ehlers et al., 2009; Meade & Craig, 2012; Schwarz, 1999; Tourangeau et al., 2000). Therefore, even if the content of the survey is kept shorter to avoid careless responding, the constraints presented by smartphones and tablets, such as smaller screens, may contribute to workload and careless response.

Additionally, the smaller screens of smartphones and tablets compared to computers likely increases cognitive load for survey takers, requiring them to remember information not in their visual field when text is cut off due to screen size. Whereas long term memory is unlimited, working memory is limited (Thorndike et al., 2009). This is fundamental to the four maxims of cognitive load theory: (1) humans have a limited working memory, which can only process a limited number of elements at any given time, (2) individuals have unlimited long term memory that can be used to overcome deficits in working memory, (3) the mind creates schemas in long term memory that assimilate information in order to reduce the burden on working memory, and (4) the mind then processes this information automatically, as opposed to consciously, further reducing the burden on working memory (Pollock et al., 2002; Thorndike et al., 2009). On smartphones, much of a user’s time is spent scrolling to read textual information clipped due to the size of the screen when on

NMO websites (Sanchez & Branaghan, 2011). Previous research has demonstrated increased scrolling results in increased cognitive load (MacIsaac et al., 2002). This should affect careless responding, as increased cognitive load serves to fatigue survey takers. Owing to the effect of the device itself on survey time-to-completion and participant cognitive load, survey takers may be more likely to respond carelessly. In light of the possible increase in survey time-to-completion and cognitive load of survey takers, I propose the following hypotheses:

Hypothesis 1: Smartphones (*H1a*) will affect time-to-completion such that those who complete a survey on a smartphone will take longer, followed by those completing a survey on a tablet (*H1b*), while those completing a survey on a computer are expected to take the least amount of time to complete a survey.

Hypothesis 2: Smartphones (*H2a*) will increase careless responding such that those who complete a survey on a smartphone will exhibit the most careless responding, followed by those completing a survey on a tablet (*H2b*), while those completing a survey on a computer are expected to demonstrate the least careless responding.

Hypothesis 3: There will be an interaction between mobile device and presence of mobile-optimization, such that the degree to which smartphones (*H3a*) and tablets (*H3b*) increase careless responding depends on presence or absence of mobile-optimization.

For the hypotheses above, content nonresponsivity will be tested across several different indices of careless responding, as careless responding can manifest itself in several distinct ways.

Open-ended comments. The move to Internet surveys renewed interest in open-ended comments (i.e., questions with no pre-determined response options), which are now generally included on organizational surveys (Kraut, 2006; Poncheri et al., 2007). The quality of open-ended comments can be critical to a survey effort as managers and key organizational decision makers often pay particular attention to open-ended responses, especially in instances where open- and close-ended questions differ in results (Poncheri et al., 2007). The increased use of mobile devices for survey completion however may have implications for the collection of open-ended responses.

For open-ended comments, the quality of data may be determined in part by the length of response (Denscombe, 2007; Hardre et al., 2012; Mehta & Sivadas, 1995). Longer response are often more refined, containing more vivid descriptions, rich with information (Hardre et al., 2012). For employees, it is hypothesized that the renewed interest in open-ended responses has been tolerated because often-times individuals type faster than they write (Thompson et al., 2003). Indeed, the assertion that employees may not mind open-ended comments for Internet surveys is supported by the increase in length of open-ended comments on online compared to paper-and-pencil surveys (Kraut, 2006). However, smartphones and tablets may make open-ended comments cumbersome. The difficulty of input is apparent when comparing speed; smartphone users' typical input speed is approximately 20 words per minute, compared to 60 words per minute on the computer (Bao et al., 2011). If Thompson and colleagues (2003) are correct about survey respondents accepting open-ended comments because of ease of entry on a computer, the move to smartphones and tablets while continuing to include open-ended questions on surveys may negatively affect quality of employee open-ended comments. Accordingly I propose the following hypothesis:

> ***Hypothesis 4:*** Smartphones (*H4a*) will affect length of open-ended comments such that those who complete a survey on a smartphone will have shorter open-ended comments, followed by those completing a survey on a tablet (*H4b*), while those completing a survey on a computer are expected to have the longest open-ended comments.

In addition, open-ended comments can lead to skipped items, also referred to as item nonresponse. Past examinations of open-ended responses versus closed-ended responses revealed more item nonresponse for open-ended responses (Reja et al., 2003). This is hypothesized to occur because of the increased burden of providing open-ended written comments (Reja et al., 2003). As mentioned above, smartphones and tablets generally make open-ended responses more cumbersome because of the technical limitations of the devices. Accordingly, I propose the following hypothesis:

> ***Hypothesis 5:*** Smartphones (*H5a*) will affect nonresponse to open-ended items such that those who complete a survey on a smartphone will skip the greatest number of open-ended questions, followed by those completing the

survey on a tablet (H5b), while those completing the survey on a computer are expected to skip the fewest open-ended questions.

Satisfaction with Mobile Surveys

In addition to data quality, considering participant reactions to organizational survey efforts is also important (Hardre et al., 2012; Thompson & Surface, 2009). Satisfaction is important to contemplate as Thompson and Surface (2007) suggested that employees' dislike or satisfaction with a particular survey medium (e.g., mobile device or computer) could influence response behavior, such as attriting before completely filling out the instrument, on an organizational survey if respondents have a negative affective reaction to the survey. Survey nonresponse is detrimental because it decreases sample size, thereby lowering statistical power. Given the importance of reactions to a survey, there is a need to consider how device may influence user acceptance of a survey initiative (Thompson et al., 2003). Currently no data exists for researchers or practitioners to answer the question of whether employees are more satisfied taking surveys on their computer or a mobile device.

The visual presentation of survey items has been shown to influence the affective impression of a user (Cho et al., 2011). As noted above, NMO- and MO-websites offer different visual mobile user experiences. Survey items on NMO-websites require participants to scroll left and right to view item content cutoff by the smaller screen (Gallizzi, 2013). This is perceived to be a poor user experience, which could affect survey respondents' satisfaction. MO-websites, on the other hand, are intentionally designed to be viewed on a smartphone or tablet, with streamlined navigation to decrease scrolling and zooming (Gallizzi, 2013).

Counteracting the potential negative effects caused by characteristics of mobile devices, the convenience of using a smartphone or tablet may alleviate concerns or increase approval. For instance, an organization's mobile workforce members may prefer the option of easy access to organizational surveys while away from the workplace. For this segment of an organization's workforce, a smartphone or tablet is more likely to have Internet access than a computer, permitting people to take a survey without the added effort of finding an Internet access point when away from office connectivity. It is therefore possible that the ability to immediately respond to a survey when a link is emailed, rather than waiting until access to a connected computer is available, may increase the acceptance of surveys taken on a smartphone or tablet. In 2001, Church posed the following question about paper-and-pencil vs. computer surveys, "Given the choice which method of response do employees prefer?" (p. 938). Following this line of inquiry, I propose the following research questions:

Research Question 1: Which survey device (i.e., smartphone, tablet, or computer) promotes the greatest satisfaction with the survey?

Research Question 2: Does level of mobile optimization (i.e., NMO vs. MO) affect survey taker satisfaction for mobile device users?

Method

Participants

Participants will be adults currently residing in the U.S. utilizing Amazon's Mechanical Turk (MTurk) crowdsourcing website. MTurk is an online marketplace that connects requesters (e.g., researchers) with individuals willing to do tasks unable to be completed by a computer, such as those requiring human intelligence. Previous investigations have found MTurk users to be more demographically diverse than university subject pools and produce data that meets or exceeds the psychometric standards of published research (Buhrmester et al., 2011). Moreover, published research not specifically investigating the efficacy of MTurk and instead examining psychological and organizational research questions has started to appear in the literature (e.g., Giacopelli et al., 2013; Stoughton et al., 2013). For a more detailed explanation of using MTurk in psychological research see Barger, Behrend, Sharek, and Sinar (2011) and Behrend, Sharek, Meade, and Wiebe (2011). To qualify for this study, participants will be required to have a computer, a smartphone, and a tablet and work 20 or more hours a week. Participants will be paid U.S. $1.00 for their participation in a *human intelligence task* (HIT), outlined below. The level of compensation is comparable to the median pay rate for research studies requiring a similar time and resource commitment.

Design

This study will use a between-groups design with random assignment to conditions. There are two independent variables of interest: (1) survey device and (2) website optimization. However, these two variables cannot be fully-crossed as survey takers utilizing a computer cannot experience a non-mobile-optimized website. Thus, participants will be randomly assigned to one of five conditions: (1) smartphone-NMO, (2) smartphone-MO, (3) tablet-NMO, (4) tablet-MO, and (5) computer. As smartphones continue to grow larger, the distinction between smartphone and tablet becomes blurred. In general, tablets range from 7- to 13-inches (Radar, 2013); this rule of thumb will be used to classify devices into the appropriate condition, with devices below 7 inches categorized a smartphones and devices above 7 inches to be categorized as tablets. There are two dependent variables of interest: (1) careless responding and (2) satisfaction with the survey. Careless responding is examined with respect to both closed- and open-ended items, and is assessed in a variety of ways, described below.

Procedure

An advertisement will be created on MTurk that contains a brief description of the study and a link to an informed consent form. The description will indicate that the study entails completing an employee opinion survey, and that in order to qualify for the study participants must own a smartphone, tablet, and a computer and work 20 or more hours each week. As of 2013, 30% of smartphone owners also own a tablet, a percentage that reflects how highly generalizable the sample is even when requiring a multitude of devices to be owned (Fingas, 2014). Additionally, the informed consent will explain to participants that their payment is contingent on completing the questionnaire on the appropriate device. After checking a box to electronically transmit their informed consent, participants will be asked to complete a survey. Participants will be randomly assigned to one of the five possible conditions via a JavaScript application embedded in the online study materials. At this point, participants will follow a link to their appropriate survey, which may require them to change devices to complete the questionnaire if they initiate the study on a computer and are assigned to a mobile condition or vice versa. Participants will be prompted, “Please navigate to [survey link] on your [device type] to complete the survey. I remind you that you must complete the survey on your [device type] to receive payment.” Additionally, a Qualtrics User Info type item will be employed to ensure that the switch from a computer to a mobile device is made for survey completion; User Info type items can limit survey completion to a specific device type (Qualtrics, 2014).

Mobile-optimization will be controlled for the NMO conditions by utilizing an iframe; an iframe is an inline frame used to embed another document (i.e., the survey) in another website, in this case one that does not permit mobile-optimization. Most survey software does not permit the option to “turn-off” mobile optimization when the capability exists. Because the study requires mobile optimization for two of the conditions the use of an iframe in a website that does not permit mobile optimization will allow the same survey software (i.e., Qualtrics) to be employed across all study conditions increasing the standardization between conditions. The survey will be five pages in length, 25 close-ended items per page, with response scale presented at the top of the page and prompt and radio button presented in matrix format and one open-ended question at the end of each page. The items for the employee opinion survey, described below, were chosen to represent the types of questions commonly used across a number of roles and industries. All of these questions will permit skipping. Participants will be asked to imagine they are responding to the survey for the organization they work 20 or more hours at each week. After the questionnaire is completed, participants will be debriefed.

Data collection will be terminated after 40 employee opinion questionnaires are completed within each of the conditions. An a priori power analysis was conducted using G*Power 3 (Faul et al., 2007). The results indicated that for a sample size of 200, analyses utilizing an F statistic with five conditions would have adequate statistical power at a value of 0.80 for $\alpha = .05$ to detect a medium effect size of 0.25 (see Cohen, 1988).

Measures

Demographics (10 items). Seven items will be administered to assess participants' age, gender, ethnicity, native language, country of birth, country of residence, conditions under which the survey is taken, hours worked per week, occupation, and education. Occupation will be assessed using the O*NET occupational taxonomy Standard Occupational Classification (SOC). O*NET has been developed under the sponsorship of the U.S. Department of Labor and is the primary source of occupation information in the United States. The SOC includes 23 major categories of occupations (e.g., Management or business and finance occupations). Participants will be asked to choose which of the 23 major categories their occupation falls under. These data will be collected to facilitate a description of the study sample and to test and control for any unintentional demographic differences between conditions. (See Appendix A)

Employee Opinion Survey (95 items). Respondents will fill out items adapted from Eisenberger, Huntington, Hutchison, and Sowa's (1986) Perceived Organizational Support

(17 items, α = XX), Hackman and Oldham's (1975) Job Satisfaction (5 items, α = XX), Kelloway, Gottlieb, and Barham's (1999) Turnover Intentions (4 items, α = XX), Bretz and Judge's (1994) Person-Organization Fit (30 items, α = XX), Hackman and Oldham's (1975) Intrinsic Work Motivation (6 items, α = XX), Moorman's (1991) Organizational Justice (18 items, α = XX), and Scarpello and Jones' (1996) Pay Fairness (15 items, α = XX) scales (see Appendix B).

Open-ended Questions (5 items). Five open-ended items will be administered to further gauge participants' employee opinion. Items were adapted from Harman, Thompson, and Surface (2009), a study of open-ended comments. An example item is, "Please use the space below to provide additional information or to make comments about the pay system at your organization that has not been covered to this point." Open-ended item comment completion will be scored continuously with scores ranging from 0 to 5. Additionally, length of open-ended comments completed will be measured using a word-count software option to determine the total number of words generated across all open-ended items.

Time-to-completion. Time-to-completion will be measured using an embedded marker in the survey content. This will be collected by the survey software; survey participants will not be required to make an entry for start and end times. Time will be measured continuously in seconds.

Indices of Data Quality. There are three types of post hoc methods for identifying careless responding: consistency indices, outlier indices, and study response time (Meade & Craig, 2012). Consistency indices refer to methods of identifying careless responders by matching similar items together, based on either the underlying construct or historical correlation, and examining whether there is a lack of consistent responding. Outlier indices look at a series of responses and the relative distances for these items to identify outliers. Finally, study response time often identifies a time threshold for careless responding, such that those respondents who take less time than the threshold are identified as careless responders.

Examining the relative merits of the different careless response indicators Meade and Craig (2012) made a number of practical recommendations. For cases in which robust correlations are of interest (e.g., employment surveys), they recommend using instructed response items (e.g., “Respond with ‘strongly agree’ for this item.”) and three post hoc careless response indices: the Even-Odd Consistency Index (Jackson, 1976), the Maximum LongString Index (Johnson, 2005), and the Mahalanobis D (Mahalanobis, 1936). In line with the recommendations of Meade and Craig (2012), each of these indices will be utilized to investigate careless response in the current study and scored so that higher values represent greater levels of careless responding.

Instructed Response Items (5 items). On each of the five pages of the survey, a single item will be included to assess participant response attention. These quality check items, recommended by Meade and Craig (2012) (e.g., “Respond with ‘strongly agree’ for this item.”), will be used as a continuous measure of respondent carelessness. Items will be scored 1 for incorrect and 0 for a correct response and summed across the five items, such that those exhibiting careless responding to the items have a higher score (see Appendix C).

Even-Odd Consistency Index. The Even-Odd Consistency Index is a consistency indicator of careless responding predicated on the idea that items from the same scale should correlate with each other for a particular individual (Huang et al., 2011). Huang and colleagues (2011) identified Even-Odd Consistency as one of the more discriminating indices of careless responding, with the power to identify careless responders in survey research while refraining from misspecifying normal patterns of response. Even-Odd Consistency will be computed by dividing the items from all of the scales on the employee opinion survey into two groups based on the order in which the items appear, even and odd (Jackson, 1976). Subscale scores will then be computed for each grouping of items (i.e., 14) based on the average value of each response for the group of items. The item groups will be corrected for length using the Spearman-Brown formula, as recommended by Jackson (1976). A within person correlation will then be calculated for the matching even and odd subscale scores to generate the final value for the Even-Odd Consistency Index. Lower individual internal consistencies are indicative of careless responding. For ease of interpretation these values will be transposed after scoring; accordingly, for all indicators of careless responding higher values will equate with increased carelessness.

Maximum LongString Index. The Maximum LongString Index is a consistency index for careless responding referring to the consecutive string of a particular response option for any given survey page (e.g., “strongly agree”). Costa and McCrae (2008) recommend LongString calculations for detecting careless responding, citing that none of their compliant study participants demonstrated particularly long strings of continuous responses for a particular response option. A response set consisting of the same response option for a given survey page is unlikely, especially given reverse worded options (Johnson, 2005). The Maximum LongString will be computed for each survey page using a Microsoft Excel array formula; an array formula can return multiple calculations on one or more of the items in an array, in this case values in a row of participant data. Like Meade and Craig (2012) I will only investigate the longest single string of response options; accordingly, the array will calculate the longest string for all options, but only return the greatest value. Again, higher scores are more likely to represent careless responding (Johnson, 2005).

Mahalanobis D. Mahalanobis distance, or Mahalanobis D, is an outlier index for identifying careless responding. Mahalanobis distance is a multivariate vector of a respondent's item response distances from the vector of response means (Meade & Craig, 2012). Ehlers et al. (2009) found Mahalanobis D to be an effective index for identifying inattentive responding to a job application, a setting where participants are likely highly motivated to respond attentively. Mahalanobis distance measures will be calculated for all study scales. Following the procedures of Meade and Craig (2012), separate distance measures will be calculated for each scale and averaged into a single Mahalanobis distance value to reduce the computational burden of using the raw, item-level data across all items. Higher values for Mahalanobis D indicate greater levels of careless responding.

Survey Satisfaction (7 items, α = XX). Respondent satisfaction with the survey device and format will be assessed using items adapted from Thompson and colleagues (2003). Items will be presented using a Likert-type scale, with responses ranging from 1 (*strongly disagree*) to 5 (*strongly agree*). An example item is, “This online format is a useful way to complete organizational surveys” (see Appendix D).

Manipulations Checks. There are two manipulations that require assessment: mobile-optimization and survey device. Accordingly, two different types of checks have been devised to ensure that participants have the correct experience on the right device.

MO Manipulation Checks (5 items, α = XX). Mobile optimization manipulations will be assessed with five items utilizing a five point Likert-scale, with responses ranging from 1 (*never*) to 5 (*always*). An example item is, “Did you enlarge the text (zoom in) at any point to better read or answer questions?” These items will only be administered to the mobile device conditions (see Appendix E).

Survey Device Checks (3 items). One item will be administered to assess the survey device utilized by the mobile condition participants. Sales data from 2013 was utilized to select the devices for the survey device list; additionally, an “other” category was included to account for devices that may not have been on the list as it was not intended to be exhaustive, but instead to pick out the “most likely” utilized devices for ease of coding. Additionally, an item will ask if respondent screen size is 7” or greater. These two items will only be administered to mobile device conditions. Finally, a Qualtrics user info type item will be embedded in the survey content of the mobile conditions to exclude all but mobile devices from taking the survey. As such, only mobile users will be able to take the mobile condition surveys (see Appendix E).

Proposed Analysis

Hypothesis 1. In order to assess *H1a* and *H1b* that mobile devices will affect time-to-completion on online surveys, a one-way analysis of variance (ANOVA) will be run using survey device (collapsed across optimization) as the independent variable and time-to-completion on the survey captured in seconds as the DV with follow-up post hoc Tukey tests.

Hypothesis 2. In order to assess *H2a* and *H2b* that mobile devices will increase careless responding compared to computers for online surveys, multivariate analysis of variance (MANOVA) will be run with survey device conditions collapsed across mobile optimization condition as the IV and the results of the continuous respondent carelessness variables as the DVs. This will be followed by both univariate ANOVAs and discriminant analysis to investigate the nature of the relationships between the variables, as recommended by Field (2005). The collapsed conditions will be used as the grouping variable and the indicators of careless responding will be entered as the independent variables for the discriminant analysis.

Hypothesis 3. In order to assess hypothesis 3 that there will be an interaction between mobile device and level of mobile-optimization, such that the degree to which smartphones (*H3a*) and tablets (*H3b*) affect careless responding depends on level of mobile-optimization a MANOVA will be run with study conditions entered as the IV and the careless responding variables as the DVs. This will be followed by both univariate ANOVAs and discriminant analysis to investigate the nature of the relationships between the variables.

Hypothesis 4. Hypothesis 4 that smartphones (*H4a*) and tablets (*H4b*) will decrease the length of open-ended comments by survey takers versus those on a computer will be assessed using a one-way ANOVA with post hoc Tukey tests with survey device (collapsed across optimization) as the IV and number of words in open-ended comments as the DV.

Hypothesis 5. In order to assess hypothesis 5 that smartphones (*H5a*) and tablets (*H5b*) will affect open-ended responses such that the use of mobile devices for survey completion will decrease completions of open-ended questions a one-way ANOVA with post hoc Tukey tests will be run with survey device (collapsed across optimization) as the IV and completion (number of open-ended items completed) as the DV.

Research Question 1. In order to address research question 1 [Which survey device (i.e., smartphone, tablet, or computer) promotes the greatest satisfaction with the survey?], a one-way ANOVA with post hoc Tukey tests will be run comparing the means for the five conditions with satisfaction as the DV.

Research Question 2. In order to address research question 2 [Does level of mobile optimization (i.e., NMO vs. MO] affect survey taker satisfaction for mobile device users?), a two-way independent ANOVA will be run with the mobile device and mobile-optimization entered as the IVs and survey satisfaction as the DV.

Appendix A.1.

Demographics Survey

Please fill in the blank or circle the number that corresponds to your answer to the following questions.

1. How old are you?
   _____ years
2. What is your gender?
   0 = Female, 1 = Male
3. What is your ethnicity?
   1 =African American, 2 = Asian American, 3 = Caucasian, 4 = Hispanic, 5 = Native American, 6 = Other
4. What is your native language? ________
5. What is your country of birth? ________
6. What is your current country of residence? ________
7. Under what conditions did you take the Survey? Check all that apply
   _____ I took the survey in the morning
   _____ I took the survey in the afternoon / midday
   _____ I took the survey in the evening / night
   _____ I took the survey while I was alone
   _____ It was possible for other people to see my responses while I took the survey
   _____ I took the survey at home where I live (e.g., your apartment, etc.)
   _____ I took the survey in a public place
   _____ I took the survey with music playing
   _____ I took the survey with the TV on
   _____ I took the survey in a distracting environment
8. How many hours do you work per week?
   _____ hours
9. What is your level of education?
   1 =Some High School, 2 = High School, 3 = Some college, 4 = College, 5 = Masters, 6 = PhD
10. Using the categories below, choose the one which best fits your occupation.
    a. Management
    b. Business and financial operations
    c. Computer and mathematical
    d. Architecture and engineering
    e. Life, physical, and social science
    f. Community and social services
    g. Legal

h. Education, training, and library
i. Arts, design, entertainment, sports and media
j. Healthcare practitioners and technical
k. Healthcare support
l. Protective services
m. Food preparation and serving related
n. Building and grounds cleaning and maintenance
o. Personal care and service
p. Sales and related
q. Office and administrative support
r. Farming, fishing, and forestry
s. Construction and extraction
t. Installation, maintenance, and repair
u. Production
v. Transportation and material moving
w. Military specific

Appendix A.2.

Employee Opinion Survey

Please read each statement carefully, and then use the rating scale below to indicate the extent to which you agree or disagree with each statement.

1 = strongly disagree
2 = somewhat disagree
3 = neither agree nor disagree
4 = somewhat agree
5 = strongly agree

Perceived Organizational Support

1. The organization values my contribution to its well-being.
2. If the organization could hire someone to replace me at a lower salary it would do so. [a]
3. The organization fails to appreciate any extra effort from me. [a]
4. The organization strongly considers my goals and values.
5. The organization would ignore any complaint from me. [a]
6. The organization disregards my best interests when it makes decisions that affect me. [a]
7. Help is available from the organization when I have a problem.
8. The organization really cares about my well-being.
9. The organization is willing to extend itself in order to help me perform my job to the best of my ability.
10. Even if I did the best job possible, the organization would fail to notice. [a]
11. The organization is willing to help me when I need a special favor.
12. The organization cares about my general satisfaction at work.
13. If given the opportunity, the organization would take advantage of me. [a]
14. The organization shows little concern for me. [a]
15. The organization cares about my opinions.
16. The organization takes pride in my accomplishments at work.
17. The organization tries to make my job as interesting as possible.

Job Satisfaction

1. Generally speaking, I am very satisfied with this job.
2. I am generally satisfied with the kind of work I do in this job.
3. I frequently think of quitting this job. [a]
4. Most people on this job are very satisfied with the job.
5. People on this job think of quitting. [a]

Turnover Intentions

1. I am thinking about leaving this organization.
2. I am planning to look for a new job.
3. I intend to ask people about new job opportunities.
4. I don't plan to be in this organization much longer.

Person-Organization Fit

1. This organization pays on the basis of individual performance.
2. This organization has a profit or gain sharing plan.
3. This organization makes promotions based mostly on individual performance.
4. This organization encourages competition between employees.
5. This organization encourages and rewards loyalty.
6. Teamwork and cooperation are valued and rewarded here.
7. When the organization has a good year it pays bonuses to the employees.
8. People generally have to work in groups to get their work done.
9. This organization offers long-term employment security.
10. This organization has a "fast-track" program.
11. This organization has/follows a promote-from-within policy.
12. The typical employee here works very hard to fulfill work expectations.
13. There is an emphasis on helping others.
14. Fairness is an important consideration in organizational activities.
15. When mistakes are made it is best be honest and "take your lumps"
16. I believe people should be paid on the basis of their individual performance.
17. When organizations make profits, I think they should share some of it with employees.
18. I believe promotions should be made on the basis of individual performance.
19. I believe competition between employees creates a healthy working environment.
20. I believe organizational loyalty should be encouraged and rewarded.
21. I believe teamwork and cooperation are valuable and should be rewarded.
22. When the organization has a good year I think it should pay bonuses to the employees.
23. I think it is better to work in groups to get work done.
24. I believe organizations should offer long-term employment security for their employees.
25. I believe organizations should have "fast-track" programs for their "best" employees.
26. I think organizations should try to promote-from-within whenever it is possible.
27. I try very hard to fulfill work expectations.
28. I place a high emphasis on helping others.
29. Fairness is an important consideration to me.

30. When I make mistakes, I am honest about it and “take my lumps.”

Motivation

1. My opinion of myself goes up when I do this job well.
2. I feel a great sense of personal satisfaction when I do this job well.
3. I feel bad and unhappy when I discover that I have performed poorly on this job.
4. My own feelings are generally not affected much one way or the other by how well I do on this job. [a]
5. Most people on this job feel a great sense of personal satisfaction when they do the job well.
6. Most people on this job feel bad or unhappy when they find that they have performed the work poorly.

Please read each statement carefully, and then use the rating scale below to indicate the extent to which you agree or disagree with each statement.

1 = strongly disagree
2 = somewhat disagree
3 = neither agree nor disagree
4 = somewhat agree
5 = strongly agree

Organizational Justice

Procedural Justice

1. The procedures used by your organization are designed to collect accurate information necessary for making decisions.
2. The procedures used by your organization are designed to provide opportunities to appeal or challenge the decision.
3. The procedures used by your organization are designed to have all sides affected by the decision represented.
4. The procedures used by your organization are designed to generate standards so that decisions could be made with consistency.
5. The procedures used by your organization are designed to hear concerns of all those affected by the decision.
6. The procedures used by your organization are designed to provide useful feedback regarding the decision and its implementation.
7. The procedures used by your organization are designed to allow for requests for clarification or additional information about the decision.

Interactional justice

1. Your supervisor considers your viewpoint.
2. Your supervisor is able to suppress personal bias.
3. Your supervisor provides you with timely feedback about decisions and the implications.
4. Your supervisor treats you with kindness and consideration.
5. Your supervisor shows concern for your rights as an employee.
6. Your supervisor takes steps to deal with you in a truthful manner.

Distributive Justice

1. You are fairly rewarded considering the responsibilities.
2. You are fairly rewarded in view of the amount of experience you have.
3. You are fairly rewarded for the amount of effort you put forth.
4. You are fairly rewarded for the work you have done well.
5. You are fairly rewarded for the stresses and strains of your job.

Pay Satisfaction

The statements below describe various aspects of your pay. For each statement, decide how satisfied or dissatisfied you feel about your pay.

1 = very dissatisfied
2 = dissatisfied
3 = neither satisfied nor dissatisfied
4 = satisfied
5 = very satisfied

1. Determining the pay for my job.
2. Determining pay raises.
3. How my pay raises are determined.
4. Determining the pay for my job relative to higher or lower level jobs than mine.
5. The way performance is reflected in my pay.
6. The frequency of pay raises.
7. Communicating pay policies and procedures.
8. Communicating pay issues of concern to me.
9. Answering questions about how my pay is determined.
10. Gathering information used to evaluate my performance.
11. Evaluating my performance.
12. Appealing performance decisions.
13. Monitoring my supervisor’s pay decisions.

14. Appealing pay decisions.
15. Resolving disagreements about my pay.

[a] reverse-scored items

Appendix A.3.

Open-ended Questions

1. Please use the space below to provide additional information or to make comments on your beliefs that the organization values your contributions that has not been covered to this point.
2. Please use the space below to provide additional information or to make comments about your satisfaction with your job that has not been covered to this point.
3. Please use the space below to provide additional information or to make comments about thoughts you have for leaving your organization that has not been covered to this point.
4. Please use the space below to provide additional information or to make comments about the sense of satisfaction you have when doing your job well that has not been covered to this point.
5. Please use the space below to provide additional information or to make comments about the pay systems at your organization that has not been covered to this point.

Appendix A.4.

Instructed Response Items

Using the scale below as a guide, indicate for each statement how much you agree or disagree with the statement.

1 = strongly disagree
2 = disagree
3 = neither agree nor disagree
4 = agree
5 = strongly agree

1. Respond with somewhat agree for this item.
2. Respond with strongly agree for this item.
3. Respond with somewhat disagree for this item.
4. Respond with strongly disagree for this item.
5. Respond with neither satisfied or dissatisfied for this item.

Appendix A.5.

Survey Satisfaction

Using the scale below as a guide, indicate for each statement how much you agree or disagree with the statement as they relate to the survey you just completed.

1 = strongly disagree
2 = somewhat disagree
3 = neither agree nor disagree
4 = somewhat agree
5 = strongly agree

1. This online format is a useful way to complete organizational surveys.
2. I am satisfied with the online process for this survey.
3. I would participate in future surveys administered this way.
4. The online format was an effective means of administration.
5. The online format was a valuable aid to assessing employee opinions.
6. The survey was administered in an efficient manner.
7. This survey format was convenient.
8. The administration of this survey was cumbersome. [a]
9. Overall, this survey format was excellent.

[a] reverse-scored items

Appendix A.6.

Manipulation Checks

Please indicate your experience with the survey you just completed by indicating for each statement how much you had to interact with the survey content on the survey you just completed.

1 = never
2 = rarely
3 = sometimes
4 = often
5 = always

Mobile Optimization

1. Did you enlarge the text (zoom in) at any point to better read or answer questions?
2. Did you have to scroll left to right at any point to better read or answer questions?
3. Did you turn your phone from portrait (longwise up-and-down) to landscape (longwise left-to-right) at any point while taking the survey?
4. Did you think the navigation buttons like “next” were difficult to use?
5. Did you think the radio buttons (the bubbles) were difficult to select?

Survey Device

1. What device did you use?
    a. iPhone
    b. Google Nexus 5
    c. HTC One
    d. Samsung Galaxy Note II
    e. Samsung Galaxy Note 3
    f. Samsung Galaxy S3
    g. Samsung Galaxy S4
    h. LG Optimus G Pro
    i. Motorola Moto X
    j. Nokia Lumina 1020
    k. iPad
    l. iPad Mini
    m. Google Nexus 7
    n. Sony Xperia Tablet Z
    o. LG G Pad 8.3
    p. Kindle Fire

q. Samsung Galaxy 7”
r. Other, please specify _______________

2. Is the screen on your device 7 inches or larger? yes/no