IDENTIFYING THE TYPES OF INSUFFICIENT EFFORT RESPONDERS

By

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ABSTRACT

With the increased use of surveys across organizations and academic arenas, ensuring the quality of data is critical. While there are many threats to validity, Insufficient Effort Responding (IER) is an underappreciated contributor. The current study employs a latent class analysis to assess the types of Insufficient Effort Responders in five archival data sets. Frequency of IER and the differential impacts of IER types on reliability are also assessed. Results indicate that there are three types of survey responders: conscientious responders, random IER responders, and patterned IER responders, each with their own characteristics. Furthermore, the removal of IER based on latent classes and a variety of detection indices are shown to have minimal but differential impact on reliability.

TABLE OF CONTENTS

LIST OF TABLES

LIST OF APPENDICES

CHAPTER 1: INTRODUCTION

Surveys are ubiquitous in today's data driven workforce. Organizations are continuously collecting survey data to assess a multitude of variables ranging from employee satisfaction to turnover intentions. Ensuring data quality is critical for survey methodologies. Checking the quality of data is a long-standing practice in which researchers employ techniques to ensure data validity. Threats to validity include negative impression management, positive impression management, extreme responders, neutral bias, and acquiescence (McGrath, Mitchell, Kim, & Hough, 2010). A unique and underappreciated threat to validity is insufficient effort responding.

Insufficient effort responding (IER) occurs when survey respondents do not pay attention to the survey items while responding (Huang, Curran, Keeney, Poposki & DeShon, 2012). This response set has many names in the literature: random responding, inattentive responding, careless responding, and insufficient effort responding. This phenomenon was originally referred to as "random responding". However, IER is often non-random and can be patterned (e.g., the participant selecting long strings of 'strongly agree.') (Huang et al., 2012; Meade & Craig, 2012). This paper will use the 'insufficient effort responding' terminology because it best exemplifies the nature of this type of validity threat; IER captures random and non-random unmotivated responding.

Despite the increase in literature indicating the magnitude of IER as a problem for survey collection methodologies, IER remains an underappreciated problem. IER negatively impacts the quality of data and can confound the statistical conclusions drawn from the data. Liu and colleagues assessed the attitudes and practices of Society of Industrial and Organizational Psychology (SIOP) members regarding IER (Liu, Bowling,

Huang, & Kent, 2013). They found that, overall, SIOP professionals seem to consider IER as a minor or moderate issue and in many cases do little to handle the threat. Additionally, SIOP professionals consider IER a larger issue with student data. However, research indicates that IER occurs frequently in other populations including recruited adults, police applicants, and employees (Berry, Wetter, Baer, Larsen, Clark, & Monroe, 1992; Curran, Kotrba, & Denison, 2010). The exact impact of IER on data quality and statistical conclusions is dependent on the type of IER (e.g., random or non-random IER). This thesis assesses the types of survey respondents in a variety of populations to build a foundation for studying the differential impact of IER by type of respondent.

CHAPTER 2: LITERATURE REVIEW

Defining Insufficient Effort Responding

It is important to distinguish between IER and other types of bad responding on surveys. Nichols and colleagues make the distinction between content responsive faking and content nonresponsivity (Nichols, Green, & Schmolck, 1989). Content responsive faking is the act of faking good or faking bad (i.e., positive and negative impression management) while content nonresponsivity involves responding to items to which the respondent did not attend (Nichols et al., 1989). For example, a respondent who is faking will actively attend to the item content and deliberately choose responses based on the desired impression (good or bad) while a respondent engaging in content nonresponsivity will simply select a response without attending to the item content. It has been suggested that these two phenomena are negatively related because faking requires carefully attending to the items; they in fact found that faking (socially desirable responding and impression management) was negatively correlated with IER. (Manicai & Rogge, 2014) IER is analogous to content nonresponsivity.

Additionally, a distinction between cognitive ability and motivation needs to be addressed in defining IER. Baer and colleagues defined IER as a respondent's unwillingness or inability to respond with attention (Baer, Ballenger, Berry, & Wetter, 1997). Yet, other authors discriminate unwillingness from inability in survey responding and define IER as the unwillingness, rather than the inability, to respond with sufficient effort (Liu, Bowling, Huang, & Kent, 2013). This inability can stem from linguistic capacity (Baer et al., 1997) or reduced cognitive resources at the back end of the survey due to survey length (e.g., survey fatigue) (Clark, Gironda, & Young, 2003). Survey

fatigue occurs when a respondent loses the ability to expend cognitive effort while IER occurs when the respondent has the cognitive resources to respond with sufficient effort but chooses not to (Liu et al., 2013). IER is broader in scope than survey fatigue and linguistic limitations because it is the unwillingness to respond with sufficient effort rather than the inability to respond with sufficient effort (Liu et al., 2013). Regardless, IER involves responding to survey items without regard to the item content.

Insufficient Effort Responding Prevalence

IER is not uncommon. Its prevalence has been assessed by researchers utilizing a variety of IER detection methods. Responding with insufficient effort can occur sporadically (partial IER) or entirely (complete IER) throughout a survey (Huang et al., 2012; Meade & Craig, 2012). Berry and colleagues found that partial IER occurs on the Minnesota Multiphasic Personality Inventory (MMPI), a widely-used personality inventory, at a moderate frequency with 29-60% of different populations engaging in partial IER (Berry et al., 1992). These populations had theoretically varying degrees of stake or interest in the outcome; their studies included undergraduate students, recruited adults, and police officer applicants (Berry et al., 1992). They found 3-7% of the population responded entirely with IER (Berry et al., 1992). Meade and Craig (2012) found that partial IER occurs with moderate prevalence with about 10-15% of respondents engaging in IER at least once. Additionally, they found 2-5% of data was rendered useless due to IER (Meade & Craig, 2012). Maniaci and Rogge (2014) also examined IER prevalence found a higher prevalence with 7.9% of participants identified as problematic due to excessive IER.

Causes of Insufficient Effort Responding

Causes of IER include respondent interest and motivation, environmental distraction, survey length, and social contact (Meade & Craig, 2012). Intrinsic motivation results in less IER and external incentives result in more IER (Maniaci & Rogge, 2014). In other words, respondents who are intrinsically motivated to complete the survey engage in less IER than respondents who are extrinsically motivated to take the survey, perhaps with a monetary incentive (Maniaci & Rogge, 2014). Additionally, Fleischer and colleagues note that low stakes data collection results in more IER; using Mturk to collect data for a research study, they found 42% IER prevalence, despite a warning that validity items were embedded in the survey (Fleischer et al., 2015). Environmental distraction is particularly influential in surveys administered online because respondents are more likely to experience distraction and engage in IER (Beach, 2001; Johnson, 2004). Survey length impacts IER with longer surveys enduring higher rates of IER, particularly in the latter half of the survey (Berry et al., 1992; Clark et al., 2003; Meade & Craig, 2012). Participant anonymity, or lack of social contact, increases the prevalence of IER (Meade & Craig, 2012).

Survey Attitudes, a respondent's attitude toward taking surveys, may also influence IER. Rogelberg and colleagues found that survey attitudes were related to respondent behaviors including response rate, following directions, and timeliness (Rogelberg, Fisher, Maynard, Hakel, & Horvath, 2001). Donegan (2007) conducted a research study to specifically examine the relationship between survey attitudes and IER. They found significant negative correlations between survey attitudes and IER; as survey attitudes became more positive, the frequency of IER decreased.

Insufficient Effort Responding Detection Methods

Survey Validity Items. Some IER detection methods are survey items included within the instrument. The infrequency approach methodology involves using items that have statistically low endorsement rates (Berry et al, 1992). Endorsing an infrequency item could be a sign of IER, but would require corroboration from another index. Bogus item approach involves using items that have a clear answer or are unlikely to be endorsed (e.g., "I often work 28 hours in a day"). Respondents who endorse bogus items would be flagged as insufficient effort responders (Beach, 2001). Another approach is the self-report method. The self-report approach involves directly asking participants whether their data should be used and asking them to report their diligence, their attention, their effort, etc. Individuals self-reporting low effort would be flagged. Directed response items are another survey item approach. Direct response items inform the respondent to answer in a certain way (e.g., "Select strongly disagree"). Respondents who miss these items are flagged. Additionally, a test-retest method can be employed by including items with identical content or psychologically similar content.

Post-hoc Indices. Some IER detection methods are statistical methods employed after completion of data collection (Meade & Craig, 2012). Time to complete the survey is a post-hoc index used to detect IER with the rationale that participants engaging in IER will be low outliers. Some post-hoc indices are aimed at capturing consistency. These include psychometric synonyms, psychometric antonyms, and individual reliability. Psychometric synonyms are items that are psychometrically and semantically similar and should be highly correlated; individuals with low consistency on psychometric synonym items would be flagged as engaging in IER. Psychometric antonyms are items that

naturally have a strong negative correlation; individuals tend to score low on one antonym item and high on the other antonym item. Individuals with low consistency on psychometric antonym items, rather than a strong negative correlation, would be flagged as engaging in IER. Individual reliability may include overall reliability across a unidimensional measure using Cronbach's alpha or reliability on all even items and all odd items on a unidimensional measure, called even-odd consistency, using the Spearman-Brown formula. Other indices capture individuals responding identically to many items in a row (i.e., over-consistency). These include maximum long-string responses and average long-string responses—individuals providing identical responses to many consecutive items would be identified as an insufficient effort responder. Additionally, multivariate outlier analysis is a useful post-hoc index for detecting IER.

Detection Method Proficiency. Meade and Craig (2012) conducted a comprehensive assessment of these detection methods. Overall, they found that detection methods are more effective with complete random responders than with partial random responders. Also, detection methods were more effective when random responders made up a larger percentage of the sample than when they made up a smaller percentage of the sample. In general, the Mahalanobis D (multivariate outlier analysis) performed best. However, in the case of normally distributed complete random responses, even-odd consistency was a more efficient detection method than Mahalanobis D. Bogus Items were validated and found to be very sensitive to IER and discriminate well between attentive and insufficient effort responders (Huang, Bowling, Liu, & Li, 2014; Meade & Craig, 2012). One problem with bogus items is that they can be humorous and respondents may endorse them because they are funny (Meade & Craig, 2012). The self-

report method was useful but should not be used alone (Meade & Craig, 2012). In general, Meade and Craig (2012) suggest using bogus or directed response items, self-report items, and a cursory look at survey completion if rigorous data cleaning is unnecessary. When more rigorous data cleaning is necessary, they suggest using the post-hoc procedures including consistency indices, long-string indices, and the Mahalanobis D.

History of Insufficient Effort Responding Detection

IER detection began with the Minnesota Multiphasic Personality Inventory (MMPI) validity scales (Nichols et al., 1989). The MMPI utilized the Test-Retest Scale and the Carelessness Response Scale; the Test-Retest Scale was composed of identical items and the Carelessness Response Scale was composed of items similar in content; both were aimed at assessing consistency (Nichols et al., 1989). The MMPI-2 includes the F, Fb, and VRIN validity scales. The F and Fb scales employ the infrequency methodology with less than 10 percent of the population able to endorse them; the Fb is aimed at the back half of the survey (Berry et al, 1992). The F and Fb capture both IER and faking (Berry et al, 1992). The VRIN scale is composed of item pairs similar in content and captures only IER (Berry et al, 1992). Since then, other instruments, such as the Multidimensional Personality Questionnaire (MPQ), California Psychological Inventory (CPI), and the Hogan Personality Inventory (HPI), have begun including IER detection indices. Additionally, IER scales have been created as stand-alone instruments. These include the random response scale, attentive responding scale, directed question scale, and the conscientious responders scale (Beach, 2001; Maniaci & Rogge, 2014; Marjanovic, Struthers, Cribbie, & Greenglass, 2014). Burke created a validity instrument,

Survey of Organizational Attitudes and Perceptions (SOAP), that is tailored to the organizational setting. It contains an infrequency scale and an inconsistency scale and has been validated for use in organizational settings (Burke, 1996; Burke 1998).

Insufficient Effort Responding as a Validity Threat

IER is a threat to validity because it negatively affects data quality. IER affects the reliability and statistical conclusions drawn from data. Osborne and Blanchard (2011) conducted a study which demonstrated that IER decreases effect sizes of experimental interventions. Maniaci and Rogge (2014) found that IER contributed error variance and decreased the reliability of unidimensional measures. Similarly, Huang and colleagues found that removing IER increased reliability and Eigen values of a unidimensional scale (Huang et al., 2012). A review on response biases in survey data suggests that IER moderates the effects of experiment manipulations (McGrath et al., 2010). Taken together, these studies conclude that IER increases the probability of a type II error.

Yet, some studies have found that IER can, in some cases, increase type I error (Credé, 2010; Fleischer, Meade, & Huang, 2015). In a study conducted by Credé (2010), results indicated that IER can inflate correlations or lead to a failure to detect existing bivariate relationships. Fleischer and colleagues also note that IER can increase error or increase reliability depending on the nature of the responding and the nature of the instrument (Fleischer et al., 2015). Specifically, these authors suggest that, while in most cases IER decreases reliability, ability tests are susceptible to increased reliability estimates when inattentive responders are present (Fleischer et al., 2015). Another research study suggested that there are three types of variance: true score variance of

attentive responders, random error variance of IER, and systematic variance associated with IER (Huang, Liu, & Bowling, 2015). Results showed that IER can cause relationships to appear that otherwise do not exist (Huang et al., 2015).

IER can affect the dimensionality and factor structure of an instrument. Research has indicated that IER in combination with negatively keyed items erroneously leads to an additional factor (Kam & Meyer, 2015; Merritt, 2012; Schmitt & Stults, 1985; Woods, 2006). Specifically, IER leads to the emergence of a second 'negatively worded' factor on a unidimensional scale. Kam and Meyer found that systematic or "patterned" responders (e.g., the participant selecting long strings of 'strongly agree') are the root of the problem—they select the same response for many similar 'normally worded' items in a row and also select similarly for the negatively keyed item. Relatively small base-rates of 5-10% IER prevalence can impact factor structure and other statistical conclusion (Credé, 2010; Woods, 2006). With recorded prevalence rates between 2 and 15%, it is clear that data validity is a major concern.

Types of Insufficient Effort Responders

These differential effects of IER on statistical conclusions suggest that the nature of IER may vary across respondents. Meade and Craig (2012) conducted a latent profile analysis on survey responders' responses to a variety of IER detection methods and discovered three classes: conscientious responders, random responders, and patterned responders. Maniaci and Rogge (2014) replicated this analysis and uncovered the same classes. Similar classes were found by Kam and Meyer (2015). Additionally, research has tied personality traits to IER corroborating the idea that there are different "types" of responders (Furnham, Hyde, & Trickey, 2015; Maniaci & Rogge, 2014; Meade &

Pappalardo, 2013). For example, more extraverted, less agreeable, less conscientious people were more likely to engage in IER (Meade & Pappalardo, 2013).

Conscientious Responders. Meade and Craig (2012) found 89% of the sample to be conscientious responders with valid survey responses. Compared to the other two classes, conscientious responders spent the most time completing the survey. They also missed few bogus items and had small average and maximum long-strings. Additionally, conscientious responders had high consistencies among psychometric synonyms, antonyms, and even-odd consistencies.

Random Responders. Meade and Craig (2012) found 9% of the sample to be random responders who respond with insufficient effort. Random responders spent less time on the survey than conscientious responders. Random responders also missed many bogus items, had low consistencies, and had small average and maximum long-strings.

Patterned Responders. Meade and Craig (2012) identified 2% of the sample as patterned responders who respond with insufficient effort. They tend to be 'overly consistent' (Meade & Craig, 2012). Similar to random responders, patterned responders spent less time on the survey than conscientious responders. Patterned responders miss many bogus items. Patterned responders, not surprisingly, had moderately high consistencies on psychometric synonyms, psychometric antonyms, and individual reliability. Additionally, compared to the other classes, patterned responders had very large average and maximum long strings.

Hypothesis 1: Within each of the five obtained data sets, two from the southeastern U.S. workforce and three from a southeastern U.S. university, we expect the frequency of Insufficient Effort Responding to be about 15% of total respondents.

Hypothesis 2: Within the obtained data sets, we expect to uncover three types of Insufficient Effort Responders including conscientious responders, patterned responders, and random responders.

Research Question 1: What is the frequency of the different types of Insufficient Effort Responders found within the obtained data sets?

Research Question 2: What is the effect of IER on scale reliability within the obtained data sets?

CHAPTER 3: METHODS

Data Sets

The present study used archival data obtained from previous studies. Five data sets were analyzed for types of IER responders. For an overview of these data sets, their measures, and their method of IER detection, see Table 1.

Data Set 1: Career Indecision. The current data set was obtained from a study assessing career indecision and low retention rates (Farrar, 2015). Data were obtained from 525 undergraduate student participants recruited through the SONA system research pool at a southeastern university. Participants were 40% male and 60% female with an average age of 19.97 (SD = 3.79). Measures included a Career Indecision Profile (65 items and four factors; Cronbach's alpha ranged from .87 to .98), Brief Calling Scale (four items and two factors; Cronbach's alpha found to be approximately .79), Maximization Inventory (34 items and three factors; Cronbach's alpha between .72 and .89), O*NET Interest Measure (60 items and six factors; no reliability estimates), IPIP (50 items and five factors; Cronbach's alpha between .77 and .86) , Vocational Identity Status Assessment (30 items and three factors; Cronbach's alpha between .79 and .82), Occupational and Organizational Commitment Scale (36 items and three factors; Cronbach's alpha between .77 and .83), Turnover Cognitions Scale (five items and one factor; Cronbach's alpha between .90 and .94) , and Academic Fit Scale (six items and one factor; Cronbach's alpha found to be approximately .75). Post-hoc indices were calculated on three measures: career indecision profile, occupational and organizational commitment scale, and the IPIP (see Appendix A for these measures). The study employed four directed response quality assurance items.

Data Set 2: Change Fatigue. The current data set was obtained from a study assessing change fatigue and organizational culture (Perel, 2015). Data were obtained from 472 United States employees working at least 25 hours a week recruited through Amazon's Mechanical Turk. Participants were 44% male and 56% female with 44% between the ages of 25 and 34. They were compensated $0.20. Measures included change fatigue (six items and one factor; Cronbach's alpha found to be approximately .84), organizational culture (six items and four factors; Cronbach's alpha between .71 and .90), organizational change (six items and two factors; Cronbach's alpha between .76 and .90), work locus of control (twenty items and one factor; Cronbach's alpha found to be about .88), emotional exhaustion (nine items and one factor; Cronbach's alpha found to be about .89), organizational commitment (nine items and one factor; Cronbach's alpha found to be about .87), and turnover intentions (five items and one factor; Cronbach's alpha found to be about .89). Post-hoc indices were calculated on two measures: organizational commitment and work locus of control (see Appendix B for these measures). The study employed 4 directed response quality assurance items.

Data Set 3: Job Analysis. The current data set was obtained from a consulting project to develop a selection and promotion system for highway patrol officers in the southeastern region of the United States. Data were obtained from approximately 732 people recruited through the consulting project requirements. Approximately 96% were male and 4% were female with an average age of 42.41 (SD = 8.65). The survey was comprised of 825 job analysis items assessing tasks, knowledge, and competencies. It also included the HEXACO-60 (60 items and 6 factors; Cronbach's alpha between .73 and .80) and the I-ADAPT measure of adaptive performance (55 items and eight factors;

Cronbach's alpha found to be about .79). Post-hoc indices were calculated on both measures. The survey employed four directed response quality assurance items embedded within the I-ADAPT and HEXACO-60 measures. See Appendix C for the I-ADAPT and HEXACO-60 items. Although the dataset is titled 'Job Analysis' for understanding the nature of the survey, job analysis items were not assessed in any way.

Data Set 4: Work Ethic. This dataset was obtained from a study assessing the factor structure of the Multidimensional Work Ethic Profile (MWEP; Wright, 2016). Data were obtained from 414 undergraduate students recruited through the SONA system research pool at a southeastern university. Measures included a scale for attitudes toward questionnaires (nine items and one factor), the MWEP (65 items and seven factors; Cronbach's alpha between .75 and .89), the MWEP short form (28 items and seven factors; Cronbach's alpha between .75 and .86), and the NEO-PI-R (240 items and five factors; Cronbach's alpha between .89 and .95). Post-hoc indices were calculated on both the MWEP and NEO-PI-R. See Appendix D for the MWEP and see Costa and McCrae (1992) for the NEO-PI-R.

Data Set 5: Big Five. The current data set was obtained from a study assessing the psychometric properties of the NEO-PI-R (Dieker, 1998). Data were obtained from 838 undergraduate students recruited through the SONA system research pool at a southeastern university. The survey was comprised of only the NEO-PI-R and the Survey of Organizational Attitudes and Perceptions (SOAP) to assess IER. Post-hoc indices were calculated on the NEO-PI-R. See Appendix E for SOAP items and see Costa and McCrae (1992) for the NEO-PI-R.

Insufficient Effort Responding Detection Methods

Direct Response Items. The direct response items for each of these datasets followed the general format of, “For quality assurance purposes, please select ‘strongly agree.’” Selecting anything but the directed response on these items was indicative of IER. Some variant of this direct response item was used in data set one (Career Indecision), data set two (Change Fatigue), and data set three (Job Analysis). Data sets four (Work Ethic) and five (Big Five) did not use directed response quality assurance items.

Survey of Organizational Attitudes and Perceptions (SOAP). The SOAP is a 40-item survey developed as an IER detection method tailored to the organizational setting. It contains an infrequency scale and an inconsistency scale and has been validated for use in organizational settings (Burke, 1996; Burke, 1998). The inconsistency scale included pairs of items with substantively similar content such as, “I often have the chance to learn new things on my job” and “I seldom have the chance to learn new things in my job.” Respondents responding inconsistently to these items, in this case by positively endorsing each item in the pair, would indicate IER. The infrequency scale included items to which disagreement is unlikely such as, “I believe that loyalty to an organization should be rewarded.” A lack of endorsement on these items was indicative of IER. Data set five (Big Five) employed the SOAP method for detecting insufficient effort responders.

Table 1

Archival Data Sets and IER Detection Method

Data set	Measure	Items	Factors	Researched Reliability	IER Detection
1. Career Indecision (Farrar, 2015)	Career Indecision Profile*	65	4	.87-.98	4 Direct Response Items
	Brief Calling Scale	4	4	.79	
	Maximization Inventory	34	3	.72-.89	
	ONET Interest Measure	60	6	-	
	IPIP*	50	5	.77-.86	
	Vocational Identity Status Assessment	30	3	.79-.82	
	Occupational and Organizational Commitment Scale*	36	3	.77-.83	
	Turnover Cognitions Scale	5	1	.90-.94	
	Academic Fit Scale	6	1	.75	
2. Change Fatigue (Perel, 2015)	Change Fatigue	6	1	.84	4 Direct Response Items
	Organizational Culture Assessment Instrument	6	4	.71-.90	
	Organizational Change	6	2	.76-.90	
	Work Locus of Control*	20	1	.88	
	Emotional Exhaustion	9	1	.89	
	Organizational Commitment Questionnaire*	9	1	.87	
	Turnover Intentions	5	1	.89	
3. Job Analysis	Job Analysis Questions	825	--	--	4 Direct Response Items
	HEXACO-60*	60	6	.73-.80	
	I-ADAPT*	55	8	.79	
4. Work Ethic (Wright, 2016)	MWEP*	65	7	.75-.89	
	MWEP Short Form	28	7	.75-.86	
	NEO-PI-R*	240	5	.89-.95	
5. Big Five (Dieker, 1998)	NEO-PI-R*	240	5	.89-.95	SOAP

*Measures assessed for IER using post-hoc indices

Statistical Analyses

Analyses were done separately for each data set. Scores were calculated for each IER index (e.g., maximum long-string, within-person standard deviation, direct response) within each data set. These scores were used to break the cases into categories for each IER index because categories are necessary for the latent class analysis. IER indices included direct assessments as well as post-hoc indices. Direct assessments were direct response questions and SOAP. Post-hoc indices included maximum long-string (maximum number of times the individual selects the same response option in a row) and within-person standard deviation (how much the individual's response option choice tends to vary across a scale or factor). All scores were calculated after list wise deletion for the specified instrument. For example, when calculating long-string for the NEO-PI-R, list wise deletion was completed for the NEO-PI-R before calculating long-string. Frequency of IER was assessed based on different indices and a latent class analysis was performed on IER indices for each dataset to identify the types of IER testing two, three, and four class models. See below for details regarding the calculation of IER indices for each data set.

Direct Response Items. Four direct response questions (e.g., "Mark strongly disagree") are used in the Career Indecision, Change Fatigue and Job Analysis datasets. An overall score on the four direct response questions in each dataset was calculated based on the number of incorrect responses with scores ranging from 0 – 4.

SOAP Items. SOAP, an attentiveness scale for organizations, was used in the Big Five dataset. Scores were calculated on both the infrequency and inconsistency SOAP scales. Higher infrequency and inconsistency scores indicate more IER. These scores

were broken into categories of IER using suggested cut-off scores provided by Burke (1996, 1998). The first category of IER was any score within 1.5 standard deviations of the mean inconsistency or infrequency score, the second category was between 1.5 and 2 standard deviations beyond the mean, and the third category consisted of cases 2 standard deviations beyond the mean.

Maximum Long-String. Maximum long-string was calculated across each measure within each of the five datasets. In the Career Indecision dataset, maximum long-string was calculated across Career Indecision, Organizational Commitment, and IPIP. This score was then translated into a categorical variable based on standard deviations away from the mean maximum long-string across cases. Individuals with maximum long-string scores within 1.5 standard deviations comprised the category of individuals not indicated by maximum long-string; those between 1.5 and 2 standard deviations were caught for moderate IER based on maximum long-string; those who were 2 standard deviations beyond the mean were caught for high IER based on maximum long-string. Maximum long-string was calculated similarly for each of the instruments within the Job analysis data set, Work Ethic data set, and Big Five data set. In the Change Fatigue dataset, due to the short nature of each of the instruments, final IER categories are based on IER across both instruments instead of separately within each instrument. Cases identified for neither instrument comprised the first group, cases identified for one of the two instruments made up the second group, and cases identified for both instruments made up the third group of IER for maximum long-string.

Within-Person Standard Deviation. Within-person standard deviation was calculated for each case across each factor in each measure for each dataset. In the Career

Indecision dataset, within-person standard deviation was calculated in each factor within Career Indecision (4 factors), Organizational Commitment (3 factors), and IPIP (5 factors). This score was then translated into a categorical variable based on standard deviations away from the mean within-person standard deviation across cases. Individuals with within-person standard deviation scores within 1.5 standard deviations of the mean comprised the category of individuals not indicated by within-person standard deviation while those over 1.5 standard deviations were indicated for IER. Then, for each instrument, levels of IER are identified based on the number of factors for which each case was identified. Cases identified for no scales comprised the first group, cases identified between 0% and 50% of scales made up the second group, and cases identified between 50% and 100% of scales made up the third group of IER for within-person standard deviation. Within-person standard deviation was calculated similarly for the measures within the Job analysis data set, Work Ethic data set, and Big Five data set. In the Change Fatigue dataset, due to the short nature of each of the instruments, final IER categories are based on IER across both instruments instead of separately within each instrument. Cases identified for neither instrument comprised the first group, cases identified for one of the two instruments made up the second group, and cases identified for both instruments made up the third group of IER for within-person standard deviation.

CHAPTER 4: RESULTS

The five data sets were analyzed separately. They were each analyzed for the frequency of insufficient effort responding, the types of insufficient effort responding as indicated from the latent class analysis, and the impact of insufficient effort responding on the reliability of instruments within the data set. IER frequencies are identified using the described indices (long-string, within-person standard deviation, direct response, SOAP) for each instrument and occasionally calculated across instruments, such as direct response. Latent class analyses were used to test the hypothesized three class model and models with one less and one more latent class than hypothesized (i.e., for two, three, and four class models). Then, reliabilities were assessed with IER removed where IER was identified and removed using the accepted latent class model as well as the original IER indices.

Career Indecision Data Set

IER Frequency. The frequency of IER varied based on the chosen index; each IER index was calculated for every instrument in the data set. See Table 2 for frequencies of IER broken down by detection method and instrument. The IER indices detecting the smallest percentage of people, each of the three long-string indices, reported frequencies just over 3%. The IER index detecting the most people, within-person standard deviation, reported frequencies between 17% and 24%. The direct response index identified 18% of responders for IER, wherein anyone missing one or more questions was identified for IER. The long-string indices identified lower frequencies of IER than the hypothesized 15% in hypothesis one. Alternately, the within-person standard deviation indices tended

to identify a higher prevalence of IER than hypothesized. Direct response was nearest to the hypothesized frequency.

Table 2
Career Indecision Data Set: Frequency of IER by Instrument

IER Index	Percent
Long-String	
Career Indecision	
No IER	96.67%
Mod IER	0.95%
High IER	2.38%
Occupational and Organizational Commitment	
No IER	95.83%
Mod IER	1.97%
High IER	2.19%
IPIP Long-String	
No IER	96.52%
Mod IER	1.00%
High IER	2.49%
Within-Person SD	
Career Indecision	
No IER	76.48%
Mod IER	22.09%
High IER	1.43%
Occupational and Organizational Commitment	
No IER	82.24%
Mod IER	13.60%
High IER	4.17%
IPIP	
No IER	76.87%
Mod IER	21.39%
High IER	1.74%
Overall Direct Response	
0 Wrong	82.17%
1 Wrong	8.40%
2 Wrong	4.51%
3 Wrong	1.84%
4 Wrong	3.07%

Latent Class Analysis and Frequencies. A latent class analysis was conducted for two, three, and four class models to test for the types of insufficient effort responders (see Table 3 for fit statistics) revealing that the three-class model was statistically the best fit. The three-class model proved better than the two-class model $\Delta\chi^2(17) = 49.38$, $p < .001$. The four-class model was not better than the three-class model $\Delta\chi^2(17) = 21.06$, $p = .22$. Two additional rules of thumb for assessing fit include a small Akaike Information Criterion (AIC) and the relative drop of G^2 in comparison to degrees of freedom (Lanza, Collins, Lemmon, & Schafer, 2007). Each of these results corroborates the chi-square test and supports hypothesis two that there would be three types of responders. The characteristics of the different classes based on response probabilities supports that the classes are patterned responders, random responders, and conscientious responders. See Table 4 for response probabilities. There were 72% in the conscientious class, 21% in the random class, and 7% in the patterned class. The conscientious class was characterized by response probabilities that were largely non-IER on all IER indices (86-99%). The random class was characterized by larger response probabilities for moderate IER on the within-person standard deviation IER indices (42-56%). The patterned class was characterized by larger response probabilities for high IER on the long-string IER indices (23-31%) and missing direct response questions (14%- 26%).

Table 3
Model Data Fit of the Two, Three, and Four Class Model of Career Indecision IER Indices

	Fit Index		
Model	χ^2 (df)	G^2	AIC
2 Class	2541.56 (3611)	282.55	348.55
3 Class	2492.18 (3594)*	233.17	333.17
4 Class	2471.12 (3577)	212.11	346.11

*$p < .05$

Table 4
Career Indecision: Item Response Probabilities

IER Index	Conscientious (72%)	Random (21%)	Patterned (7%)
Response Category 1: No IER			
CI Long-String	0.98	1.00	0.65
OC Long-String	0.99	0.92	0.69
IPIP Long-String	0.99	0.97	0.61
CI Within-Person SD	0.87	0.51	0.44
OC Within-Person SD	0.94	0.43	0.82
IPIP Within-Person SD	0.87	0.43	0.75
Direct Response	0.86	0.88	0.21
Response Category 2: Moderate IER			
CI Long-String	0.01	0.00	0.04
OC Long-String	0.01	0.05	0.08
IPIP Long-String	0.00	0.00	0.15
CI Within-Person SD	0.13	0.48	0.35
OC Within-Person SD	0.06	0.42	0.00
IPIP Within-Person SD	0.12	0.56	0.06
Direct Response	0.09	0.05	0.14
Response Category 3: High IER			
CI Long-String	0.01	0.00	0.31
OC Long-String	0.00	0.03	0.23
IPIP Long-String	<0.01	0.03	0.24
CI Within-Person SD	0.00	0.01	0.21
OC Within-Person SD	0.00	0.14	0.18
IPIP Within-Person SD	<0.01	0.01	0.19
Direct Response	0.03	0.04	0.25
Response Category 4: Three missed direct questions			
Direct Response	0.01	0.00	0.14
Response Category 5: Four missed direct questions			
Direct Response	0.01	0.03	0.26

Reliabilities. See Tables 5-7 for reliabilities. The reliability of the Career Indecision factors, Occupational Commitment factors, and IPIP Factors do not appear to change much with different types of IER removed. That said, the small differences in reliability tend indicate a larger reliability for data subsets without random responders, direct response IER, within-person standard deviation IER, and all bad responders

(patterned and random). The data subset without long-string IER mostly revealed slightly lower reliabilities, but this result is less stable across measures. The data subset without patterned IER was mixed in its impact on reliability. The largest, positive differences emerged when within-person IER was removed.

Table 5
Cronbach's Alpha for the Four Career Indecision Scales

		Type of IER Removed					
	All	RR	PR	PRR	DR	LR	WR
Neuroticism/Negative Affectivity	0.92	0.92	0.92	0.92	0.92	0.92	0.93
Choice/Commitment Anxiety	0.96	0.96	0.96	0.96	0.97	0.97	0.97
Lack of Readiness	0.86	0.87	0.85	0.86	0.85	0.86	0.88
Interpersonal Conflicts	0.87	0.88	0.87	0.88	0.87	0.87	0.91

Note: RR: Random Responders Removed, PR: Patterned Responders Removed, PRR: Patterned and Random Responders Removed, DR: Direct Responders Removed, LR: Long String Responders Removed, WR: Within-Person Standard Deviation Removed

Table 6
Cronbach's Alpha for the Three Organizational Commitment Scales

		Type of IER Removed					
	All	RR	PR	PRR	DR	LR	WR
Affectivity	0.84	0.85	0.85	0.85	0.85	0.84	0.86
Continuity	0.84	0.84	0.85	0.85	0.85	0.84	0.86
Normative	0.81	0.82	0.81	0.82	0.81	0.80	0.82

Note: RR: Random Responders Removed, PR: Patterned Responders Removed, PRR: Patterned and Random Responders Removed, DR: Direct Responders Removed, LR: Long String Responders Removed, WR: Within-Person Standard Deviation Removed

Table 7

Cronbach's Alpha for the Five IPIP Factors

		Type of IER Removed					
	All	RR	PR	PRR	DR	LR	WR
Extraversion	0.88	0.89	0.90	0.90	0.90	0.90	0.90
Conscientiousness	0.86	0.87	0.88	0.87	0.88	0.88	0.88
Agreeableness	0.82	0.83	0.80	0.83	0.80	0.79	0.82
Neuroticism	0.86	0.87	0.86	0.87	0.86	0.86	0.88
Openness	0.80	0.82	0.82	0.81	0.83	0.83	0.84

Note: RR: Random Responders Removed, PR: Patterned Responders Removed, PRR: Patterned and Random Responders Removed, DR: Direct Responders Removed, LR: Long String Responders Removed, WR: Within-Person Standard Deviation Removed

Change Fatigue Data Set

IER Frequency. The frequency of IER varied based on the chosen index; each IER index was calculated across instruments in the data set. See Table 8 for frequencies of IER broken down by detection method. In this data set, the IER index detecting the smallest percentage of people was direct response with a detected frequency of 11% wherein anyone missing one or more question was identified as an insufficient effort responder. The long-string index was similar in its detection frequency, identifying 11% as insufficient effort responders. The IER index catching the most insufficient effort responders, within-person standard deviation, was also similar to the previous indices, identifying 15% as insufficient effort responders. This index is in line with hypothesis one and the other indices are very near hypothesis one.

Table 8
Change Fatigue Data Set: Frequency of IER Across Instruments

IER Index	Percent
Overall Long-String	
No IER	88.58%
Mod IER	9.09%
High IER	2.33%
Overall Within-Person SD	
No IER	84.78%
Mod IER	13.74%
High IER	1.48%
Overall Direct Response	
0 Wrong	89.01%
1 Wrong	5.71%
2 Wrong	1.06%
3 Wrong	1.48%
4 Wrong	2.75%

Latent Class Analysis and Frequencies. A latent class analysis was conducted for two, three, and four class models to identify the types of survey responders (see Table 9 for fit statistics) revealing that the three-class model was not statistically significantly better than the two-class model, $\Delta\chi^2(9) = 7.78$, $p = .56$. The four-class model was not better than the three-class model $\Delta\chi^2(9) = 4.46$, $p = .88$. Although the AIC is not smallest for the three-class model, the large drop of G^2 in proportion to the drop in degrees of freedom suggests that the three-class model may be the best fit. This result provides partial support for hypothesis two that there would be three types of responders. The characteristics of different classes based on response probabilities are less clear, but provide some support that the classes are patterned responders, random responders, and conscientious responders. See Table 10 for response probabilities. There were 65% in the conscientious class, 27% in the random class, and 8% in the patterned class. The

conscientious class was characterized by response probabilities that were largely non-IER on all IER indices (79-90%) but also had larger probabilities for moderate IER on the within-person standard deviation index. The random class was also characterized by response probabilities that were largely non-IER but also had about 5% for high IER on within-person standard deviation, suggesting it may be the random class. The patterned class was characterized by larger response probabilities for high IER on the long-string IER index (19%) and missing direct response questions (6-34%).

Table 9
Model Data Fit of the Two, Three, and Four Class Model of Change Fatigue IER Indices

	Fit Index		
Model	χ^2 (df)	G^2	AIC
2 Class	1281.42 (27)	14.60	48.6
3 Class	1273.64 (18)	6.82	58.82
4 Class	1269.18 (9)	2.36	72.36

*$p < .05$

Table 10
Change Fatigue: Item Response Probabilities

IER Index	Conscientious (65%)	Random (27%)	Patterned (8%)
Response Category 1: No IER			
Overall Long-String	0.86	1.00	0.74
Overall Within-Person SD	0.79	0.94	1.00
Direct Response	0.90	0.94	0.60
Response Category 2: Moderate IER			
Overall Long-String	0.13	0.00	0.07
Overall Within-Person SD	0.21	0.00	0.00
Direct Response	0.08	0.02	0.00
Response Category 3: High IER			
Overall Long-String	0.01	0.00	0.19
Overall Within-Person SD	0.00	0.06	0.00
Direct Response	0.00	0.04	0.00
Response Category 4: Three missed direct questions			
Direct Response	0.02	0.00	0.06
Response Category 5: Four missed direct questions			
Direct Response	0.00	0.00	0.34

Reliabilities. See Table 11 for reliabilities. The reliability of Locus of Control and Organizational Commitment do not appear to change much with different types of IER removed. As with the previous data set, the small differences in reliability tend indicate a larger reliability for data subsets without random responders, direct response IER, within-person standard deviation IER, and all bad responders (pattern and random). Again, removing long-string IER revealed lower reliabilities and removing patterned IER had mixed impact on reliability. As with the previous data set, the largest, positive differences emerged when within-person IER was removed.

Table 11

Cronbach's Alpha for Single-Scales in the Change Fatigue Data

		Type of IER Removed					
	All	RR	PR	PRR	DR	LR	WR
Locus of Control	0.88	0.89	0.89	0.89	0.89	0.88	0.91
Organizational Commitment	0.94	0.94	0.94	0.94	0.94	0.92	0.95

Note: RR: Random Responders Removed, PR: Patterned Responders Removed, PRR: Patterned and Random Responders Removed, DR: Direct Responders Removed, LR: Long String Responders Removed, WR: Within-Person Standard Deviation Removed

Job Analysis Data Set

IER Frequency. The frequency of IER varied based on the chosen index; each IER index was calculated for every instrument in the data set. See Table 12 for frequencies of IER broken down by detection method and instrument. The IER indices identifying the fewest number of people for IER, each of the two long-string indices, reported frequencies of 6% and 7%. The IER index identifying the largest number of people for IER in this data set was the direct response index, identifying 39% of the data set for IER. Within-person standard deviation indices reported frequencies of 18% and 32%. The long-string indices identified lower frequencies of IER than the hypothesized 15% in hypothesis one. Alternately, the within-person standard deviation indices and direct response index tended to identify a high prevalence of IER than hypothesized.

Table 12
Job Analysis Data Set: Frequency of IER by Instrument

IER Index	Frequency
Long-String	
HEXACO	
No IER	93.73%
Mod IER	0.57%
High IER	5.70%
I-ADAPT	
No IER	92.78%
Mod IER	0.00%
High IER	7.22%
Within-Person SD	
HEXACO	
No IER	82.13%
Mod IER	16.16%
High IER	1.71%
I-ADAPT	
No IER	67.87%
Mod IER	31.56%
High IER	0.57%
Overall Direct Response	
0 Wrong	61.12%
1 Wrong	18.88%
2 Wrong	7.10%
3 Wrong	3.93%
4 Wrong	8.97%

Latent Class Analysis and Frequencies. A latent class analysis was conducted for two, three, and four class models to identify the types of insufficient effort responders (see Table 13 for fit statistics) revealing that the three-class model was a better fit than the two-class model, $\Delta\chi^2(13) = 55.92$, $p < .001$. The four-class model was not better than the three-class model $\Delta\chi^2(13) = 7.98$, $p = .84$. This is corroborated by the small AIC for the three-class model. This result supports hypothesis two that there would be three types of responders. The characteristics of the different classes based on response probabilities

supports that the classes are patterned responders, random responders, and conscientious responders. See Table 14 for response probabilities. There were 65% in the conscientious class, 28% in the random class, and 7% in the patterned class. The conscientious class was characterized by response probabilities that were largely non-IER on all IER indices (70-100%). The random class was characterized by larger response probabilities for moderate IER on the within-person standard deviation IER indices (31-100%). The patterned class was characterized by larger response probabilities for high IER on the long-string IER indices (78-97%) and missing direct response questions (5%- 67%).

Table 13

Model Data Fit of the Two, Three, and Four Class Model of Job Analysis IER Indices

	Fit Index		
Model	χ^2 (df)	G^2	AIC
2 Class	2680.42 (379)	124.23	174.23
3 Class	2621.50 (366)*	65.31	141.31
4 Class	2613.58 (353)	57.38	159.38

*$p < .05$

Table 14
Job Analysis: Item Response Probabilities

IER Index	Conscientious (65%)	Random (28%)	Patterned (7%)
Response Category 1: No IER			
HEXACO Long-String	1.00	1.00	0.14
I-ADAPT Long-String	1.00	0.99	0.03
HEXACO Within-Person SD	0.88	0.62	1.00
I-ADAPT Within-Person SD	0.95	0.00	0.84
Direct Response	0.71	0.54	0.03
Response Category 2: Moderate IER			
HEXACO Long-String	0.00	0.00	0.08
I-ADAPT Long-String	0.00	0.00	0.00
HEXACO Within-Person SD	0.12	0.31	0.00
I-ADAPT Within-Person SD	0.04	1.00	0.16
Direct Response	0.19	0.23	0.05
Response Category 3: High IER			
HEXACO Long-String	0.00	0.00	0.78
I-ADAPT Long-String	0.00	0.01	0.97
HEXACO Within-Person SD	0.00	0.07	0.00
I-ADAPT Within-Person SD	0.01	0.00	0.00
Direct Response	0.06	0.10	0.05
Response Category 4: Three missed direct questions			
Direct Response	0.01	0.07	0.19
Response Category 5: Four missed direct questions			
Direct Response	0.04	0.06	0.68

Reliabilities. See Tables 15-16 for reliabilities. The reliability of the HEXACO and I-ADAPT factors change more drastically after removing the different types of IER than in previous data sets. Factor reliabilities were usually larger for data subsets without random responders and without within-person standard deviation IER. The data subset without long-string IER mostly revealed lower reliabilities, but this result was less stable across the two measures. Data subsets without patterned IER, without all bad responders (pattern and random), and without direct IER was mixed in its impact on reliability. For

I-ADAPT, the largest, positive differences emerged when within-person IER was removed. For HEXACO, removing random responders or within-person IER had a similarly positive impact on reliability.

Table 15
Cronbach's Alpha for the Eight I-ADAPT Factors

		Type of IER Removed					
	All	RR	PR	PRR	DR	LR	WR
Crisis	0.90	0.92	0.85	0.86	0.88	0.85	0.92
Culture	0.86	0.89	0.81	0.83	0.81	0.81	0.88
Work Stress	0.81	0.87	0.73	0.77	0.77	0.73	0.86
Interpersonal	0.84	0.88	0.73	0.75	0.75	0.72	0.85
Learning	0.92	0.94	0.88	0.88	0.88	0.87	0.93
Creativity	0.81	0.85	0.75	0.79	0.75	0.75	0.83
Physical	0.70	0.73	0.65	0.68	0.67	0.64	0.76
Uncertainty	0.79	0.81	0.75	0.77	0.77	0.75	0.83

Note: RR: Random Responders Removed, PR: Patterned Responders Removed, PRR: Patterned and Random Responders Removed, DR: Direct Responders Removed, LR: Long String Responders Removed, WR: Within-Person Standard Deviation Removed

Table 16
Cronbach's Alpha for the Six HEXACO-60 Factors

		Type of IER Removed					
	All	RR	PR	PRR	DR	LR	WR
Honesty-Humility	0.68	0.72	0.61	0.62	0.61	0.60	0.73
Emotionality	0.64	0.65	0.65	0.67	0.68	0.65	0.61
Extraversion	0.71	0.73	0.72	0.73	0.77	0.72	0.73
Agreeableness	0.69	0.69	0.69	0.70	0.70	0.69	0.68
Conscientiousness	0.78	0.81	0.73	0.75	0.76	0.74	0.81
Openness to Experience	0.74	0.73	0.75	0.75	0.76	0.74	0.72

Note: RR: Random Responders Removed, PR: Patterned Responders Removed, PRR: Patterned and Random Responders Removed, DR: Direct Responders Removed, LR: Long String Responders Removed, WR: Within-Person Standard Deviation Removed

Work Ethic Data Set

IER Frequency. The frequency of IER varied based on the chosen index; each IER index was calculated for every instrument in the data set. See Table 17 for frequencies of IER broken down by detection method and instrument. The IER indices detecting the most people for IER, each of the two long-string indices, reported frequencies of 1% and 3%. The IER indices detecting the largest number of people, each of the within-person standard deviation indices, identified 16% and 25% of the data set for insufficient effort responding. Each of the long-string indices identified lower frequencies of IER than the hypothesized 15% in hypothesis one. Alternately, one within-person standard deviation index identified a similar frequency to the hypothesized 15% while the other identified a larger frequency of IER than hypothesized.

Table 17
Work Ethic Data Set: Frequency of IER by Instrument

IER Index	Frequency
Long-String	
MWEP	
No IER	97.43%
Mod IER	0.51%
High IER	2.06%
NEOPI	
No IER	99.39%
Mod IER	0.31%
High IER	0.31%
Within-Person SD	
MWEP	
No IER	75.06%
Mod IER	22.37%
High IER	2.57%
NEOPI	
No IER	83.74%
Mod IER	8.59%
High IER	7.67%

Latent Class Analysis and Frequencies. A latent class analysis was conducted for two, three, and four class models to identify the types of IER (see Table 18 for fit statistics). Although the three-class model was not statistically better than the two-class model, it was approaching significance, $\Delta\chi^2(9) = 15.04$, $p = .09$. The four-class model was not better than the three-class model $\Delta\chi^2(9) = 1.12$, $p = .99$ Although the AIC is not smallest in the three-class model, the drop in G^2 in proportion to degrees of freedom indicates that the three-class model is a better relative fit. This result supports hypothesis two that there would be three types of responders. The characteristics of the different classes based on response probabilities support that the classes are patterned responders, random responders, and conscientious responders. See Table 19 for response probabilities. There were 80% in the conscientious class, 18% in the random class, and 2% in the patterned class. The conscientious class was characterized by response probabilities that were largely non-IER on all IER indices (86-99%). The random class was characterized by larger response probabilities for moderate and high IER on the within-person standard deviation IER indices (14-55%). The patterned class was characterized by larger response probabilities for high IER on the long-string IER indices (17-84%).

Table 18
Model Data Fit of the Two, Three, and Four Class Model of Work Ethic IER Indices

	Fit Index		
Model	χ^2 (df)	G^2	AIC
2 Class	954.84 (63)	17.11	51.11
3 Class	939.80 (54)	2.06	54.06
4 Class	938.68 (45)	0.94	70.94

*$p < .05$

Table 19
Work Ethic: Item Response Probabilities

IER Index	Conscientious (80%)	Random (18%)	Patterned (2%)
Response Category 1: No IER			
MWEP Long-String	0.99	1.00	0.00
NEO-PI-R Long-String	0.99	1.00	0.83
MWEP Within-Person SD	0.86	0.31	0.48
NEO-PI-R Within-Person SD	0.96	0.20	1.00
Response Category 2: Moderate IER			
MWEP Long-String	0.01	0.00	0.16
NEO-PI-R Long-String	0.00	0.00	0.00
MWEP Within-Person SD	0.14	0.55	0.52
NEO-PI-R Within-Person SD	0.04	0.34	0.00
Response Category 3: High IER			
MWEP Long-String	0.00	0.00	0.84
NEO-PI-R Long-String	0.00	0.00	0.17
MWEP Within-Person SD	0.00	0.15	0.00
NEO-PI-R Within-Person SD	0.00	0.46	0.00

Reliabilities. See Tables 20-21 for reliabilities. The reliability of the NEO-PI-R and MWEP factors do not appear to change much with different types of IER removed. The small differences in reliability were inconsistent between the measures. In the NEO-PI-R, these differences tended to reflect minimally larger reliabilities for all data subsets. In the MWEP, reliabilities are largely consistent across data subsets and even small differences have inconsistent impact on reliability. For the MWEP, the largest, positive differences emerged when within-person standard deviation IER was removed.

Table 20

Cronbach's Alpha for the Five NEO-PI-R Factors

		Type of IER Removed				
	All	RR	PR	PRR	LR	WR
Extraversion	0.89	0.88	0.89	0.89	0.89	0.90
Conscientiousness	0.86	0.86	0.87	0.87	0.87	0.87
Agreeableness	0.86	0.86	0.86	0.86	0.86	0.85
Neuroticism	0.89	0.90	0.90	0.90	0.90	0.89
Openness	0.86	0.87	0.86	0.87	0.86	0.88

Note: RR: Random Responders Removed, PR: Patterned Responders Removed, PRR: Patterned and Random Responders Removed, LR: Long String Responders Removed, WR: Within-Person Standard Deviation Removed

Table 21

Cronbach's Alpha for the Seven MWEP Factors

		Type of IER Removed				
	All	RR	PR	PRR	LR	WR
Hard Work	0.86	0.86	0.85	0.86	0.85	0.86
Centrality	0.84	0.84	0.84	0.83	0.84	0.83
Self Reliance	0.88	0.88	0.88	0.88	0.88	0.89
Wasted Time	0.78	0.78	0.77	0.77	0.77	0.78
Delayed Gratification	0.78	0.78	0.78	0.77	0.78	0.80
Morality	0.82	0.82	0.81	0.82	0.81	0.84
Anti-Leisure	0.85	0.86	0.86	0.87	0.86	0.86

Note: RR: Random Responders Removed, PR: Patterned Responders Removed, PRR: Patterned and Random Responders Removed, DR: Direct Responders Removed, LR: Long String Responders Removed, WR: Within-Person Standard Deviation Removed

Big Five Data Set

IER Frequency. The frequency of IER varied based on the chosen index; each IER index was calculated for every instrument in the data set. See Table 22 for frequencies of IER broken down by detection method and instrument. The IER index detecting the fewest people in this data set was SOAP inconsistency, identifying 5% of the data set for IER. The other SOAP scale, infrequency, also detected a minimal number of people and identified 8% of the data set for IER. The long-string index identified a

similar IER frequency, identifying 9%. The IER index detecting the largest number of people was within-person standard deviation, which identified 18% of the data set for IER. The SOAP scales and long-string index identified frequencies below the hypothesized 15% while the within-person standard deviation index identified a frequency above the hypothesized 15%.

Table 22
Big Five Data Set: Frequency of IER by Instrument

IER Index	Frequency
NEO-PI-R Long-String	
No IER	91.36%
Mod IER	2.68%
High IER	5.96%
NEO-PI-R Within-Person SD	
No IER	81.67%
Mod IER	13.11%
High IER	5.22%
SOAP Inconsistency	
No IER	94.63%
Mod IER	2.08%
High IER	3.29%
SOAP Infrequency	
No IER	92.00%
Mod IER	3.30%
High IER	4.70%

Latent Class Analysis and Frequencies. A latent class analysis was conducted for two, three, and four class models to uncover the different types of responders (see Table 23 for fit statistics). The three-class model was not statistically better than the two-class model $\Delta\chi^2(9) = 11.86$, $p = .22$. The four-class model was not better than the three-class model $\Delta\chi^2(9) = 9.48$, $p = .39$. AIC is smallest for the two-class model and the drop in G^2 does not support the three-class model. Overall, the two-class model appears best.

This does not support hypothesis two. The characteristics of different classes based on response probabilities indicate that the classes are likely conscientious responders and general IER. See Table 24 for response probabilities. There were 89% in the conscientious class and 11% in the IER class. The conscientious class was characterized by response probabilities that were largely non-IER on all IER indices (82-99%) and some response probabilities that were moderate IER (1-13%). The IER class was characterized by larger response probabilities for moderate and high IER on all IER indices (1-44%).

Table 23
Model Data Fit of the Two, Three, and Four Class Model of Big Five Indices

	Fit Index		
Model	χ^2 (df)	G^2	AIC
2 Class	1857.38 (63)	37.04	71.04
3 Class	1845.52 (54)	25.18	77.18
4 Class	1836.04 (45)	15.70	85.70

*$p < .05$

Table 24
Big Five: Item Response Probabilities

IER Index	Conscientious (89%)	IER (11%)
Response Category 1: No IER		
NEO-PI-R Long-String	0.91	0.92
NEO-PI-R Within-Person SD	0.82	0.76
SOAP Inconsistency	0.99	0.59
SOAP Infrequency	0.99	0.27
Response Category 2: Moderate IER		
NEO-PI-R Long-String	0.03	0.02
NEO-PI-R Within-Person SD	0.13	0.15
SOAP Inconsistency	0.01	0.10
SOAP Infrequency	0.01	0.29
Response Category 3: High IER		
NEO-PI-R Long-String	0.06	0.06
NEO-PI-R Within-Person SD	0.05	0.09
SOAP Inconsistency	0.00	0.31
SOAP Infrequency	0.00	0.44

Reliabilities. See Table 25 for reliabilities. The reliability of the NEO-PI-R did not change much with different types of IER removed. Minimally larger reliabilities were present for data subsets without all bad responders (patterned and random), without long-string IER, and without within-person standard deviation IER. The largest changes in reliability were in the negative direction: smaller reliabilities were seen where inconsistent responders and infrequent responders were removed, seemingly inconsistent with previous findings.

Table 25

Cronbach's Alpha for the Five NEO-PI-R Factors

		Type of IER Removed				
	All	BR	ICR	IFR	LR	WR
Extraversion	0.88	0.89	0.86	0.85	0.89	0.89
Conscientiousness	0.88	0.88	0.81	0.84	0.88	0.89
Agreeableness	0.88	0.88	0.80	0.72	0.88	0.88
Neuroticism	0.90	0.91	0.79	0.83	0.91	0.90
Openness	0.88	0.89	0.85	0.84	0.89	0.89

Note: BR: LCA Bad Responders Removed, ICR: Inconsistent Responders Removed, IFR: Infrequent Responders Removed, LR: Long String Responders Removed, WR: Within-Person Standard Deviation Removed

CHAPTER 5: DISCUSSION

Overall Pattern of Results

Hypothesis 1: Frequency of IER. The frequency of IER varied based on the IER index utilized for detection. Within-person standard deviation, the detection index that identified people who significantly varied their responses across a unidimensional scale, tended to identify the largest frequency of people for insufficient effort responding along with direct response, the detection index that asked participants to respond to a quality assurance item (e.g., "please select 'strongly agree'"). Long-string, the post-hoc IER index that detected people who selected the same response many times in a row (e.g., someone selected 'strongly agree' for many consecutive items), reigned as an index that identified a small number of people for IER. The percentage of respondents detected for IER by the different indices was relatively stable across data sets. Illustrating this stability, across the five data sets, long-string indices detected between 1 and 12% of cases for IER; within-person standard deviation detected between 15-32% of cases for IER; direct response questions detected between 11 and 35% of cases of IER. Overall, results fluctuated around the 15% mark and tended to support the Hypothesis 1. However, the fluctuations in IER frequency detected by indices between data sets were substantial enough to suggest that there are extraneous factors impacting the frequency of IER.

Hypothesis 2: Types of IER. The results of this study indicate that there are likely different types of survey responders: conscientious, patterned IER, and random IER, lending support for Hypothesis 2. Furthermore, each of these types was represented by specific IER indices. Conscientious responders were represented by mostly no IER

across indices with some within-person standard deviation probabilities and occasionally direct response probabilities. Patterned IER was most often represented by long-string indices and high direct response (e.g., missing many direct response questions). Random IER was often represented by within-person standard deviation and moderate direct response (e.g., missing only a moderate amount of direct response questions).

Research Question 1: Frequency of IER Types. The frequency of IER types within each data set was variable. The proportion of patterned responders was between 2% and 9% while the proportion of random responders was between 18 and 28%. These proportions are also reflected in the IER indices that characterize each group (e.g., patterned responders were characterized by long-string, which also had a lower detection frequency). In the data set that resulted in only two latent classes (Big Five), the proportion of bad responders was about 11%. All of these proportions of IER fluctuate around the 15% hypothesized in Hypothesis one. Patterned responders may be rarer than random responders. Alternately, the difference in frequencies between patterned and random IER may be due to the nature of the index; perhaps random responding detection indices are too liberal and detecting some responders who are actually conscientious and long-string indices are too conservative and missing some bad responders.

Research Question 2: IER and Reliability. Reliability analyses were done on the scales within each instrument with IER removed based on each detection index and based on the results of the latent class analysis. The impact of IER on reliability was dependent on the type of IER detection index and type of responder identified by the latent class analysis. In most cases, removing the different types of IER had minimal impact on reliability. That said, removing the random responder class and indices

associated with that class (within-person SD and moderate direct response) tended to result in larger, more favorable reliabilities. Removing the patterned responder class and indices associated with that class (long-string and high direct response) had mixed impact on reliabilities, but more often than not resulted in slightly lower reliabilities. Overall, removing within-person standard deviation cases appeared to have the most positive impact on reliability over direct response and long-string. However, in some data sets, removing cases identified by within-person standard deviation also resulted in the largest loss of data. Therefore, removing IER based on direct response may be the ideal alternative for a positive impact on reliability, avoiding a loss of data, and capturing both patterned and random IER.

Research and Applied Implications

From a detection standpoint, the results of this study suggest that direct response and within-person standard deviation detect more people for IER than maximum long-string, which tends to detect fewer people. It is probable that within-person standard deviation is also catching conscientious responders with the bad responders. In the same vein, the long-string index may be missing bad responders. As noted above, removing responders detected by within-person standard deviation had the most positive impact on reliability, and therefore, may be a better index. In other data sets, removing bad responders overall (those in either the patterned or random class), also yielded positive results for reliability. While the increase in reliability is a desirable outcome, it may be an artificial benefit because the patterned IER responders are still present. In other words, the researcher may gain a benefit relative to Type II error but be ignoring the impact on Type I error. Further, the decision to remove different types of responders may have an

impact on other psychometric properties not assessed in this manuscript. It is recommended from these results that the researcher use a variety of detection indices because they catch different people. In consideration of the ease of application of these different detection methods, it may be most practical for researchers to simply employ the direct response method. Further, the results of the latent class analysis indicated that the resulting classes do not yield more helpful information than simply employing a variety of indices that are representative of their respective classes (i.e., patterned responders are highly similar to responders identified by long-string indices). The largest applied contribution of this manuscript was that researchers should use direct response items in their survey endeavors, whether in a research or applied setting.

Extraneous Impact

As previously mentioned in the conclusion about hypothesis one, the frequency of IER remained relatively stable across the five data sets and tended to identify a range of frequencies for IER that included the hypothesized 15%. That said, the individual IER indices fluctuated enough across the five data sets to suggest that there are other factors impacting IER and its detection. These factors likely include participant population, motivation, survey length, and recruitment strategy. First, the data sets were pulled from different populations, some including students and others including people in the workforce. Different sets of participants may be differentially motivated to respond attentively; low stakes data collection is more likely to result in IER (Fleischer et al., 2015). Interestingly, the job analysis data set could be deemed the “highest stakes” survey because the results may impact those workers—but this data set had the largest number of people caught by within-person standard deviation and direct response

questions. However, this result is not surprising when one considers another extraneous factor: survey length. Survey length also differed across data sets with the Job Analysis data set being the longest survey. Survey fatigue may be a large factor impacting IER in the Job Analysis data set (Clark, Gironda, & Young, 2003). Other characteristic differences including the recruitment strategy (Manici & Rogge, 2014), mode of the survey (Meade & Craig, 2012), and type of survey instruments (Meade & Craig, 2012) could impact results. The Change Fatigue data set employed a recruitment strategy wherein survey responders were paid for their participation, but the mode of the survey was Mturk, resulting in a low-stakes data collection method. Other data sets differed in their mode of data collection with one completed via Qualtrics, and others using paper and pencil. In regard to the type of survey, the measures differed across data sets and this may have had an impact on IER through interest in the survey material (Meade & Craig, 2012). That being said, even with these differences, the findings were relatively similar across data sets with fluctuations around the hypothesized 15%.

Limitations

There are several limitations with the current study. As previously noted, these datasets were obtained from a variety of participants using different survey methodologies. Furthermore, the type and number of IER indices were not consistent across datasets. The only dataset that resulted in a two-class model, the Big Five data set, employed only one instrument—this implies that identifying IER across multiple instruments is necessary to detect the nuanced effects of IER. Another limitation is apparent in the Change Fatigue dataset which employed two instruments, each comprised of a single scale. Within-person standard deviation will by definition detect people for

IER who are more variable; more scales are necessary to ascertain that the randomness is consistent across other instruments and ensure that they are insufficient effort responders rather than conscientious responders.

Similarly, another limitation was with the inconsistent way people were detected and removed while assessing reliability. Reliability was conducted on all factors/scales by removing IER based on that specific instrument (e.g, reliability of HEXACO honesty/humility is assessed by removing IER detected on the HEXACO). In the change fatigue data set, it is done differently: people were removed based on IER across both measures (e.g., reliability of Locus of Control is assessed by removing IER detected across Locus of Control and Occupational Commitment). This was done differently because the measures in the Change Fatigue data set were short and unidimensional.

As a final limitation, list-wise deletion of missing data caused cases to be removed that may have been engaging in IER, impacting the results of the latent class analysis. More specifically, if an individual case within the Job Analysis data set was identified for IER on the HEXACO but had missing data on the I-ADAPT, their impact of IER in the I-ADAPT was not assessed. This is an issue because research suggests a relationship between inattentiveness and missing data (Johnson, 2004). The list-wise deletion procedure may have resulted in lost information about the nature of IER.

Future Research

The current study used archival data from a variety of different sources. Consequently, they are comparing data from a variety of samples that ultimately may be different from each other and confound the results of the present study. Future research should collect data to directly assess the impact of these extraneous factors. Although,

this study suggests that the types of IER may be relatively consistent across populations and survey methodologies. Future research should also conduct a latent class analysis in other datasets with more IER indices (e.g., consistency indices, multivariate outliers, etc.) to determine if the three types of survey responders (conscientious responders, patterned IER, and random IER), are found in other datasets with the same item response probabilities.

Another interesting direction for future research involves the analysis of missing data. The analyses in this manuscript were done with list-wise deletion. If research indicates that missing data are associated with IER, then there may be implications regarding how to manage missing data. Specifically, a future research study may look at conducting all analyses with and without partial missing data to see whether imputation results in imputing bad responses.

In the limitations section, it is mentioned that data are identified for IER inconsistently with some people removed based on their detection in a single instrument while others are removed based on their detection across instruments. Future researchers may consider assessing the impact of including IER indices or assessing post-hoc indices for every measure of interest or only a few measures. Namely, it would be useful to assess whether one can remove someone from an entire data set if they were identified for only one included instrument rather than identified across instruments.

Also, this study assessed IER based on a cut-off score meant to detect moderate to severe IER. Future research could identify what cut-off scores would be best for removing people to obtain the greatest psychometric benefits. Perhaps removing only severe offenders would yield positive results without losing power.

Conclusion

This manuscript contributes to the IER literature in several ways. First, it provides corroborating evidence that two types of IER are patterned and random IER, each with their own characteristics (Kam & Meyer, 2015; Manicai & Rogge, 2014; Meade & Craig, 2012). Second, while results suggest the impact of extraneous variables, the results are relatively consistent suggesting that the frequency and type of IER may be stable across populations, participant motivation, recruitment strategies, utilized instruments, and survey mode. With additional evidence that IER can occur in a dataset from an applied setting (i.e., data from a job analysis), there are implications for survey practitioners in organizations such that they should also be aware of IER and take preventative and detective precautions. Third, while this research suggests there that removing people identified for within-person IER may have the greatest benefit on reliability, the results are minimal, and there may still be consequences associated with ignoring the patterned responders. Direct response was identified as an effective and practical alternative.

Overall, remaining cognizant of the types of IER will be helpful for researchers and practitioners as they design and implement their surveys. It would be best to include a variety of indices and to weigh the benefits of removing people; certainly, those on the extreme end of any index should be considered for removal. Including direct response items is a good starting point. Further, considering that the latent classes were largely reflected by certain indices, the practicality of conducting a latent class analysis was minimized.

The main goal of this research was to serve as a foundation for future IER studies and build toward an understanding of the conditions under which type I and type II errors

are increased through IER. In serving as a platform for further IER research, this manuscript was successful.

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APPENDICES

APPENDIX A: Career Indecision Data Set

Career Indecision

1. When I experience a setback, it takes me a long time to feel good again.
2. I often feel like crying.
3. I'd be going against the wishes of someone important to me if I follow the career path that most interests me.
4. I am uncomfortable committing myself to a specific career direction.
5. I strive hard to achieve my goals.
6. I often feel tired and worn out.
7. I frequently feel overwhelmed.
8. I am easily embarrassed.
9. I think I take failures and setbacks harder than a lot of people I know.
10. I really have a hard time making decisions without help.
11. I need to learn more about what I want from a career.
12. My interests change so much that I cannot focus on one specific career goal.
13. I often feel discouraged about having to make a career decision.
14. I plan ahead when I have to make an important decision.
15. I sometimes feel directionless.
16. I always think carefully about decisions I have to make.
17. I worry about what other people think of me.
18. I'm having a hard time trying to decide between a couple of good career options.
19. I thoroughly consider the consequences of a decision before I make it.
20. I need a clearer idea about my abilities and talents before I can make a good career decision.
21. I'm conflicted because I find a number of different careers appealing.
22. I need to learn more about myself before I can make a good career decision.
23. When bad things happen in my life, I just keep going because I know things will get better soon.
24. It's difficult for me to choose a career because I like so many different things.
25. If something goes wrong, I have a hard time forgetting about it and concentrating on present tasks.
26. I often hope that my problems would just go away.
27. I usually am able to carry out the plans I make.
28. I like to keep myself open to various career opportunities rather than committing to a particular career.
29. People who are important to me give me contradictory information about the career I should pursue.
30. I think I am a worthwhile person.
31. I feel very confident that I will be able to achieve my career goals.
32. I feel stuck because I don't know enough about occupations to make a good career decision.
33. Important people in my life do not support my career plans.
34. I often get so sad that it's hard to go on.

35. I am familiar with my career options, but I'm just not ready to commit to a specific occupation.
36. Given enough time and effort, I believe I can solve most problems that confront me.
37. I am a worrier.
38. When making important decisions, I tend to focus on what will go wrong.
39. I often feel fearful and anxious.
40. After I have made a decision about an important issue, I continue to think about the alternatives I didn't choose.
41. I have found myself sleeping a lot less or a lot more recently.
42. I need to learn more about the interests I have before I can make a good career decision.
43. Important people in my life disagree about the career I should pursue.
44. I often feel insecure.
45. Stressful situations frequently make me ill.
46. I often feel ashamed of myself.
47. I'm concerned that my interests may change after I decide on a career.
48. I am quite confident that I will be able to overcome obstacles to getting the career I want.
49. I am not sure I can commit to a specific career because I don't know what other options might be available.
50. I'm concerned that my goals may change after I decide on a career.
51. I try to excel at everything I do.
52. I need more information about occupations in which I might be successful.
53. Important people in my life have discouraged me from pursuing the career I want.
54. I will be able to find a career that fits my interests.
55. I always work productively to get the job done.
56. I don't have enough occupational information to make a good career decision.
57. I need a lot of encouragement and support from others when I make a decision.
58. I need to learn how to go about making a good career decision.
59. I am quite confident that I will be able to find a career in which I'll perform well.
60. I usually don't have a lot of confidence in my decisions unless my friends give me support for them.
61. I need more information about careers I might like.
62. I often feel nervous when thinking about having to pick a career.
63. I'm having a hard time narrowing down my career interests.
64. I verify my information to ensure I have all the facts before making a decision.
65. I don't know much about the occupations I'm considering.

Organizational Commitment

1. My major is important to my self-image.
2. I regret having chosen my major.
3. I am proud to be in my major.
4. I dislike being in my major.
5. I do not identify with my major.
6. I am enthusiastic about my major.
7. I have put too much into my major to consider changing now.
8. Changing my major now would be difficult for me to do.
9. Too much of my life would be disrupted if I were to change my major.
10. It would be costly for me to change my major now.
11. There are no pressures to keep me from changing my major.
12. If you are reading this closely, please mark agree for this question.
13. Changing my major now would require considerable personal sacrifice.
14. I believe people who have been trained in a profession have a responsibility to stay in that profession for a reasonable period of time.
15. I do not feel any obligation to remain in my major.
16. I feel a responsibility to my major to continue in it.
17. Even if it were to my advantage, I do not feel that it would be right to leave my major now.
18. I would feel guilty if I left my major.
19. I am in my major because of a sense of loyalty to it.
20. I would be very happy to spend the rest of my academic career with MTSU.
21. I really feel as if MTSU's problems are my own.
22. I do not feel a strong sense of "belonging" to MTSU.
23. I do not feel "emotionally attached" to MTSU.
24. I do not feel like "part of the family" at MTSU.
25. MTSU has a great deal of personal meaning for me.
26. Right now, staying with MTSU is a matter of necessity as much as desire.
27. It would be very hard for me to leave MTSU right now, even if I wanted to.
28. Too much of my life would be disrupted if I decided I wanted to leave MTSU now.
29. I feel that I have too few options to consider leaving MTSU.
30. If I had not already put so much of myself into MTSU, I might consider going elsewhere.
31. One of the few negative consequences of leaving MTSU would be the scarcity of available alternatives.
32. I do not feel any obligation to remain with MTSU.
33. Even if it were to my advantage, I do not feel it would be right to leave MTSU now.
34. I would feel guilty if I left MTSU now.
35. MTSU deserves my loyalty.
36. I would not leave MTSU right now because I have a sense of obligation to the people in it.
37. I owe a great deal to MTSU.

IPIP

1. Often feel blue.
2. Dislike myself.
3. Am often down in the dumps.
4. Have frequent mood swings.
5. Panic easily.
6. Rarely get irritated.
7. Seldom feel blue.
8. Feel comfortable with myself.
9. Am not easily bothered by things.
10. Am very pleased with myself.
11. Feel comfortable around people.
12. Make friends easily.
13. Am skilled in handling social situations.
14. Am the life of the party.
15. Know how to captivate people.
16. Have little to say.
17. Keep in the background.
18. Would describe my experiences as somewhat dull.
19. Don't like to draw attention to myself.
20. Don't talk a lot.
21. Believe in the importance of art.
22. Have a vivid imagination.
23. Tend to vote for liberal political candidates.
24. Carry the conversation to a higher level.
25. Enjoy hearing new ideas.
26. Am not interested in abstract ideas.
27. Do not like art.
28. Avoid philosophical discussions.
29. Do not enjoy going to art museums.
30. Tend to vote for conservative political candidates.
31. Have a good word for everyone.
32. Believe that others have good intentions.
33. Respect others.
34. Accept people as they are.
35. Make people feel at ease.
36. Have a sharp tongue.
37. Cut others to pieces.
38. Suspect hidden motives in others.
39. Get back at others.
40. Insult people.
41. Am always prepared.
42. Pay attention to details.
43. Get chores done right away.
44. Carry out my plans.

45. Make plans and stick to them.
46. Waste my time.
47. Find it difficult to get down to work.
48. Do just enough to get by.
49. Don't see things through.
50. Shirk my duties.

APPENDIX B: Change Fatigue Data Set

Work Locus of Control

1. My job is what I make of it
2. On my job, I can pretty much accomplish whatever I set out to accomplish
3. If I know what I want out of a job, I can find a job that gives it to me
4. If I were unhappy with a decision made by my boss, I would do something about it
5. Getting the job I want is a matter of luck
6. Getting a salary raise is generally a matter of good fortune
7. I'm capable of doing the job well if I make the effort
8. In order to get a really good job, I would need to have family members or friends in high places
9. I believe that promotions are usually a matter of good fortune
10. When it comes to landing a really good job, who I know is more important than what I can do
11. I would be given a promotion based on how well I perform on the job
12. In order to get a salary raise, I would have to know the right people
13. For me to be an outstanding employee on most jobs, it would take a lot of luck
14. Getting rewarded on my job would depend on how well I perform
15. When required, I can have a good deal of influence on my supervisor
16. When I make plans on my job, I am almost certain to make them work
17. Although I might have the necessary abilities, I will not be given leadership responsibility without appealing to those in positions of power
18. It's not always wise for me to plan ahead on the job because things turn out to be a matter of good or bad fortune
19. When I get what I want on a job, it's because I worked hard for it
20. Whether or not I advance on the job depends on whether I'm lucky enough to be in the right place at the right time

Organizational Commitment

1. I am willing to put in a great deal of effort beyond what is normally expected in order to help my organization be successful.
2. I talk up my organization to my friends as a great place to work.
3. I would accept almost any type of job assignment in order to keep working for my organization.
4. I find that my values and the organization's value are very similar.
5. I am proud to tell others that I am part of my organization.
6. My organization really inspires my best job performance.
7. I am extremely glad that I chose my current organization to work for over others I was considering at the time I joined.
8. I really care about the fate of my organization.
9. For me, this is the best of all possible organizations for which to work.

APPENDIX C: Job Analysis Data Set

HEXACO

1. I would be quite bored by a visit to an art gallery.
2. I plan ahead and organize things, to avoid scrambling at the last minute.
3. I rarely hold a grudge, even against people who have badly wronged me.
4. I feel reasonably satisfied with myself overall.
5. I would feel afraid if I had to travel in bad weather conditions.
6. I wouldn't use flattery to get a raise or promotion at work, even if I thought it would succeed.
7. I'm interested in learning about the history and politics of other countries.
8. I often push myself very hard when trying to achieve a goal.
9. People sometimes tell me that I am too critical of others.
10. I rarely express my opinions in group meetings.
11. I sometimes can't help worrying about little things.
12. If I knew that I could never get caught, I would be willing to steal a million dollars.
13. I would enjoy creating a work of art, such as a novel, a song, or a painting.
14. When working on something, I don't pay much attention to small details.
15. People sometimes tell me that I'm too stubborn.
16. I prefer jobs that involve active social interaction to those that involve working alone.
17. When I suffer from a painful experience, I need someone to make me feel comfortable.
18. Having a lot of money is not especially important to me.
19. I think that paying attention to radical ideas is a waste of time.
20. I make decisions based on the feeling of the moment rather than on careful thought.
21. People think of me as someone who has a quick temper.
22. On most days, I feel cheerful and optimistic.
23. I feel like crying when I see other people crying.
24. I think that I am entitled to more respect than the average person is.
25. If I had the opportunity, I would like to attend a classical music concert.
26. When working, I sometimes have difficulties due to being disorganized.
27. My attitude toward people who have treated me badly is “forgive and forget”.
28. I feel that I am an unpopular person.
29. When it comes to physical danger, I am very fearful.
30. If I want something from someone, I will laugh at that person's worst jokes.
31. I’ve never really enjoyed looking through an encyclopedia.
32. I do only the minimum amount of work needed to get by.
33. I tend to be lenient in judging other people.
34. In social situations, I’m usually the one who makes the first move.
35. I worry a lot less than most people do.
36. I would never accept a bribe, even if it were very large.

37. People have often told me that I have a good imagination.
38. I always try to be accurate in my work, even at the expense of time.
39. I am usually quite flexible in my opinions when people disagree with me.
40. The first thing that I always do in a new place is to make friends.
41. I can handle difficult situations without needing emotional support from anyone else.
42. I would get a lot of pleasure from owning expensive luxury goods.
43. I like people who have unconventional views.
44. I make a lot of mistakes because I don't think before I act.
45. Most people tend to get angry more quickly than I do.
46. Most people are more upbeat and dynamic than I generally am.
47. I feel strong emotions when someone close to me is going away for a long time.
48. I want people to know that I am an important person of high status.
49. I don't think of myself as the artistic or creative type.
50. People often call me a perfectionist.
51. Even when people make a lot of mistakes, I rarely say anything negative.
52. I sometimes feel that I am a worthless person.
53. Even in an emergency I wouldn't feel like panicking.
54. I wouldn't pretend to like someone just to get that person to do favors for me.
55. I find it boring to discuss philosophy.
56. I prefer to do whatever comes to mind, rather than stick to a plan.
57. When people tell me that I'm wrong, my first reaction is to argue with them.
58. When I'm in a group of people, I'm often the one who speaks on behalf of the group.
59. I remain unemotional even in situations where most people get very sentimental.
60. I'd be tempted to use counterfeit money, if I were sure I could get away with it.

I-ADAPT

1. I usually over-react to stressful news
2. I feel unequipped to deal with too much stress
3. I am easily rattled when my schedule is too full
4. I am usually stressed when I have a large work load
5. I often cry or get angry when I am under a great deal of stress
6. I am able to maintain focus during emergencies
7. In an emergency situation, I can put aside emotional feelings to handle important tasks
8. I think clearly in times of urgency
9. I am able to be objective during emergencies
10. I usually step up and take action during a crisis
11. I make excellent decisions in times of crisis
12. I believe it is important to be flexible in dealing with others
13. I tend to be able to read others and understand how they are feeling at any particular moment
14. My insight helps me to work effectively with others
15. I am an open-minded person in dealing with others
16. I am perceptive of others and use that knowledge in interactions
17. I try to be flexible in dealing with others
18. I adapt my behavior to get along with others
19. I take responsibility for acquiring new skills
20. I take actions to improve work performance deficiencies
21. I often learn new information and skills to stay at the forefront of my profession
22. I quickly learn new methods to solve problems
23. I am continually learning new skills for my job
24. I take responsibility for staying current in my profession
25. I try to learn new skills for my job before they are needed
26. I see connections between seemingly unrelated information
27. I am good at developing unique analyses for complex problems
28. I am an innovative person
29. When resources are insufficient, I thrive on developing innovative solutions
30. I am able to look at problems from a multitude of angles
31. I need for things to be “black and white”
32. I become frustrated when things are unpredictable
33. I am able to make effective decisions without all relevant information
34. I tend to perform best in stable situations and environments
35. When something unexpected happens, I readily change gears in response
36. I can adapt to changing situations
37. I perform well in uncertain situations
38. I easily respond to changing conditions
39. I can adjust my plans to changing conditions

APPENDIX D: Work Ethic Data Set

MWEP

1. It is important to stay busy at work and not waste time.
2. I feel uneasy when there is little work for me to do.
3. If I want to buy something, I always wait until I can afford it.
4. I feel content when I have spent the day working.
5. Life would be more meaningful if we had more leisure time.
6. To be truly successful, a person should be self-reliant.
7. One should always take responsibility for one's actions.
8. I would prefer a job that allowed me to have more leisure time.
9. Time should not be wasted, it should be used efficiently.
10. Even if I were financially able, I would not stop working.
11. I get more fulfillment from items I had to wait for.
12. I schedule me day in advance to avoid wasting time.
13. A hard day's work is very fulfilling.
14. The more time I can spend in a leisure activity, the better I feel.
15. One should always do what is right and just.
16. I would take items from work if I felt I was not getting paid enough.
17. Nothing is impossible if you work hard enough.
18. The less time one spends working and the more leisure time one has, the better.
19. Things that you have to wait for are the most worthwhile.
20. Working hard is the key to being successful.
21. Self-reliance is the key to being successful.
22. If one works hard enough, one is likely to make a good life for oneself.
23. I constantly look for ways to productively use my time.
24. Hard work makes one a better person.
25. One should not pass judgment until one has heard all of the facts.
26. People would be better off if they depended on themselves.
27. Work takes too much of our time, leaving little time to relax.
28. One should live one's own life independent of others as much as possible.
29. A distant reward is usually more satisfying than an immediate one.
30. It is very important for me to always be able to work.
31. More leisure time is good for people.
32. One must avoid dependence on other persons whenever possible.
33. Even if I inherited a great deal of money, I would continue to work somewhere.
34. I do not like having to depend on other people.
35. By working hard a person can overcome every obstacle that life presents.
36. I try to plan out my workday so as not to waste time.
37. You should never tell lies about other people.
38. Any problem can be overcome with hard work.
39. How a person spends their time is as important as how they spend their

money.
40. Even if it were possible for me to retire, I would still continue to work.
41. Life without work would be very boring.
42. I prefer to save until I can afford something and not buy it on credit.
43. The world would be a better place if people spent more time relaxing.
44. I strive to be self-reliant.
45. If you work hard you will succeed.
46. The best things in life are those you have to wait for.
47. Anyone who is able and willing to work hard has a good chance of succeeding.
48. Stealing is all right as long as you don't get caught.
49. The job that provides the most leisure time is the job for me.
50. Having a great deal of independence from others is very important to me.
51. It is important to treat others as you would like to be treated.
52. I experience a sense of fulfillment from working.
53. A person should always do the best job possible.
54. It is never appropriate to take something that does not belong to you.
55. Only those who depend on themselves get ahead in life.
56. Wasting time is as bad as wasting money.
57. There are times when stealing is justified.
58. People should have more leisure time to spend in relaxation.
59. It is important to control one's destiny by not being dependent on others.
60. By simply working hard enough, one can achieve one's goals.
61. People should be fair in their dealings with others.
62. The only way to get anything worthwhile is to save for it.
63. Leisure time activities are more interesting than work.
64. A hard day's work provides a sense of accomplishment.
65. A distaste for hard work usually reflects a weakness of character.

APPENDIX E: Big Five Data Set

SOAP- Inconsistency

1. I have little freedom to do my job in my own way
2. I have a great deal of freedom to do my job in my own way
3. I have an incompetent boss
4. I have a competent boss
5. My employer provides health insurance as a fringe benefit
6. My employer does not provide health insurance has a fringe benefit
7. Most employees in this organization plan to quit as soon as possible
8. Most employees in this organization plan to stay for a long time
9. My job is boring
10. My job is interesting
11. My pay is unfair for the work I do
12. My pay is fair for the work I do
13. I prefer a job that is quite challenging
14. I prefer a job that is not too challenging
15. I seldom have the chance to learn new things in my job
16. I often have the chance to learn new things in my job
17. The organization I work for has a good reputation
18. The organization I work for has a bad reputation

SOAP- Infrequency

1. I like my boss to keep me informed about what is going on
2. I like to be recognized by others for good work
3. I believe that my job performance is inadequate
4. I do not get along with most of my co-workers
5. I take pride in a job well done
6. I dislike my job more than anyone else who works here
7. My job is the most fun and enjoyable thing in my life
8. I consider my boss to be my best friend
9. I have none of the resources I need to do my job well
10. I prefer working for an organization that offers opportunities for advancement
11. Considering the job I have, I believe that my pay is too high
12. I have made a number of enemies at my work place
13. Succeeding in my work makes me feel good about myself
14. I feel that it is important for workers to be treated with respect on the job
15. I believe that loyalty to an organization should be rewarded
16. I think that every organization should have a means of handling employee complaints
17. There are some aspects of my job that I enjoy more than other aspects
18. Some work days are very tiring for me
19. I make a large number of errors performing my job
20. The organization I work for has a poor reputation

APPENDIX F: Data Release Agreement

DATA RELEASE AGREEMENT

Colonel Tracy Trott agrees to make available to **Hung Loan Nguyen and Megan Wertheimer** the following:

Data requested: **THP Job Analysis Survey data**

Purpose for which the data are to be used:

To be analyzed and interpreted in order to complete a thesis for the purposes of the partial fulfillment of the requirements for the degree of Master of Art in Industrial Organizational Psychology.

Conditions:

Hung Loan Nguyen and Megan Wertheimer agrees that the data will not be released in whole or in part to any individual or organization, other than the thesis advisor, **Dr. Michael Hein**, without prior written consent from THP. This restriction applies to all reorganizations of the data, in whole or in part, and to integrations of the data with information from other sources.

Hung Loan Nguyen and Megan Wertheimer agrees to clearly acknowledge the source of the data supplied by THP whenever such data are used in any report, publication, document or public communication.

The data provided may only be used in reports or presentations directly related to the purpose described above.

THP makes no warranties as to the accuracy of the data nor its suitability for **Hung Loan Nguyen** and **Megan Wertheimer**'s purpose.

THP does not guarantee exclusivity of use of the data.

It is understood that **Hung Loan Nguyen and Megan Wertheimer** will destroy all electronic or paper copies of the data (excluding products generated from the data such as reports, maps, documents or public communications) at the termination of this agreement. Data will remain housed on Dr. Hein's computer.

By signing this agreement, and accepting the data, **Hung Loan Nguyen and Megan Wertheimer** agrees to be bound by the above conditions.

9/8/16

Hung Loan Nguyen Date

9/8/16

Megan Wertheimer Date

Col TC Trott 9/7/16

Tracy Trott Date

APPENDIX G: IRB Approval

IRB
INSTITUTIONAL REVIEW BOARD
Office of Research Compliance,
010A Sam Ingram Building,
2269 Middle Tennessee Blvd
Murfreesboro, TN 37129

MIDDLE TENNESSEE STATE UNIVERSITY

IRBN007 – EXEMPTION DETERMINATION NOTICE

Tuesday, September 13, 2016

Investigator(s): Megan Wertheimer (PI), and Dr. Michael Hein (FA)
Investigator(s') Email(s): mew7f@mtmail.mtsu.edu
Department: Psychology Department

Study Title: Identifying the Types of Insufficient Effort Responders
Protocol ID: 17-1002

Dear Investigator(s),

The above identified research proposal has been reviewed by the MTSU Institutional Review Board (IRB) through the **EXEMPT** review mechanism under 45 CFR 46.101(b)(2) within the research category *(4) Study involving existing data*. A summary of the IRB action and other particulars in regard to this protocol application is tabulated as shown below:

IRB Action	EXEMPT from further IRB review***	
Date of expiration	NOT APPLICABLE	
Participant Size	Sample sizes for each of the five data sets are as follow: 525, 472, 732, 414, 838.	
Participant Pool	Undergraduate student participants with an average age of about 20 years and adults with average ages of about 30 and 40.	
Mandatory Restrictions	Should get permission from data collectors or owners.	
Additional Restrictions	Approval for only using existing data not for collecting data.	
Comments	N/A	
Amendments	**Date** N/A	**Post-Approval Amendments** None

***This exemption determination only allows above defined protocol from further IRB review such as continuing review. However, the following post-approval requirements still apply:

- Addition/removal of subject population should not be implemented without IRB approval
- Change in investigators must be notified and approved
- Modifications to procedures must be clearly articulated in an addendum request and the proposed changes must not be incorporated without an approval
- Be advised that the proposed change must comply within the requirements for exemption
- Changes to the research location must be approved – appropriate permission letter(s) from external institutions must accompany the addendum request form
- Changes to funding source must be notified via email (irb_submissions@mtsu.edu)