TECHNOLOGICAL JOB DISRUPTIONS: THE EFFECTS OF AUTOMATING OR AUGMENTING TECHNOLOGIES ON WORKER OUTCOMES

by

MURIEL G. CLAUSON

(Under the Direction of W. Keith Campbell)

ABSTRACT

The current study examines the relationship between disruptive technologies and outcomes for workers, as moderated by organizational support and controlling for technology proclivities. Drawing upon disruptive innovation theory, technology readiness, and organizational support theory, the present study is an experimental, 2 (augmentation, automation) x 3 (low-support, high-support, absence of support information) between-subjects design, examining the outcomes of perceived job security and affective well-being. I conducted a 2x3 analysis of covariance (ANCOVA) for two dependent variables of interest. I found support for a main effect, such that employees will have worse outcomes when they perceive a threat that their job will be automated. I did not find support for a main effect of organizational support on outcomes or for a moderating effect of the support of the organization on the relationship between the nature of the technology and the outcomes. These results indicate a relationship between disruptive technologies and worker outcomes.

INDEX WORDS: Augmentation, automation, technological job disruptions, technology readiness, organizational support, affective well-being, job security

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MURIEL G. CLAUSON

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MURIEL G. CLAUSON

Major Professor: W. Keith Campbell
Committee: Karl Kuhnert
Kristen Shockley

Electronic Version Approved:

Suzanne Barbour
Dean of the Graduate School
The University of Georgia
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DEDICATION

Thank you to the people who infuse every life experience with joy, including the development of this thesis. Karl, Junanne, and Kaben, you are master encouragers and I can't thank you enough for always supporting my new endeavor. Karl and Keith, you have become dear friends and I'm abundantly thankful to have had you both as advisors. Billy and Sandy, thank you for laying the foundation for so much happiness that exists today. Olivia and Alex, I couldn't have dreamed up a better cohort to share this journey and the rest of life with. Philip, thank you for permeating life with delight and for being my best friend. I'm dedicating this thesis to Olga. Olga, you are the one who was there for every step of grad school and the preceding decades. Your eighteen and a half years of friendship are the lens with which I see love, loyalty, and contentedness. You are deeply missed and your life is celebrated.

TABLE OF CONTENTS

Page

LIST OF TABLES

Page

CHAPTER 1

INTRODUCTION

The process and impact of technological disruptions have become popular areas of research in recent years, as society is faced with more interaction with technology than ever before. The majority of what is considered technology emerged on our planet within the last few decades and there has been more change in both science and technology in the last half century than in the previous 50,000 years (Kurzweil, 2005). Advanced technologies enabled by massive amounts of data, such as artificial intelligence and robotics, have garnered a mix of enthusiasm and concern as the world watches their capabilities amplify each year. Within the last half decade, society has witnessed a machine learning algorithm beat the world champion in the highly specialized Go strategy game (Dwyer, 2017), homes and hotels constructed solely by robotic 3D printers (Grossman, 2017), and AI enabled image recognition software that can diagnose lung disease better than radiologists (Rajpurkar et al., 2017). Many scholars have begun to consider what this major influx of technological advancement will mean for workplaces and workers, both today and into the near future. A 2013 study from Frey and Osborne sparked growing interest in the topic of technological job disruptions when they proposed that 47% of all employed workers in the United States are working in jobs that could be replaced by technology within the next 10-20 years, with estimations far more dire for the worldwide workforce (Frey & Osborne, 2013).

Yet a major critique of the work by Frey and Osborne (2013) is that the mere potential to automate a task does not necessary equate to employment losses (Arntz, Gregory, & Zierahn, 2016). Accordingly, experts have begun to discuss the nature of technological changes at work in two major ways: *automating* and *augmenting*. A technology that is *automating* can be defined as a technology that has the capability to operate as a full replacement of a human worker (Mason, 2016). A technology that is *augmenting* can be defined as a technology that can perform some function of a human worker's role as a means of freeing a human worker to accomplish more higher order or integral work tasks (Manyika et al., 2017). Putting this simply, *automation* replaces the worker, while *augmentation* empowers them. It is important to note that the same technology can be adopted in an *automating* or *augmenting* fashion depending upon various societal constraints and the choices of an organization. For example, an artificial intelligence decision-making platform could be applied in a work context to review data inputs and aide in the decision-making for a loan processor who is freed up to focus on other elements of their job such as customer service (augmentation), or the same technology could be used to replace loan processors while the firm trusts the artificial intelligence decision-making tool to make decisions autonomously (automation). Since disruptive technology applications can point to two very different implications for workers, the *automation* and *augmentation* distinction will likely be an important component of job disruption scientific inquiry moving forward, yet this distinction has not been tested empirically.

While scholars have begun to explore macro impacts of technologies that have *automated* or *augmented* workers, we know very little about how the nature of technological changes at work impact worker outcomes. The majority of technological job disruption research thus far has been predictive analyses of labor changes drawing upon labor data (see Frey & Osborne, 2013) or a criticism of these methods (see Autor, 2014). Some scholars have called for a more person-centric approach in light of technological changes (see Weiss & Rupp, 2011; Weiss, 2013) and others have explored potential worker outcomes conceptually (see Acemoglu & Restrepo, 2017; Autor, 2015), yet research empirically identifying outcomes for workers faced with technological disruptions at work remains elusive. Additionally, we do not have much of an understanding of how contextual and individual factors affect these relationships. Scholars have not begun to consider the role of the support of an organization or an individual's proclivity toward technology may modify the impact of disruptive technologies on worker outcomes.

It is critical that scholars begin to identify the potential impact of *automating* or *augmenting* disruptive technologies on workers. Firstly, this is important because the threat of such technologies harming workers has gained international attention. Speculation on the topic has emerged, with increasing frequency, in political discourse (see Whitehouse – Office of the President, 2016), popular press (see Miller, 2017), organizational policy (see Bryant, 2017), and more. With a general lack of evidence-based findings, the conversation has often been sensationalized with many negative messages being sent to workers without evidence-based support for those claims. As workers make decisions regarding their careers, and technological impact may be a factor in such decisions, it is crucial that there is more reliable information available on this topic. Secondly, this is important because predictive analyses indicate that technological job disruptions are coming. While estimates range from job losses impacting half of the workforce (Frey & Osborne, 2013) to less than ten percent of the workforce (Arntz, Gregory, & Zierahn, 2016), agreement remains that technology will increasingly have the capability to perform work tasks that were formerly the exclusive domain of human workers (Frey & Osborne, 2017; Manyika et al., 2017). If these changes are coming, whether they are broad-sweeping or impact smaller segments of workers, it is critical to begin to identify how these effects will be felt and can be mitigated. This is important because many of these predictions equate to potential job losses which can lead to a wide array of hardship for workers. Finally, this is important because there are early indications that technology has already altered some opportunities for workers. Brynjolfsson and McAfee (2011) observed that productivity and total employment have been represented by tangential and near equal lines when graphed since World War II, until year 2000 when the lines began to diverge – signaling that, for the first time, economic growth is not in parallel with the creation of jobs (Rotman, 2013). This divergence became substantial in 2011, sparking Brynjolfsson and McAfee (2011) to declare this as a "great decoupling" of productivity and employment that they assert has been brought on by disruptive technologies. Considering that many of the fears relating to technology disrupting jobs are that this may have major social (see Arntz et al., 2016), economic insecurity (see Rotman, 2013), and worker well-being (see McAfee, 2013) implications, it is important that these ideas begin to be tested empirically. Above all, the matter of worker wellbeing is an important one in this context. Weiss (2013) argues that work is an important human function and that there is an important subjective experience associated with working. If these technological changes are realized, a significant human experience may be altered. Despite this threat, the implications are not necessarily negative as the technologies can be applied in two very different ways, *augmenting* or *automating*, which likely relate to very different outcomes for workers. This is why the *augmentation* and *automation* distinction needs to be better understood. The current research can provide valuable information regarding the implications of disruptive technologies in the workplace, as well as how these effects may depend upon whether the technology is applied in an *automating* or *augmenting* fashion. Additionally, it will extend current research regarding technological disruption to the disruptive technology realm.

Accordingly, the purpose of this study is to apply an experimental design to address an important gap in the research by examining the relationship between the nature of a disruptive technology at work, the organizational support, and the individual technology proclivities of an individual on affective well-being and job security outcomes. The experimental design is fitting for the research questions for this study as the issue of disruptive technology being experienced in differing ways often depend upon perceptions of a so far unknown phenomenon. Nature of the disruptive technology was chosen as a variable to symbolize whether the technology is poised to *automate* (replace) or *augment* (assist) in the function of a work task. Organizational support was chosen as a variable to identify how contextual factors may alter the impact of disruptive technologies. Additionally, technology readiness was selected as a control variable that may alter these relationships. Specifically, I examined experimentally how the support of an organization moderates the effect of the disruptive technology (*automating* or *augmenting*) on two outcomes for workers: affective well-being and perceived job security, controlling for individual technology readiness. I conducted this research through the theoretical lens of disruptive innovation theory (Christensen, 1997) and organizational support theory (Eisenberger, Huntington, Hutchinson, & Sowa, 1986; Shore & Shore, 1995), which guided the inquiry into worker outcomes as they relate to the nature of disruptive technologies at work.

To set up the present study, several domains will be explored. The following sections will begin with an overview of the changing capabilities of technologies. This will include a glimpse into the pace of change of technology today and why this might differ from past times of technological advancement. Secondly, the concept of technological disruptions will be explored. This includes an overview of predicted technological disruptions, disruptive innovation theory (Christensen, 1997) and the phenomenon of subjective threat. Next, organizational support will be explained and applied to the context of subjective threat. Additionally, the role of technology readiness for worker acceptance of technology will be explored. Finally, the present study's methods, results, and conclusions will be presented.

CHAPTER 2

THE CHANGING CAPABILITIES OF TECHNOLOGIES

In order to understand the present state of concern regarding technological job disruptions, it is important to first understand the capabilities of technology today and the rate at which these capabilities are growing. Perhaps the most influential scholarly work regarding the pace of technological change stems from Moore's Law (1965) which is a means of explaining how exponential technological growth has been possible. This prominently discussed paradigm is based in Moore's identification that the number of transistors that were able to fit on an integrated circuit were doubling every twelve to eighteen months (Moore, 1965). This doubling trend has now largely held for over 50 years. The reason this doubling of circuit capacity is important, is that it represents our general computing capacity and is known as exponential technological change (Schaller, 1997; Kurzweil, 2005). This exponential technological change is the reason that individuals now have more computing power in their smartphones than the entire computing power of the NASA program in 1969 (Kurzweil, 2005). To understand the pace of technological change, it can be useful to consider this in contrast to linear change. While taking thirty linear paces would result in moving thirty meters, taking thirty exponential paces would result in traveling over a billion meters – which is roughly twenty-six trips around the earth.

Drawing upon Moore's Law and the idea of exponential technological change, Kurzweil (2004) proposed the Law of Accelerating Returns, a systems theory of evolution, to describe a category of technologies that he referred to as exponential technologies – artificial intelligence, robotics, nanotechnologies, bioinformatics, data science, and others. He posited that exponential technologies evolve in a similar pattern to biological organisms, because they learn and adapt through the same iterative cycles of trial and error. The explanation for how exponential technologies follow this pattern, and what makes them unique technologies in contrast to others, is that they are information-enabled. This means that they learn and advance through trial and error as well as inputs from their environment, in a similar, though not identical, fashion as humans develop. In light of this accelerated development and the general nature of the development of these technologies, many have proposed that technological job disruptions are a growing risk for today's workers in a way that past technological advances were not.

CHAPTER 3

TECHNOLOGICAL DISRUPTIONS

It is important to understand the concepts of Moore's Law (Moore, 1965) and the Law of Accelerating Returns (Kurzweil, 2004) in order to understand why today's technological job disruption concerns may be different than those that have been held historically. Despite the recent surge in technological unemployment interest, both within and outside academia, this is not the first instance of growing fear around the topic (see Mokyr, Vickers, & Ziebarth, 2015) – concerned policy-makers, organizations, and workers date back to the dawn of textile machines. Despite various points of technological disruption concern throughout recent history, technological advances over the past two centuries have not, for the most part, destroyed jobs faster than the creation of new jobs. The phenomenon of new jobs being created faster than they are being destroyed is known as the capitalization effect (Aghion & Howitt, 1994) and this effect has largely characterized the major technological advances and their effect on work in recent history. A good example of this is the ATM machine – an invention that sparked concern over bank teller jobs, yet, over the last ten years, we have witnessed more people holding these jobs following the wide adoption of these devices than before as the entire banking industry has grown in tandem with this new technology (Pethokoukis, 2016). In light of such examples, some scholars claim the fears associated with new technologies are overblown, pointing out either the shortcomings of current disruptive technologies (see Chui, Manyika, & Miremadi, 2015) or that the mere potential to automate a task does not necessary equate to employment losses (see Arntz, Gregory, & Zierahn, 2016). Additionally, there are domains that many experts agree will remain the exclusive competencies of human workers for some time or indefinitely. Frey and Osborne (2013) identify what they refer to as "engineering bottlenecks" as the realm where a human may need to step in and perform tasks that cannot be clearly defined by common and repeating rules. Other tasks currently discussed as more resilient to technological advances include social intelligence and creativity (Arntz et al., 2016).

On the contrary, others state that advanced automation and digitalization are changing the nature of job tasks that can be replaced by technologies – reaching into the realm of some of the job tasks that previously had been thought of as most human in nature (Autor, 2013). While developing new skills, often higher order skills, has been touted as the solution for workers to advance alongside such technologies, Brynjolfsson and McAfee (2011) project that workers will not be able to keep up with the pace of technological advancement. An example that they point to is the field of radiology, where there are already image recognition technologies that perform many diagnostic screenings better than the physician. Despite these competency areas, some argue that if an organization can be more profitable applying a technology, even an imperfect technology, over a human worker, that the organization will likely do so (Rotman, 2013).

While Frey and Osborne (2013) identified that 47% of jobs were at risk of automation in the United States, Autor (2014; 2015) called their methods into question and pointed out that automation of an entire occupation is likely the wrong level of analysis to begin with, rather it is the tasks that make up the job that may be susceptible. This logic is based in the idea that tasks are more nuanced than jobs, and provide a more accurate picture of a work function than a broad-sweeping job role. In line with this viewpoint, analyses led by scholars associated with The Organization of Economic Cooperation and Development (OECD) found that the Frey and Osborne (2013) estimations are far too high when this task-centered model is taken into account, and, in reality, job automation risks reside closer to 9% of all OECD country workers in the coming 10-20 years (Arntz et al., 2016). This more optimistic outlook is currently in the minority in this literature, yet even the most optimistic predictions point to a real threat of technological job disruptions at about ten percent of the current workforce.

In the face of the threat of technological job disruptions presented in predictive findings, a small amount of scholarly work has begun to consider potential implications for workers. Early research efforts have explored job disruptions in specific labor sectors. Many of the examples of technological job disruptions that can already be felt today have occurred in the manufacturing sector, sparked by mechanization functions implemented in warehouses, yet there are examples of highly skilled work being replaced by technology, such as some highly trained medical job functions (Cohn, 2013). Additionally, scholars have explored what the positive implications of these technologies may be for workers. Positive implications have been found to largely be the by-product of routine, mundane tasks being handled by advanced technologies which allow workers to instead focus on the more complex, meaningful components of their jobs (Manyika et al., 2017). While negative implications of technological job disruptions have garnered the majority of public interest, this line of inquiry is largely missing from scientific literature.

Disruptive Innovation Theory and Subjective Threat. Although research regarding technological job disruptions is scarce, there is a larger body of research examining the impact of general technological disruption. The most widely recognized theory is the disruptive innovation theory which was seminally proposed by Christensen (1997) and describes the process by which disruption occurs (Daneels, 2004). Christensen proposed that technological disruption occurs at the point when a novel technology improves to meet demands above and beyond the mainstream technology (Bower & Christensen, 1995; Christensen, 1997). The entrant technology, is initially inferior to the incumbent technology on various dimensions, but is able to offer some contrasting value – such as greater precision. Over time, the entrant technology is further developed and the incumbent technology is only maintained. Disruption occurs when the entrant technology is able to catch up with the incumbent technology and it becomes difficult for the incumbent technology to compete with respect to accelerated development – a replacement of incumbent with entrant (Christensen, 1997). Specifically, disruptive technological innovation is less expensive for the customer or organization, is more accessible to use or apply, and applies a business model that meaningfully overlaps with the incumbent (Wessel, 2016; Chiaroni et al., 2016).

While disruptive innovation theory has traditionally been thought of as the technological disruption process between an older technology and a more novel technology, this framework can also be useful in considering the disruption between incumbent human worker and entrant technology. Particularly relevant to the purpose of this study, is the element of subjective threat. When the entrant technology begins to gain the capabilities of the incumbent, the entrant becomes a threat to the incumbent (Bower & Christensen, 1995). The more the entrant is able to replace the incumbent, the greater this threat becomes. This idea of threat based on replacement aligns with the distinction of *automation* and *augmentation*. *Automation* would likely illicit a much higher level of threat than *augmentation*, as *automation* represents a technology that replaces the human worker while *augmentation* represents a technology that frees the human worker to perform other higher order tasks. Aligning the ideas of *automation* and *augmentation* with disruptive innovation theory, *automation* can be thought of as disruption and the possibility of this disruption is a subjective threat to the worker, while *augmentation* is not disruption and is less likely to represent a threat to the worker.

Subjective threat has been represented as a component of many job stress models. Notably for the present work, the AAA (appraisals, attributions, adaptations) model (Mackey and Perrewe, 2014) posits that workers are faced with either challenge or hindrance organizational stressors and this leads to a primary appraisal. The primary appraisal branches into three different judgements: threat, challenge, or irrelevant. This primary appraisal process may function quite differently depending upon the information that the worker has regarding the stressors. In the case of disruptive technology, the technology may be seen as more threatening if it is seen as *automating* rather than *augmenting*, as this establishes a more direct impact on the worker's interests, such as keeping his or her job at the organization. Next, the model branches into either positive or negative emotional affective states that may be felt by the worker based on their primary assessment, with negative affective states associated with the threat judgement. In the next portion of the AAA model a secondary analysis takes place where the worker assesses any personal liabilities, such as job insecurity. These analyses in turn influence job strain and wellbeing outcomes. For this present work, the AAA model provides an interesting perspective on how the implicit subjective threat, associated with the disruptive technology, alter affective wellbeing and job security outcomes for the worker as a part of a greater job strain process.

Threat is a phenomenon that has been represented implicitly in scholarly work as a function of a broader phenomenon such as job security (see Heany, Israel, & House, 1994). In a review of the job security literature, Greenhalgh and Rosenblatt (1984) identified subjective threat as a key process through which employees made assessments regarding their status within their organization which influenced their affective well-being outcomes. Affective well-being can be thought of as the either high or low pleasure and high or low arousal emotional states that surface in job-related contexts (Van Katwyk, et al., 2000). Relatedly, in studies exploring potential stressors (subjective threat) at work, ambiguity around stressors (heightened subjectivity due to a lack of clarity regarding the stressor) was associated with negative affective outcomes, such as anxiety and frustration, which are low pleasure, high arousal affective well-being outcomes. (Spector, Dwyer, & Jex, 1988).

While subjective threat typically has not appeared as the variable of interest in empirical studies relating to job security, it has explicitly or implicitly been a component of the broader process (Sverke, Hellgren, & Naswall, 2002). Threat perceptions often occur for workers in three primary ways (Greenhalgh, 1983; Greenhalgh & Rosenblatt, 1984). First, subjective threat can arise for employees based upon rumors that have a potential to have a deleterious impact on those individuals, such as rumors about job loss. Second, perception of threat can arise when an organization provides unintentional cues to workers. For example, organizational leadership may invest heavily in mechanistic manufacturing robots for a production plant and not provide any additional signal to workers regarding how these technology acquisitions will impact the people in the organization with manufacturing roles. Finally, threat perception can occur when an organization shares an intended organizational message that is perceived as threatening. It is important to note that the organization or party sharing the message does not need to intend for the message to be threatening in order for employees to view it as such. This is particularly salient to the present topic of technological job disruptions, as many workers are faced with the possibility of technology threatening their jobs (Autor, 2013) and thus they feel threatened, but may not have any concrete reason to be concerned at present.

An additional parameter that is important to consider is the perceived severity of a subjective threat. The severity of a threat at work has been represented in two primary ways in scholarly literature (Greenhalgh & Rosenblatt, 1984). First, the severity of threat can be understood as both the importance and the scope of the potential loss for the worker in question. This is an important component to consider again in the context of *automation* and *augmentation*. While *automation* and *augmentation* both lend to some component of a worker's job being replaced by technology, *augmentation* involves the technology replacing an element of that job that is likely less important and less of a loss to the worker – on the contrary, it can often be a benefit. Thus, if threat is felt by the worker in an *augmentation* scenario, that threat is likely to be felt as less severe than in the case of *automation*. Secondly, the severity of threat relates to the subjective probability that the loss will occur for the worker. This relates not only to whether or not the replacement actually occurs, but also if that replacement is perceived as a loss to the worker. If a technology replaces a function that the worker deemed as rudimentary and non-integral to their role (*augmentation*), then this technology is less likely to elicit a threat perception.

Subjective threat is an important consideration in the broader technological disruption discussion, as it is well established that felt subjective threat is detrimental to worker's perceived job security and affective well-being (Sverke et al., 2002). In a meta-analytic review of empirical work regarding subjective threat relating to a job role, heightened job insecurity and lower affective outcomes were two of the most prevalent outcomes associated with the phenomenon (Sverke et al., 2002). Aligning both disruptive innovation theory and the phenomenon of subjective threat in an employment context, it becomes evident that the nature of a technology (*automation* or *augmentation*) is likely to influence both affective well-being and perceptions of job security for a worker. The present work proposes to extend disruptive innovation theory, which incorporates threat of replacement, by aligning with the notion of subjective threat to understand how the nature of a technology may alter outcomes for workers. In light of the likelihood of replacement, severity of threat, and the potential for loss, it is proposed that workers faced with a technology packaged as *automating* will experience lower job security and lower affective well-being than those presented an *augmenting* technology, as a function of subjective threat. Being given the opportunity to leverage a disruptive technology at work may be seen as a benefit to one's professional development and performance. However, it may also signal that one's job will be replaced by the technology. This distinction may not depend on what the actual technology is capable of, but how an organization applies such a technology to their workers in relation to their job role and contribution, as supported by the various channels of communication that can serve as antecedents to subjective threat. Considering the disruptive innovation theory and the tendency to perceive new entrants as a threat if they reflect the incumbent (Bower & Christensen, 1995; Christensen, 1997) – in this case the entrant technology and the incumbent human worker – the severity of threat is likely to be perceived differently depending on whether the technology is *automating* or *augmenting*. I anticipated a main effect of the type of technology presented, such that a technology presented as a replacement of a job role (*automation*) will elicit a greater threat response and worse outcomes for workers. I proposed two different technology presentation types, to compare the effects of a technology that empowers a worker to do their job better (*augmenting*) and a technology that replaces the worker's job role (*automating*). Thus, I proposed:

Hypothesis 1: Individuals who are presented an *automating* technology will experience (a) lower perceived job security and (b) lower affective well-being compared to those who are presented an *augmenting* technology.

CHAPTER 4

ORGANIZATIONAL SUPPORT

While technological disruptions may pose a threat to workers and lead to negative outcomes, it is important to consider what factors may mitigate such effects. One such realm is the perception that a worker holds about the support of his or her organization. Organizational support of employees and the perceptions that employees have of such support are two frequently discussed phenomena (Rhoades & Eisenberger, 2002). Originally, perceived organizational support was considered as an important component of social exchange theory (Emerson, 1976; Cropanzano & Mitchell, 2005), where both the organization and employee consider the relative support shown to one another (Wayne, Shore, & Liden, 1997). Following beginnings in a social exchange theory lens, more focused inquiry into the phenomenon itself was explored following the proposal of organizational support theory (Eisenberger, Huntington, Hutchinson, & Sowa, 1986; Shore & Shore, 1995). Organizational support theory suggests that employees develop beliefs about the extent to which their organization values their contribution and well-being in order to determine the organization's willingness to reward and meet the needs of the employee. Recent work has begun to focus on a worker-centric lens with this theory – perceived organizational support. Perceived organizational support can be described as the general belief that employees hold about the extent to which their organization values their contribution and cares for their general well-being (Rhoades & Eisenberger, 2002), which can be fostered through acts of goodwill and transparency toward employees such as disclosing results of an engagement survey and resulting development plans.

In the technological job disruption context, organizational support is a potential area where negative effects for workers can be mitigated. This idea is supported by many existing findings relating to organizational support. A review of organizational support literature found that high levels of organizational support related to better outcomes for workers in many realms (Rhoades & Eisenberger, 2002) including perceived job security (see Cropanzano et al., 1997) and affective well-being (see Witt, 1991). A recent meta-analytic examination of organizational support also found that high organizational support relates to these outcome (Kurtessis, et al., 2017), and found that organizational support fosters expectations that are positive regarding the future which helps to reduce appraisals of threat (Kurtessis, et al., 2017; Lazarus & Folkman, 1984).

One important facet of perceived organizational support is employees' belief that their organizations will provide aid and support to them when it is needed (Shore & Shore, 1995; Rhoades & Eisenberger, 2002). This becomes particularly salient when it is necessary to deal with stressful or threatening situations (George, Reed, Ballard, Colin, & Fielding, 1993). This felt need is often the result of a salient event for the employee. In the case of technological job disruptions, an employee will not only be faced with a technology that is *automating* or *augmenting*, but they will also likely experience the subjective threat and resulting outcomes differently in accordance with their beliefs about the kind of aid and support that their organization is likely to offer to them during this transition. If a new technology is applied in an augmenting fashion in a workplace, yet the worker experiences poor organizational support which makes him or her feel that they are not valued by their employer, the augmenting technology may be viewed as more threatening than if the same technology application was paired with an organization that is highly supportive of their workers. This same distinction is likely with *automating* applications. A worker with a highly supportive employer may see the technology as less threatening because they trust that their employer values them and will still support them alongside this new technology, while a worker with low support is likely to perceive this threat much more acutely. Perceived organizational support has been found to influence the general affective reactions that an employee has toward his or her job, including general satisfaction at work and emotional responses (Witt, 1991). Additionally, perceived organizational support has been found to play an important role in the strain that is felt by an employee faced with a stressor at work. In light of the established linkage between organizational support and the mitigation of subjective threat perceptions and resulting outcomes, the following is proposed:

Hypothesis 2: There is a main effect of organizational support on job security and affective well-being, such that those who are presented with high-support will experience (a) lower perceived job security and (b) lower affective well-being compared to those who are presented with low-support.

Additionally, an important component of perceived organizational support is a belief that the organization wishes to retain the individual as an employee (Allen, Shore, & Griffeth, 1999). This is particularly salient when the employee is faced with a knowledge that there is a climate for downsizing or similar activities at neighboring organizations. This is an important consideration in a technological job disruptions context, as an *automating* technology is associated with a threat of replacement while an *augmenting* technology is not. For this reason, organizational support is likely to function differently in instances of *automating* and *augmenting* technologies. Specifically, those who are faced with an automating technology at work are already more likely to perceive greater threat to their job roles, than those who are faced with an *augmenting* technology. Organizational support is associated with trust that one's employer will retain him or her at the organization; thus employees who feel that their job role is under threat (*automating*) are more in need of the reassurance that their organization can be trusted to retain them compared to those who are not under such threat (*augmenting*). Without this support, they are likely to suffer more in terms of job security and affective well-being, given the larger perceived threat of the technology.. Thus, the following is proposed:

Hypothesis 3: There will be an interaction between the technology condition and organizational support. The nature of the interaction is such that low support leads to a) lower perceived job security and b) lower affective wellbeing in the automating condition than in the augmenting condition.

CHAPTER 5

TECHNOLOGY READINESS

Another important layer of inquiry as it relates to technological disruptions is at the individual level, as individual level factors may mitigate the effects of *automation* or *augmentation*. Individual differences relating to comfort and acceptance of technology at work have long been established in scholarly work, including generational differences (see Bennett & Maton, 2010), personality differences (see Svendsen, Johnsen, Almas-Sorensen, & Vitterso, 2013), and cultural differences (see Elliot, Meng, & Hall, 2008). For example, scholars have found that there are significantly different levels of comfort with technology for individuals who are less trusting versus more open when they are faced with the option to perform self-check-in at the airport and self-check-out at the grocery store (Lin, Shih, & Sher, 2007). Relatedly, age and self-perception of computer skill level were found to be related to acceptance and use of mobile banking platforms (Kleijnen, Wetzels, & De Ruyter, 2004).

An established measure of individual differences with regards to technology acceptance is the Technology Readiness Index, developed by Parasuraman (2000). The Technology Readiness Index identifies the willingness and level of preparedness that a worker has in the acceptance and implementation of a new technology at work. The measure focuses on four major individual difference traits: innovativeness, optimism, discomfort, and insecurity. While optimism relates to an optimistic belief in technology and innovativeness relates to a pioneering spirit, discomfort and insecurity relate to a perception of lack of control and a general distrust of technology, respectively (Lin, Shih, & Sher, 2007). The more technologically accepting and prepared workers score high in both innovativeness and optimism on the measure, as well as low in discomfort and insecurity. Additionally, the Technology Readiness Index has been applied to research inquiry in the realms of sustainability project acceptance (Molla et al., 2008), medical device use by medical professionals (Caison, Bulman, & Neville, 2008), and primary school teachers accepting digitized homework assignment methods (Summak, Baglibel, Samancioglu, 2010). Walczuch, Lemmink, and Streukens (2007) unmasked a particularly relevant finding, that personality, as measured by the Technology Readiness Index, influenced what extent of the capacity of the technology was leveraged in a customer service job role. While the Technology Readiness Index has been utilized extensively in scholarly work focusing on novel technologies, studies applying the measure to the acceptance of more disruptive technologies are lacking.

Although the Technology Readiness Index has not been applied to more advanced technologies, such as artificial intelligence and robotics, thus far, there are many elements of the model that align with the issue of technological job disruptions. Particularly relevant is the perception of threat from a technology. Two facets of the Technology Readiness Index relate to the idea of threat directly: optimism and insecurity. Optimism focuses on one's belief that technology is ultimately good and serves a positive purpose (Lin, Shih, & Sher, 2007). Those scoring lower on this facet are perhaps more likely to perceive technology as damaging and as having negative implications for themselves and others – perceiving the technology as a threat. Additionally, insecurity is a facet associated with concern about technology and that the capabilities of technology may be damaging – again, a likely threat perception. Thus, people who are higher in technology readiness are less likely to view any type of technology as a threat, whether *automating* or *augmenting*. Considering these two facets of the Technology Readiness Index, it is likely that a worker who is lower on technology readiness would have a heightened threat perception of a disruptive technology at work. This means that, regardless of the presentation of the technology as *automating* or *augmenting*, individuals who associate technology in general with a threat will perceive any technology presentation as more threatening than other individuals. Thus, technology readiness may explain the relationship between the nature of technology and outcomes. In light of this, technology readiness should be included as a control variable in the model in order to ensure that the results pertaining to nature of technology are not simply the carryover effects of pre-existing technology proclivities. Therefore, I propose technology readiness as an important control variable for the present study and hypotheses will be tested with and without the inclusion of the covariate.

CHAPTER 6

METHOD

Participants

An online experiment was conducted with 535 respondents via Amazon's Mechanical Turk (MTurk) with a final usable sample size of 440 participants (*female*=159, *male*=281, *mean age*=34.9, ethnicity: white=68.7%, Asian=14.3%, Hispanic=8%, black=7%, other=2%, average hours worked per week=45.84, average tenure at current organization=5.85). All of the participants who were eliminated failed to correctly answer one or more attention checks. Participants were eligible to take part in this experiment if they were over the age of 18 and worked at least 30 hours per week. Both female and male participants were eligible to participate. Based on an a priori power analysis using G*power software, the sample size was deemed as having sufficient power for the study design with an effect size of f=.25, six conditions, an alpha of .05, and a power of .95.

Procedure

Participants were recruited via MTurk using a paragraph describing the study and the requirements for eligibility. Participants were paid $0.60 for completion of the full study. They completed a pre-screening survey to ensure eligibility. If they meet all study requirements in the prescreening, they were sent to the informed consent document. After they had provided informed consent, the participants read a set of instructions. Next, they were randomly assigned to one of six conditions. The experiment was a 2 (automation, augmentation) X 3 (low-support, high-support, absence of support information) between-subjects design. The absence of support information condition was added as an exploratory condition in order to ascertain what the perceptions of support would be if no support information was provided.

Prior to any manipulation, participants completed a survey measuring his or her technology readiness. Next, participants were told to assume the role of an employee at True Financial working as a loan officer. They were told that the leadership team within the organization are eager to be early adopters of a new advanced technology, EDGE-AI, and that they will need to decide whether or not they want to adopt this technology for use in his or her job role. The decision element of the manipulation exists to elicit the idea of threat of change as opposed to an inevitable organizational change. They were then told that in addition to deciding whether or not they will use the technology, they also provided feedback on his or her impressions of EDGE-AI and technology more generally. They were given an email from his or her fictitious supervisor to increase the fidelity of this request, who explained the type of technology (*automation* or *augmentation*, depending on the condition). The email also explained the reasons that led True Financial to want to adopt the technology (low-support, high-support, absence of support information), and ask that they complete the technology rating form. Participants in the absence of support information conditions were not given this section of the email and were not given any indication of the support of the organization. After reading this email, they were asked if they choose to adopt the technology at work, then given the technology rating form including the Technology Readiness Index (Parasuraman, 2000) and outcome measures, and then given a demographic questionnaire. Regardless of his or her decision regarding adopting the technology, they still filled out the technology rating form and demographic questionnaire. After answering all questions in the survey, participants were debriefed on the study and thanked for participating. See Appendix A for the full manipulation materials.

The only two pieces of information that were manipulated across conditions were the presentation of the technology and the organizational support (as represented by the organization's motive for adopting the technology). The presentation of technology was one of two levels: *automation* or *augmentation*. The organizational support was one of three types: low-support, high-support, or absence of support information. All other information was kept identical across the six experimental conditions. Prior to the final data collection, a pilot study was conducted following the procedure outlined above. The pilot study included 52 participants after 11 of the 63 survey respondents failed to pass attention checks. Pilot analyses indicated that study conditions were consistent with manipulation checks. For nature of technology, those in the automation condition responded that the technology was more threatening (M=4.50 , SD=.57) and the augmentation condition rated the technology as less threatening (M=2.40 , SD=1.34). Additionally, those in the high support condition (M=4.83 , SD=1.13) rated that they received higher support than the low support condition (M=3.38, SD=1.69) and the lack of support information condition was between high and low support (M=4.47, SD=.81).

Measures (see Appendix A).

Technology readiness. Technology readiness was measured using Parasuman and Colby's (2015) Streamlined Technology Readiness 2.0 Index measure based upon Colby and Parasuman's (2001) Technology Readiness Index measure. Participants were asked to rate his or her general impressions of technology on a 5-point Likert scale, ranging from strongly disagree (1) to strongly agree (5), and composites were calculated for the items relating to optimism, innovativeness, discomfort, and insecurity. Discomfort and insecurity responses were reverse coded for analysis. Optimism was measured using a three-item scale; an example item is "I like the idea of doing business via computers because you are not limited to regular business hours." Innovativeness was measured on a two-item scale, with items including "I can usually figure out new hi-tech products and services without help from others," for example. Discomfort was measured using a two-item scale, with items including "New technology is often too complicated to be useful." for example. Insecurity was measured using a three-item scale, with items including "I do not feel confident doing business with a place that can only be reached online," for example. Results indicated that the technology readiness scale displayed satisfactory reliability in the present study, with a coefficient alpha of .76.

Technology adoption decision. Participants were asked to report whether they would adopt EDGE-AI for use in his or her job role. They were asked "Do you agree to use EDGE-AI in your job as a loan processor?" with only the options of yes or no. This item is included to increase the fidelity of the manipulation and was not included in analyses.

Perceived job security. Perceived job security was measured using six item measure developed for this study adapted from Bartol, Liu, Zeng, & Wu's (2009) measure adapted from the psychological contract inventory (Rousseau, 2000). Prior to answering these items, participants were reminded to answer as if they are a loan processor at True Financial. Participants were asked to rate a series of 5-point Likert scales, ranging from strongly disagree (1) to strongly agree (5), and a composite was calculated after reverse scoring items. Two original items were taken directly from Bartol, Liu, Zeng, & Wu's (2009) scale. These two items were "My organization has made a commitment to me for only short-term employment" (reverse scored) and "My organization has given me the impression that I am welcome to remain as part of the organization on a long-term basis if I want." One items from the original measure was deemed problematic prior to administering the survey due to the nature of the wording. That item reads, “My organization can terminate my employment at any time” (reverse scored). This item’s wording appeared problematic because the contents of the statement are objectively true of anyone working in an at-will labor economy (which is likely true of all respondents as they certified that they are from the United States). In order to correct for this wording, while still capturing the sentiment, additional items were created for the measure and pilot tested. Addition items were added and pilot tested to lengthen the measure. The measure was adapted to its final version following the pilot testing of several additional items. Pilot testing indicated that the job security scale did not have a satisfactory reliability with a coefficient alpha of .69, though a prior study found satisfactory reliability with this scale with an alpha of .72 (Bartol et al., 2009). Results indicated that the scale would be substantially more reliable if the problematic original item was removed (alpha if deleted =.84). Following the removal of this scale item, the reliability of the job security scale was much higher with a coefficient alpha of .84. Of the final items included, one was intended specifically to mimic the sentiment of the problematic item to maintain content validity. This item read, “It is unlikely that I will lose my job in the near future.” The final scale consisted of six items.

Affective well-being. Affective well-being was measured using a twelve-item measure developed for this study and adapted from Van Katwyk, Fox, Spector, and Kelloway’s Job-related Affective Well-being Scale measure (2000). The measure was adapted to reflect the technology in question for this study – EDGE-AI. This resulted in each item beginning with a mention of the technology in question. Participants were asked to rate his or her general impressions of the technology adoption on a 5-point Likert scale, ranging from strongly disagree (1) to strongly agree (5), and composites were calculated first for negative affective (reverse-coded items) and positive affective items, and then for four affective subtypes: low pleasurable-high arousal, low pleasurable-low arousal, high pleasurable-high arousal, high pleasurable-low arousal. For analyses, each subscale was combined for a composite score of affective wellbeing, as the scale is typically scored (Uncu, Bayram, & Bilgel, 2006). All items were preceded with "Being asked to use EDGE-AI at work would make me feel…" followed by various affective states including low pleasurable-high arousal – "angry," low pleasurable-low arousal – "discouraged," high pleasurable-high arousal – "enthusiastic," and high pleasurable-low arousal – "relaxed." Analyses indicated strong scale reliability for affective well-being with a coefficient alpha of .91.

Manipulation checks. Participants were also given manipulation checks to verify that the experimental manipulation was successful. Participants were asked to rate their agreement on a five-point Likert scale for three items measuring the technology manipulation developed for this study. These items ascertained how threatening (*automation*) or non-threatening (*augmentation*) the technology was perceived to be. An example item is, "Edge-AI is a threat to my job." These items were composite scored with higher values indicating that the technology was perceived as more threatening. To check the organizational support manipulation, items were administered from the short version, eight item scale from Eisenberger, Huntington, Hutchison, and Sowa (1986) of perceived organizational support. Participants were asked to rate a series of 5-point Likert scales, ranging from strongly disagree (1) to strongly agree (5), and a composite was calculated after reverse scoring four items. Prior to reading the items, participants were reminded to answer as if they are a loan officer at True Financial. Sample items include, "My organization really cares about my well-being," "The organization cares about my general satisfaction at work," and "The organization takes pride in my accomplishments at work." Neves and Eisenberger (2014) found an alpha of .91 for this short version of the survey.

Demographics. Participants were also asked to indicate their age, gender, ethnicity, the number of hours they work each week, and their tenure at their current organization.

Attention Checks. Participants were administered a series of attention checks to ensure that they were paying attention while answering the items within the survey. There was a total of six attention checks included in the study. There were two types of attention checks used: agreement scale items and single answer items. An example item for an agreement scale attention check is, "I have never brushed my teeth," with responses ranging from strongly disagree to strongly agree on a five-point Likert scale. An example of a single answer attention check item is, "Please select toast from the following options," with toast listed as one of a series of responses below. Participants were removed from final analysis if they rated somewhat agree or strongly agree on the agreement scale items or if they selected the incorrect option on a single correct answer item.

CHAPTER 7

RESULTS

Preliminary Analysis

Prior to formal data analysis, data cleaning was conducted. Participants were removed from the dataset who failed any one or more of the six attention checks included in the study which represented a variety of attention check styles. This is important both because participants will often satisfice, selecting the simplest answer when completing a survey and because a variety of attention check styles is important in an MTurk context where respondents are more likely to spot attention check patterns than traditional respondents (Hauser & Schwarz, 2016). Of those removed for failing attention checks, 82 failed two or more attention checks and 13 failed one attention check. No other respondents were omitted from analysis, as no outliers outside the range of plausible values for scales were identified. Following removal due to attention checks, the final sample size for the study was 440. Descriptive statistics (number of responses, means, standard deviations, minimum and maximum values, number of items, and coefficient alphas) were calculated for each study variable and are presented in Table 1. Prior to further analyses, negatively-valenced items were reverse-coded as indicated in the full study survey in Appendix A. Finally, I tested for outliers by examining data points that were more than three standard deviations above or below the mean. No outliers were detected.

Manipulation Checks. Manipulation checks were conducted to verify group-level effect of condition. To test that nature of technology and organizational support were properly manipulated, a one-way analysis of variance (ANOVA) was conducted for each variable, this

7.1

Table 1

Descriptive Statistics

	N	*Mean*	*SD*	*Min*	*Max*	*n-items*	*alpha*	*R*(1)	*R*(2)	*R*(3)
Technology Readiness (1)	440	3.87	.603	2.30	5.00	10	.76		.07	.13*
Affective Well-being (2)	440	3.29	.886	1.00	5.00	12	.91	.07		.68*
Perceived Job Security (3)	440	3.07	.864	1.00	5.00	5	.84	.13*	.68*	
Gender (female)	159									
Gender (male)	281									
Age	440	34.9	9.71	18	67					
Ethnicity (white)	297									
Ethnicity (Asian)	63									
Ethnicity (Hispanic)	36									
Ethnicity (black)	32									
Ethnicity (other)	12									
Work hours (weekly)	440	45.84	9.37	10	91					
Tenure at job	440	6.03	5.49	.5	38					

included the condition as the IV and the corresponding manipulation check scale composite as the DV. The result of comparison between the two conditions for nature of technology yielded a significant effect, $F(1, 438) = 55.226$, $p<.000$), meaning that those participants who were given an *augmenting* vignette (M=2.43, SD=1.19) were less likely to perceive the technology as threatening, and those who were given an *automating* vignette (M=3.59, SD=1.24) were more likely to perceive the technology as threatening. The organizational support manipulation was also significant, $F(2, 437) = 4.922$, p=.008); those who were given a low support vignette (M=2.05, SD=1.04) were more likely to perceive low support from the organization, and those with a high support vignette (M=3.41, SD=.99) were more likely to perceive high support. It is important to note that the control group, absence of support information (M=3.34, SD=1.05), reported scores similar to the high-support condition (M=3.41, SD=.99) on the manipulation check scale and that these scores were close to the midpoint of the scale.

Assumptions. To perform analyses for hypothesis testing utilizing ANCOVA and ANOVA, it was necessary to first ensure that the assumptions of those analyses were met. For the analyses in questions, this included three components. First, I tested that the variables were normally distributed. I did so by analyzing the skewness, kurtosis, and distribution on a histogram of the data. All values for skewness were between -1 and 1 (technology readiness = -.212, affective wellbeing = -.334, job security = -.093), demonstrating that the data does not have skewness issues (Grayetter & Wallnau, 2014). Additionally, there was no evidence of kurtosis issues as each kurtosis value (technology readiness = -.708, affective wellbeing = -.703, job security = -.483) is roughly equal with or less than three times the standard error for kurtosis (technology readiness, affective wellbeing, job security = .232) (Trochim & Donnelly, 2001). In addition, the distribution was assessed by viewing the data displayed on a histogram with the normal curve applied and the data followed the normal distribution curve quite closely. Second, I tested for homogeneity of variances. The groups in question had roughly equal sample sizes for both technology condition (augmentation=220, automation=220) and support condition (low=141, high=153, none=146). A Levene's test (Levene, 1960) was conducted and found that the homogeneity of variances assumption was met as the results were not significant (*levene statistic*=1.247, p=.265). Finally, the independence of cases assumption was met, as it was verified that all participants entered unique user identification codes assigned to unique M-Turk worker accounts and there was no overlap between participants. Analyses indicated that the assumptions were met and that planned formal analyses could be completed.

Hypothesis Testing

To test hypothesis 1, 2, and 3, I first conducted a 2x3 analysis of variance (ANOVA) for each of the two dependent variables of interest (job security and affective well-being). By using ANOVA, I examine the main effect of nature of technology (Hypothesis 1), the main effect of organizational support (Hypothesis 2), and the interaction between technology and organizational support (Hypothesis 3). Full results of the ANOVA analyses are presented in Table 2 and Table 3.

7.2

Table 2

ANOVA Results for Perceived Job Security

	df	*F*	*d*	*p*
Nature of technology	1	57.785	.72	.001
Organizational support	2	1.232	.05	.293
Nature of technology x Organizational support	2	.031	.09	.970
Residual	434			

*Significant at the p<0.05 level.

7.3

Table 3

ANOVA Results for Affective Well-being

	df	*F*	*d*	*p*
Nature of technology	1	37.02	.57	.001
Organizational support	2	2.29	.20	.103
Nature of technology x Organizational support	2	.64	.24	.526
Residual	434			

*Significant at the p<0.05 level.

For hypothesis 1a and 1b, I expected that an *augmenting* technology would relate to a) higher job security and b) higher affective well-being than an *automating* technology. The hypothesis was supported for a) job security ($F(1, 434) = 57.785$, p=.001, d=.72), such that participants who were presented with an *augmenting* technology (M=3.56, SD=.85) were more likely to report higher job security, than those who were presented an *automating* technology (M=2.92, SD=.93), and was supported for b) affective well-being ($F(1, 434) = 37.025$, p=.001, d=.57), such that participants who were presented with an *augmenting* technology (M=3.54, SD=.93) were more likely to report higher affective well-being, than those who were presented an *automating* technology (M=3.05, SD=.76).

For hypothesis 2a and 2b, I expected that high organizational support would relate to a) higher job security and b) higher affective well-being than low organizational support. This hypothesis was not supported for a) job security ($F(2, 434) = 1.232$, p=.293, d=.05), and was also not supported for b) affective well-being ($F(2, 434) = 1.648$, p=.103, d=.20). See tables 6 and 7 for means and standard deviations for both conditions. In addition to high and low support conditions, a lack of support information condition was included for exploratory reasons. Analysis of the exploratory lack of support information condition indicated that respondents reported job security levels (M=3.33, SD=.94) which were slightly higher than both the low support (M=3.17, SD=.99) and high support (M=3.22, SD=3.24) conditions, these differences were not significant ($F(2,437)$=1.36, p=.26). Analysis of the lack of support information condition indicated that respondents reported affective wellbeing levels (M=3.36, SD=.89) which were higher than the low support condition (M=3.17, SD=.92) and nearly equal to the high support condition (M=3.34, SD=.85), these differences were approaching significance ($F(2,437)$=2.62, p=.07).

For hypothesis 3a and 3b, I expected that nature of technology and organizational support would interact to relate to job security and affective well-being, such that low support leads to a) lower job security and b) lower affective well-being in the *automating* condition than in the *augmenting* condition. This interaction effect was not supported for a) job security ($F(2, 434) =.031$, $p=.970$, $d=.09$). See table 4 for means and standard deviations. Additionally, the interaction was not supported for b) affective well-being ($F(2, 434) = .644$, $p=.526$, $d=.24$). See table 5 for means and standard deviations.

As technology readiness was established as an important control variable for the present study, analyses were repeated for all hypotheses with the inclusion of the covariate. To test hypothesis 1, 2, and 3 with the covariate, I conducted a 2x3 analysis of covariance (ANCOVA) for each of the two dependent variables of interest (job security and affective well-being). By using ANCOVA, I examine the main effect of nature of technology (Hypothesis 1), the main effect of organizational support (Hypothesis 2), the interaction between technology and organizational support (Hypothesis 3), while controlling for the covariate of technology readiness. Full results of the ANCOVA analyses are presented in Table 6 and Table 7.

7.4

Table 4

Means and Standard Deviations for Job security

	M	*SD*
Nature of Technology		
Automation	2.92 (2.92)	.93 (.93)
Augmentation	3.56 (3.56)	.85 (.85)
Organizational Support		
High support	3.22 (3.24)	.91 (.91)
Low support	3.17 (3.16)	.99 (.99)
Lack of support information	3.33 (3.31)	.94 (.94)
Nature of Technology x Organizational Support		
Automation		
High support	2.91 (2.92)	.83 (.83)
Low support	2.83 (2.84)	.97 (.97)
Lack of support information	3.00 (2.99)	.98 (.98)
Augmentation		
High support	3.53 (3.56)	.88 (.88)
Low support	3.50 (3.48)	.89 (.89)
Lack of support information	3.65 (3.64)	.77 (.77)

*Results in parentheses include the covariate – technology readiness.

7.5

Table 5

Means and Standard Deviations for Affective Wellbeing

	M	*SD*
Nature of Technology		
Automation	3.05 (3.05)	.76 (.76)
Augmentation	3.54 (3.54)	.93 (.93)
Organizational Support		
High support	3.34 (3.35)	.85 (.85)
Low support	3.17 (3.17)	.92 (.92)
Lack of support information	3.36 (3.36)	.89 (.89)
Nature of Technology x Organizational Support		
Automation		
High support	3.15 (3.15)	.95 (.95)
Low support	2.93 (2.94)	.90 (.90)
Lack of support information	3.06 (3.05)	.93 (.93)
Augmentation		
High support	3.54 (3.55)	.70 (.70)
Low support	3.41 (3.40)	.88 (.88)
Lack of support information	3.67 (3.66)	.76 (.76)

*Results in parentheses include the covariate – technology readiness.

7.6

Table 6

ANCOVA Results for Perceived Job Security

	df	*F*	*d*	*p*
Covariate				
Technology Readiness	1	7.581		.006
Main Effects				
Nature of Technology	1	58.018	.72	.001
Organizational Support	2	1.054	.05	.350
Nature of Technology x Organizational Support	2	.002	.09	.998
Residual	433			

*Significant at the p<0.05 level.

7.7

Table 7

ANCOVA Results for Affective Well-being

	df	*F*	*d*	*p*
Covariate				
Technology Readiness	1	2.189		.140
Main Effects				
Nature of Technology	1	36.848	.58	.001
Organizational Support	2	2.315	.20	.100
Nature of Technology x Organizational Support	2	.610	.24	.544
Residual	433			

*Significant at the $p<0.05$ level.

For hypothesis 1a and 1b, I expected that an *augmenting* technology would relate to a) higher job security and b) higher affective well-being than an *automating* technology. This main effect was supported for a) job security ($F(1, 433) = 58.02$, p=.001, d=.72), such that participants who were presented with an *augmenting* technology (M=3.56, SD=.85) were more likely to report higher job security, than those who were presented an *automating* technology (M=2.92, SD=.93), and for b) affective well-being ($F(1, 433) = 36.85$, p<.000, d=.58), such that participants who were presented with an *augmenting* technology (M=3.54, SD=.93) were more likely to report higher affective well-being, than those who were presented an *automating* technology (M=3.05, SD=.76).

The findings for hypothesis 2a and 2b were not significant without the covariate and remained so with its inclusion. I expected that high organizational support would relate to a) higher job security and b) higher affective well-being than low organizational support. This main effect was not supported for a) job security ($F(2, 433) = 1.05$, p=.350, d=.05) and was not supported for b) affective well-being ($F(2, 433) = 2.32$, p=.100, d=.20). See tables 6 and 7 for means and standard deviations for each condition.

The findings for hypothesis 3a and 3b were also not significant without the covariate and remained so with its inclusion, I expected that nature of technology and organizational support would interact to relate to job security and affective well-being, such that low support leads to a) lower job security and b) lower affective well-being in the *automating* condition than in the *augmenting* condition. This interaction effect was not supported for a) job security ($F(2, 433) = .002$, p=.998, d=.09) and was not supported for b) affective well-being ($F(2, 433) = .610$, p=.544, d=.24) See tables 6 and 7 for means and standard deviations for both conditions.

CHAPTER 8

DISCUSSION

The purpose of this study was to determine if the nature of a disruptive technology (*augmenting* or *automating*) in a work application influences outcomes for workers. While technologies applied in the workplace have frequently been studied in management, economic, and psychology literatures, a type of technology known as disruptive technologies, that may be perceived as more threatening than less advanced technologies, have not been explored. This study was meant to begin this conversation by looking at a simple, yet important distinction of disruptive technologies: the support of a worker (*augmentation*) or the replacement of a worker (*automation*). Specifically, the effect of the nature of a technology (*augmenting* or *automating*) and organizational support on job security and affective well-being was analyzed controlling for the technology readiness of individuals.

First, the main effect of the type of disruptive technology (*automating* or *augmenting*) on the outcomes of job security and affective wellbeing was explored. This main effect finding was significant both with the inclusion and exclusion of the technology readiness control variable. This result indicates that the nature of a disruptive technology, and whether that technology is applied in a manner that threatens to replace the worker or assist the worker is an important distinction as it relates to both job security and affective wellbeing outcomes for workers. The results indicate that when a disruptive technology is applied in an organization, if workers perceive that the organization is *augmenting* them (assisting them at work) rather than *automating* them (replacing them at work) with the disruptive technology, than the workers are likely to have both higher levels of job security as well as higher affective well-being than the alternative. Additionally, technology readiness was included as an important covariate. Both analyses, with and without the covariate, yielded the same results. This indicates that the differences associated with the nature of technology are not a byproduct of individual differences, such as technology readiness, alone. At the same time, these findings can provide some early indications of the relationship between the variables of interest and help to steer future research directions that explore this more fully.

I expected that organizational support would relate to higher job security and affective wellbeing. This finding was not supported with or without the inclusion of the covariate. Furthermore, these levels were near the midpoint of the Likert scale. This was true in spite of the manipulation checks indicating that the organizational support manipulations were associated with the variables of interest, though the high support group levels were slightly higher. This may indicate that organizational support does not play an important role in this process or this may indicate that either organizational support is difficult to capture in an online experimental design or that the manipulation did not go far enough in demonstrating strong organizational support in this fictitious scenario. Due to the non-significant result, further work would be needed to better understand this relationship. For example, a study that captures an individual's self-reported organizational support in their real job is likely a better way to accurately capture this phenomenon than trying to manipulate this in an online study. Additionally, if an experimental approach is taken, several alternative organizational support manipulations can be tested in a pilot study to ascertain which is most effective. Interestingly, the lack of support information condition, which was collected as exploratory, often mirrored results of the high support condition. This is an interesting finding that a lack of support information condition led to the same outcomes as a condition meant to elicit impressions of high support. This indicates that participants perhaps assumed the organization was generally supportive when information was lacking, which is an interesting assumption made by the participants on behalf of their fictitious employer.

I predicted an interaction between the technology condition and organizational support on outcomes. This relationship was predicted based upon the idea that those who are presented with a technology with the potential to replace them would have a greater need for the organization to be supportive. Essentially, organizational support matters more when the employee is faced with a disruption that is more threatening (*automating*) than a disruption that is empowering (*augmenting*). This finding was not supported with or without the inclusion of the covariate.

Theoretical Implications

The results of the present study help to shed light on the theoretical underpinnings associated with disruptive technologies in a work context. The findings support the extension of disruptive innovation theory (Christensen, 1997) and the related phenomena of subjective threat into the domain of technological disruptions that directly impact human workers. There is substantially more to be learned regarding this distinction, but the present study helps us to understand that there are different ways to perceive disruptive technologies and that these perceptions can alter the felt subjective threat and resulting outcomes. The present study, and the perspective it offers, differs from yet complements other research utilizing disruptive innovation theory. Disruptive innovation theory has traditionally been thought of as a model for the potential replacement of a technology by a technology, whereas the present study was focused on the potential replacement of human worker by a technology. While this is a departure, this new interpretation aligns with traditional disruptive innovation theory in the definitional sense, with a disruptive technology defined as (1) less expensive for the customer or organization; (2) more accessible to use; and (3) applies a business model that meaningfully overlaps with the incumbent (Wessel, 2016; Chiaroni et al., 2016). In light of this, disruptive innovation theory may operate as a means with which to theoretically ground research that involves very novel technologies and ideas. Models such as this one can be useful for research in the technological job disruption domain as these technologies are currently in the stage that they are mostly being perceived as a threat and are not yet a reality for many individuals. While understanding the resulting impact of disruptive technologies and technological job disruptions is of great import, it is also important to understand the impact of the mere threat of such technologies on workers.

Further important implications relate directly to the idea of subjective threat, specifically the AAA (appraisals, attributions, adaptations) model (Mackey and Perrewe, 2014), and how it functions. The premise of the study was set up to mimic a situation with an uncertain, subjective threat experience. Subjective threat was not measured directly, and future research would benefit from direct measurement of this phenomenon, so interpretations are limited. Despite this, subjective threat was an implicit part of the process between technology perception and outcomes. The present study aimed to capture subjective threat by presenting an idea and allowing the individual to process that information in their own way, as is the common approach in AAA applications (e.g. Heany, Israel, & House, 1994). Thus, participants were not using a disruptive technology or even told that they will need to use a disruptive technology, rather the study was designed to present the technological disruption as a change that they did not know the full outcome of and would have to process in their own subjective way. This was meant to mimic the current climate around technological job disruptions and to elicit subjective threat as it has been studied in other contexts. Subjective threat perceptions are thought to occur for workers in three primary ways (Greenhalgh, 1983; Greenhalgh & Rosenblatt, 1984), including rumors, unintentional messages from leadership, and intentional messages from leadership perceived as threatening. Note, the party sharing the message does not need to intend for the message to be threatening in order for employees to view it as such. Practically, disruptive technologies are not always threatening to a worker and tied to negative outcomes, but they can be, and this is often how they are thought of in relation to work. This study extends this idea by showing that a determinant of the impact that a technology has on a worker depends upon the way in which they perceive the nature of a disruptive technology (*automating* or *augmenting*). This is an interesting distinction at present as most disruptive technologies are not currently being implemented in workplaces, but there is a wide-spread dialogue that they will be implemented soon. In this context, perceptions of the technologies capabilities in relation to one's own can shape how threatening they appear to be.

Where the present work may appear to diverge from prior work is that support was not found for the relationship between organizational support and outcomes (job security and affective wellbeing) as it is outlined in organizational support theory (Eisenberger, Huntington, Hutchinson, & Sowa, 1986; Shore & Shore, 1995). Whereas prior work has found a robust relationship between these variables, the differences between support conditions were not significant. Additionally, the interaction between the nature of the technology and organizational support was not significant, which drew from organizational support theory (Eisenberger, Huntington, Hutchinson, & Sowa, 1986; Shore & Shore, 1995) and the idea that low organizational support may relate to more negative outcomes when a worker experiences greater subjective threat. Perhaps both findings point to the same explanation that organizational support was not successfully manipulated in such a way that workers truly entered into the reality of their given scenario. While the manipulation checks were successful, inconsistencies with the theoretical frameworks of organizational support indicate that it may be difficult for participants to genuinely register and feel support, or a lack thereof, when they are participating in a short, fictional study. While participants were perhaps aware of high support or low support sentiments in their vignette, and were able to answer manipulation checks appropriately, it is likely more difficult to actually enter into this fictitious scenario and frame it as their own experience. This likely led participants to not internalize support in the same way that they would in the real world. This will be important to keep in mind in future studies aiming to answer such questions. Future research including organizational support as a buffer can choose to ask participants about their true work experience with organizational support or include organizational support as an intervention in a situation where workers face subjective threat associated with technology. This method may be particularly suited to professions that are currently predicted to be effected by automation, such as truck driving and radiology. Ultimately, to draw meaningful conclusions about the role that organizational support does or does not play in this context would require additional work that more effectively elicits a genuine response to support.

One final theoretical implication relates to the phenomena of technology readiness (Parasuraman, 2000). Technology readiness was included as a covariate in the model as a means of ensuring that the differences were reflective of the nature of the technology and not just representative of differing comfort levels with technology. While technology readiness was an important and relevant variable, the findings remained unchanged with and without its inclusion. Thus, it is important to note that individual differences regarding technology surely matter yet are not the full story of one's experience with subjective threat relating to disruptive technologies. Though no hypotheses were framed around the main effect of technology readiness on job security and affective wellbeing, these relationships were significant. This supports the idea that technology readiness is an important variable to consider for studies that look at questions of technology perceptions and resulting outcomes. Additionally, this sheds light on how individual differences do exist with technology comfort and that this is an important phenomenon to be cognizant of in future advanced technology research.

Practical Implications

As the topic of job automation is quite prominent in current discourse from policy, popular press, and organizational leadership, it is important for these parties to be aware of the distinction between *augmenting* and *automating* technologies when they discuss projections for technological disruption. As this study demonstrates that an *augmenting* technology can be less threatening than an *automating* technology to workers, it is important to provide clarity to the public on what is actually being predicted for technologies relating to various jobs. At present, most reports and articles refer to all technologies as *automating*, or a replacement, when in reality these technologies are often projected to *augment*, not replace, the worker. This distinction could provide a more balanced perspective on the future of work discussion.

Additionally, the present study may shed light on the importance of how organizations approach the implementation of new technologies. Organizational leaders can understand that when they insert a novel technology into a workplace, that explaining the impact of the technology, if it is *augmenting*, can help to control for some negative outcomes for workers. This is especially critical when messages are being provided regarding a new technology. As subjective threat models demonstrate that intention of threatening messages is not necessary for a message to be perceived in a threatening way (Mackey & Perrewe, 2014).

Finally, this study sheds light on the importance of recognizing that comfort with technological change is not just dependent upon one's comfort with technology generally, but also the nature of the technology in question. In light of this, organizations can keep in mind that individuals may have many differences in how they perceive the role of and threat of disruptive technologies, but there are similarities in how a worker may perceive a technology that threatens to replace them. Thus, organizations can work to communicate effectively with workers with a variety of comfort levels with technology when they implement such changes. Perhaps this means being very clear about the capabilities of the technology rather than using buzzwords or science-fiction terminology, and not assuming that technology positive workers will have an immediate comfort with all disruptive technologies brought into the workplace.

Limitations

Although the present work includes some contributions to the literature, there are limitations to be noted. First, and as previously mentioned, the present study likely did not successfully manipulate perceived organizational support. As a previously supported main effect of organizational support on job security and affective well-being was not supported, it is likely that there was an issue with the way in which organizational support was manipulated in this study. Alternatively, this could be a byproduct of the manipulation of the type of technology appearing directly prior to the organizational support manipulation in the vignette. The technology section may have framed the thinking of the participants before they had a chance to consider their fictitious employer's motives. To fully understand the importance of precedence of conditions in a vignette on outcomes, future research would need to alter delivery order of technology and support conditions.

Another limitation of the study centers on the delivery of the study through a technology platform. The limitations here were two-fold. First, it is difficult to ascertain the attentiveness of respondents and the legitimacy of his or her answers. Second, the technology readiness scores skewed toward the upper end on average (mean=3.87), which may be a byproduct of individuals who work online (Amazon's Mechanical Turk) possessing a higher level of comfort and acceptance of technology than the general population. This is a limitation because this means that the sample in question perhaps has a strong comfort with technology that does not represent the distribution of technology comfort in the general population. At the same time, the technology readiness scale may reflect technologies that the majority of people are comfortable with since it was developed in the year 2000 (Parasuraman, 2000) which is some time ago on the time scale of technology. An updated measure of technology readiness that takes into account more advanced technologies may be beneficial.

Another limitation of the work was the sample. While a sufficient sample size was ultimately obtained, nearly a fifth of participants were eliminated due to failure on attention checks. In light of this, the sample pool in question may not be of the highest quality for a study that requires careful attention to detail and processing the information in vignettes. Additionally, Amazon's Mechanical Turk is a paid platform that compensates at a low rate, so participants are individuals who both have access to work from computers and are interested in performing work for a low compensation rate. This likely makes the sample not wholly representative of the population of interest.

A final limitation of the present work is the experimental design. As the study was aiming to understand the implicit subjective threat associated with disruptive technologies, this was very difficult to achieve in a vignette format delivered online as this is perhaps a difficult mode for inciting this subjective threat response. As this is an issue that is salient to many workers in true work settings, this response may have been elicited much more effectively through workers reflecting on their own jobs rather than adopting a role for the study.

Future Directions

As technological disruption research is a growing area, there are many future directions for research relating to the present study. First, the present work can be extended directly through survey research where individuals are asked to reflect on the application of disruptive technologies in their own job role. This would help to extend the present work and correct for some of the disadvantages of the present cross-sectional design.

Secondly, there are many opportunities for studies that further explore the distinction between *augmenting* and *automating* technologies. There are several individual differences, organizational, and societal variables that would be of interest to consider in this context. For example, individual difference studies can explore how different generations and personality types respond to these technologies. Organizationally, the culture of an organization and how that influences responses to technologies would be of interest. With regards to societal differences, labor economies with contract models versus at-will employment models would be interesting differences to understand. Furthermore, considering the antecedents of perceiving the technologies as threatening, understanding the process of threat perception more directly, and exploring a wide-range of outcome variables would be a compelling line of research. Antecedents are of interest as many projections have been made around the future of work and researchers can explore if prior knowledge of predictions alters responses. Additionally, previous experience with layoffs or downsizing, driven by technology or otherwise, would be of interest. With regard to threat perception, future studies would benefit from measuring subjective threat directly. Relevant outcomes of interest are numerous, including engagement, proactivity (with protean career behaviors and other career planning behaviors), organizational citizenship behaviors, and more. There is substantially more that needs to be understood about how this distinction functions, the antecedents of perceptions around disruptive technology, the individual differences that are salient in this process, and the interventions that can be associated with shaping such perspectives and resulting outcomes.

Another interesting area of future research would be a focus on subjective threat directly. While subjective threat was a latent component of the model explored in this study, subjective threat was not measured directly. As this component of the present study was so integral to the outcomes in question, further work would benefit from examining this variable. Additionally, research could be conducted considering the varying antecedents of subjective threat in this context, including rumors and intentional organizational messages.

Finally, in order to test this distinction in a salient context, it would be of interest to conduct field studies with actual disruptive technology adoption. Considering that the same disruptive technology can be perceived as both *augmenting* or *automating*, it would be interesting to determine if the same technology intervention, understood differently by different individuals, alters the perception of threat and relevant outcomes for those individuals.

Conclusion

The current study addressed an important gap in the technological job disruption literature. The impact of the nature of a disruptive technology, organizational support, and technology readiness were considered relating to the outcomes of job security and affective well-being. In summary, it was found that *augmenting* technologies are related to higher job security and affective well-being for individuals than *automating* technologies, though these differences were very small. Although organizational support did not influence the outcomes as predicted, this study still provides a contribution to the technological job disruption literature. The results suggest that the way individuals perceive the capabilities and application of a disruptive technology can alter their sense of job security and affective well-being relating to their work.

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APPENDIX A

ELIGIBILITY SCREEN, MANIPULATION, & SURVEY

(Pre-Questionnaire)

First, you will be asked to rate your agreement with several statements. Please consider each statement carefully before providing your answer.

Please rate your agreement with the following statements.

(Technology Readiness)

(1= strongly disagree, 5 = strongly agree)

1 2 3 4 5

Q1: I can usually figure out new hi-tech products and services without help from others. (Innovativeness 1)

Q2: New technology is often too complicated to be useful. (Discomfort 1)

Q3: I like the idea of doing business via computers because you are not limited to regular business hours. (Optimism 1)

Q4: When I get technical support from a provider of a high-tech product or service, I sometimes feel as if I'm being taken advantage of by someone who knows more than I do. (Discomfort 2)

Q5: Technology gives people more control over their daily lives. (Optimism 2)

Q6: I do not consider it safe giving out credit card information over a computer. (Insecurity 1)

Q7: In general, I am among the first in my circle of friends to acquire new technology when it appears. (Innovativeness 2)

Q8: I do not feel confident doing business with a place that can only be reached online. (Insecurity 2).

(Attention check:) I have never brushed my teeth.

Q9: Technology makes me more efficient in my occupation. (Optimism 3)

Q10: If you provide information to a machine or over the internet, you can never be sure if it really gets to the right place. (Insecurity 3)

(Manipulation)

Please assume the role of a loan officer at True Financial company.

A large part of your job is reviewing and making decisions about applications for loans.

(Attention Check:) What role have you been assigned at True Financial company?

Accountant

Loan processor

Supervisor

Analyst

Since you are a loan officer at True Financial, your task is to review the information regarding this a technology and make a decision about whether or not you will use this technology at work in your role.

Please proceed to the email from your supervisor.

Please read the following passage carefully. You will be asked to make ratings and answer questions about what you read in the passages.

(Augmentation – Low-Support Condition)

From: Alex Stevens

Sent: Thursday, March 1, 2018 1:34:56 PM

Subject: Decision needed regarding new technology.

Good Afternoon,

There is a new loan processing artificial intelligence tool called EDGE-AI that combines the most advanced machine learning methods and state-of-the-art computer algorithms that mimic human intelligence.

With EDGE-AI, you will be aided in both your analysis of loan applications and your decision regarding loan application approval. Through trials with this technology, loan processers have reported that this tool makes their job easier, their decisions are of a higher quality, and they are freed up to focus on other important elements of their job.

You may be wondering why True Financial has decided to invest in this advanced technology.

At True Financial, we are market leaders. It is important to this organization that we get out ahead of the competition, drive large profit margins, and succeed for our shareholders. This is why we consistently strive to cut costs and increase revenue. We believe advanced technologies such as EDGE-AI are the future of a more affordable workforce.

Please let me know if you would like to adopt the following technology for your role here at True Financial. If you choose to adopt the technology, we expect that you will use this tool for all of your loan processing projects starting immediately.

Thank you,

Alex Stevens

Director of Loan Processing

True Financial Company

Astevens@truefinancial.com

(Augmentation – High-Support Condition)

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True Financial Company

Astevens@truefinancial.com

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True Financial Company

Astevens@truefinancial.com

(Questionnaire)

Do you agree to use EDGE-AI in your job as a loan processor? (For fidelity of manipulation – not included in analyses.)

1 = Yes

2 = No

(Attention check):

Paying attention and reading the instructions carefully is critical, if you are paying attention please choose option 3 below.

1 2 3 4 5

Please rate your agreement with the following statements as if you are the loan processor at True Financial.

(Perceived Job Security)

(1= strongly disagree, 5 = strongly agree)

1 2 3 4 5

Q1: My organization has made a commitment to me for only short-term employment. (reverse scored)

Q2: My organization has given me the impression that I am welcome to remain as part of the organization on a long term basis if I want.

Q3: My organization can terminate my employment any time.

(Attention check:) I live on planet earth.

Q4: It is likely that I will lose my job in the near future.

Q5: It is unlikely that I will lose my job in the near future.

Q6: I am concerned about being made redundant.

(Attention check):

Paying attention and reading the instructions carefully is critical. if you are paying attention please choose option 1 below.

1 2 3 4 5

Please rate your agreement with the following statements as if you are the loan processor at True Financial.

(Affective Well-being)

Being asked to use EDGE-AI at work makes me feel:

(1= strongly disagree, 5 = strongly agree)

1 2 3 4 5

Q1: Excited (HPHA)

Q2: Angry (LPHA)

Q3: At-ease (HPLA)

Q4: Discouraged (LPLA)

Q5: Inspired (HPHA)

Q6: Anxious (LPHA)

Q7: Satisfied (HPLA)

Q8: Gloomy (LPLA)

Q9: Ecstatic (HPHA)

Q10: Frightened (LPHA)

Q11: Relaxed (HPLA)

Q12: Bored (LPLA)

(Manipulation Check – Nature of Technology)

Please rate your agreement with the following statements as if you are the loan processor at true financial.

(1= strongly disagree, 5 = strongly agree)

1 2 3 4 5

Q1: Edge-AI would replace me in my current work tasks.

Q2: Edge-AI is a threat to my job.

Q3: Edge-AI is not a threat to replace me at work. (R)

Please answer each item as if you are the loan processor at True Financial.

(Manipulation Check – Perceived Organizational Support)

(1= strongly disagree, 5 = strongly agree)

1 2 3 4 5

Q1: The organization really cares about my well-being.

Q2: The organization supports my career.

Q3: The organization shows very little concern for me. (R)

(Attention check:) Select somewhat agree.

Please proceed to the next page to tell us a little bit about yourself.

At this stage, please answer the items as yourself.

(Demographics)

(Attention check:) If you are reading this select “toast”.

1 = toast

2 = scone

3 = waffle

4 = pancake

What is your gender?

1 = Male

2 = Female

3 = Other

What is your age?

[Open-ended]

Please specify your ethnicity.

1 = White

2 = Hispanic or Latino

3 = Black or African American

4 = Native American or American Indian

5 = Asian / Pacific Islander

6 = Other

What is your occupation?

What industry do you work for?

How many hours per week of paid work do you do outside of MTurk?

How many years have you been with your current organization?

(Attention check:) Were you honest in answering this survey? (Your answer has no impact on your compensation or completion of this study).

1 = Yes

2 = No

3 = Sometimes

Thank you, you have reached the end of the study. We appreciate your time. Please proceed to the next page for the debriefing form.

(Debrief)

Thank you very much for participating in our study. The purpose of this study was to examine how the proposal of an advanced technology at work influences worker affective well-being and job security perceptions. There were six conditions in this study, which changed the type of advanced technology listed for the employee and the degree of support offered by the organization.

Because we, the researchers, did not want participants to be aware of the fact that this study was about attitudes about technology (in order to gain unbiased responses), you were told you would make a decision about the proposed technology. However, the decision is not a part of the study analysis and was intended to mask the purpose of the study. This was the only deception involved in this study, and was necessary to fully mask the purpose of the study. There was no other deception involved in this study.

If you have any questions about the nature of the study or the deception described above, please contact Karl Kuhnert or Muriel Clauson.

Thank you very much again for your participation.