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# Investigating the Determinants of Disaster Recovery Technology Investment Choice in Small and Medium-sized Enterprises

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# Investigating the Determinants of Disaster Recovery Technology Investment Choice in Small and Medium-sized Enterprises

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A dissertation submitted in partial fulfillment of the requirements for the degree of Doctor of Philosophy
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We hereby certify that this dissertation, submitted by Faranak Afshar, conforms to acceptable standards and is fully adequate in scope and quality to fulfill the dissertation requirements for the degree of Doctor of Philosophy.

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An Abstract of a Dissertation Submitted to Nova Southeastern University in Partial Fulfillment of the Requirements for the Degree of Doctor of Philosophy.

# Investigating the Determinants of Disaster Recovery Technology Investment Choice in Small and Medium-sized Enterprises

By

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Due to the importance of small and medium-sized enterprises (SMEs) as drivers of economic growth, it is essential to explore the security issues impacting SMEs' success and failure. One of the main security risks that could significantly impair the operability of the organizations is the permanent loss of data due to man-made and/or natural disasters and interruptions. Research has shown that SMEs are not taking disaster preparedness for their computer and networking systems as seriously as they should. This dissertation is an attempt to explain the process of a risky choice, specifically the decision maker's choice of not investing in disaster recovery technologies (DRT) to protect the firm. This study applied a revised model of determinants of risky decision-making behavior suggested by Sitkin and Weingart (1995) to a context of DRT investment in the real world. The model was empirically tested using survey data collected from a list of technology investment decision makers of SMEs located in the northeastern United States. Analysis and results of the collected survey data suggest the revised model can be applied to the real world context. The executive's characteristics, experience, and traits such as positive outcome history, risk propensity, risk perception, and decision framing influence the decision to invest in data protective technologies in SMEs. Specifically, the results of the analysis indicated that risk propensity is affected by outcome history and risk perception is affected by decision framing. In addition, risk propensity affected risk perception and risk perception affected the choice of DRT investment. Furthermore, decision framing had moderate effect on DRT investment

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# Chapter 1

# Introduction

## 1.1 Background

There has been increased emphasis on the importance of small and medium-sized enterprises (SMEs) as drivers of economic growth in the United States, Canada and the European Union (EU) (Banham & He, 2010). This provides a compelling background to explore the issues impacting SMEs' success and failure. To increase profitability and competitive edge, many SMEs are investing in information technology (IT) infrastructure (Cline & Guynes, 2001; Schniederjans & Hamaker, 2004). As the firms' dependency on IT has increased, the information system's threats and security issues have increased (Gordon & Loeb, 2002; Johnson & Koch, 2006; Straub & Welke, 1998). Hence, the importance of system security, disaster recovery, business continuity, and IT resilience planning has been reiterated (Kundu, 2004). Risks from IT disruptions now rank with earthquakes and hurricanes in potential economic loss (Gupta, 2000; Lewis et al., 2003; Viscusi, 2006). Man-made threats such as computer viruses and worms, employee misconduct, infrastructure failures, and terrorist attacks, as well as natural disasters such as hurricanes and tsunamis, can cause systems interruptions that could significantly impair the operability of the organization (Nelson, 2006). Investing in disaster recovery technologies (DRT) has been one of the main methods to protect a firm's data. However, many SMEs decision makers are making the risky choice of not investing in DRT (Prekumar, 2003).

## 1.2 Problem Statement

The need for understanding a risky choice's essential elements is "urgent and is at the heart of systematic improvements of public policy" and our economic welfare (Slovic, 2000). The lack of investing in DRT is a risky choice that puts the firm at risk by making it more vulnerable to business interruptions and operational failure, which in return may result in permanent closure of the firm (Gupta, 2000; Lewis et al., 2003; Viscusi, 2006). In addition, lack of DRT investment could have devastating effects on the global economy due to the significant contribution of SMEs to its well-being (Love & Irani, 2004; Michel-Kerjen, 2010). There is an essential need to investigate the key factors in making risky choice of lack of DRT investment for small to medium-sized firms. Those at risk often misperceive the likelihood and consequences of extreme events and act as if these disasters will not happen to them (Michele-Kerjan & Slovic, 2010). Enough is not known about the process of making risky choices. Hence, it is imperative to identify the key factors that are influencing choices in the context of DRT investment in order to understand the lack of disaster recovery protection in SMEs.

## 1.3 Importance of Research Problem

With increasing interconnectivity of networks, adequate disaster preparedness and business continuity planning are no longer a luxury but a basic requirement (Hecht, 2002). However, SMEs lag behind in investing in technologies such as disaster recovery tools to protect their firm (Prekumar, 2003). Most small to medium-sized firms are managed by individuals rather than boards. Many of the decision makers are also the main principals of the firm. SME's owner's attitudes towards protective technologies have not improved significantly in the past decade (Johnson & Koch, 2006).

Several studies have shown the importance of the decision maker's risky behavior determinants such as risk perception, attitude, and framing in IT investment and adoption (Grandon & Pearson, 2004; Keil et al., 2000; March & Shapira, 1987; Nguyen, 2009). In addition, research has shown that an individual's biases play an important role in the final risky choice (Kahneman & Tversky, 2000; Kunreuther & Pauly, 2004; Slovic, 2000; Slovic et al., 1982; Thaler, 1980). However, there has not been any scholarly research on the key factors influencing the lack of DRT investment in SMEs.

The SMEs' risky choice could have a catastrophic effect on our economic welfare (Michel-Kerjan & Slovic, 2010; Slovic, 2000) due to the increased social and economic interdependencies of our global environment. The absence of scholarly research has created a challenge to understanding the SME's lack of DRT investment. Man-made threats such as hacking, system intrusion, and terrorist attacks could have a disastrous impact on the firm's bottom line (Saleem et al., 2008). Other catastrophic events such as natural disasters have shown to paralyze organizations, cities, and entire countries (Viscusi, 2006). The potential reoccurrence of such incidences presents a need for crisis management and disaster recovery technologies for SMEs (Saleem et al., 2008). SMEs have become dependent on information technologies in most aspects of day to day operations. The data generated from these transactions needs to be protected as a part of business continuity and disaster recovery processes. Despite the proven positive influence of IT in business operations, SMEs have been slow in adopting disaster recovery technologies to protect their investment. This research is aimed at studying the key factors influencing the SME decision maker's lack of DRT investment.

### 1.4 Definitions of Terms

The definitions of terms that are being used in this study are as follows:

*Business Continuity/IT Resilience Planning*: The planning to ensure that critical business functions will be available to customers, suppliers, regulators, and other entities that must have access to those functions at the time of interruption. Disaster recovery planning is a part of overall business continuity activities and is usually referred to as "information systems recovery procedures" (Saleem et al., 2008).

*Disaster Recovery Technologies (DRT):* The contingency planning guide for Federal Information Systems (NIST, 2011) offers a comprehensive explanation to standardize the business continuity and risk management for federal systems. In this study, the researcher is using part of the NIST guideline since SMEs usually lack the resources to implement complete BC and DR procedures and technologies. For the purpose of this study, DRT include the implemented technologies that SMEs are using to recover from minor to major systems interruptions. It could be minimum steps such as backing up the data, storing it offsite, testing the restore periodically, and maintaining the backup software and hardware technologies, to much more elaborate procedures such as a private "hot site" that is designed to have duplicate systems running at the same time.

*Small and Medium-Sized Enterprises (SMEs):* The definition of what constitutes an SME varies in different parts of the world. In the United States, SMEs have been defined as small firms with less than 500 employees which represented more than 94 percent of all employers nation-wide, generated 60 to 80 percent of all new jobs annually, and accounted for the net gain of 1.86 million new jobs in 2004 (United States Business Administration, 2006).

*System Risk:* The likelihood that a firm's information systems are insufficiently protected against certain kind of damage or loss (Straub & Welke, 1998).

**1.5 Summary**

With increasing information systems, network, cloud computing, and Internet usage, SMEs need to protect themselves against system interruptions, vulnerability, and data loss. The significance of SMEs' well-being to our economy is evident (Love & Irani, 2004). SMEs' lack of investment in business continuity and disaster recovery technologies could result in catastrophic outcomes to the firm and to the economy in case of a disastrous event. To understand the lack of investment choice in disaster recovery technologies, this study will explore the relationship of the SMEs owner/manager risk perception, risk propensity, problem framing, and outcome history to the DRT investment choice. For the rest of this paper, a review of SMEs characteristics and their technology investment behavior and information system security are provided in chapter two. The review of the theoretical framework and research methodology are provided in chapter three.

# Chapter 2

# Review of Literature

## 2.1 Introduction

This chapter will review the research in regard to SME characteristics, their investment in information systems technology, system risks and the measures that SMEs executives are taking to protect the data generated by their systems.

## 2.2 Small and Medium-sized Enterprises and Information Technology

Small and medium-sized enterprises (SMEs) represent a major business sector that makes a significant contribution to an economy's well-being (Love & Irani, 2004). According to the United States Business Administration (2006), SMEs included firms with less than 500 employees which represented more than 94 percent of all employers nation-wide. In addition, they generated 60 to 80 percent of all new jobs annually, and accounted for the net gain of 1.86 million new jobs in 2004.

SMEs, as one of the fastest growing sectors of the economy, have become critically dependent on information systems for their daily operations (Ives & Learmonth, 1984; Iyer & Sarkis, 1998; Prekumar, 2003; Schniederjans & Hamaker, 2004; Walker, 2004). These firms are increasingly investing in information technology (IT) in order to gain a competitive advantage, increase profitability by lowering production and labor costs, and improve data management (Ives & Learmonth, 1984; Iyer & Sarkis, 1998; Levy et al., 2001; Nguyen et al., 2007; Schniederjans & Hamaker , 2004). Business owners and managers have become dependent on IT and its generated data to effectively shorten product development life-cycle, increase market share (Gerson et al., 1992), and enhance the business processes (Levy et al., 2001). Despite the proven positive influence of IT

in business operations, SMEs have been slow in adopting disaster recovery technologies to protect their investment. In a study to examine IT perception and adoption in 96 SMEs in Ireland, 47% of the firms were at serious risk due to IT security weaknesses. Most of these companies had no adequate virus protection and data recovery procedures in place. Furthermore, 75% of the companies' IT strategy and IT vendor selection skills were classified as poor or very poor (Enterprise Ireland, 2004).

Research has shown that SMEs' owner-managers have a major impact on the firm's technology purchasing behavior (Nguyen, 2009). Major factors that have influenced the IT adoption in SMEs could stem from management's unclear perception of the value of the adoption (Levy et al., 2001) and the lack of resources compared to the large firms (Calessen, 2005). In addition, Davis (1989) proposed the technology adaption model (TAM) suggesting the ease of use and the perceived usefulness were major factors influencing attitudes toward adoption of technologies such as ATM and email. Other studies have shown the association between individual perceptions and behavior, such as the theory of planned behavior (TPB) that has been successful in predicting and explaining behavior across a wide variety of domains, including the use of information technology (Grandon &Pearson, 2003). Tallon et al. (2000) argues that executives rely on their perceptions in determining whether a particular IT investment creates strategic value for the firm. The models mentioned above are based on innovations having near-term and clear-cut outcomes where DRT investment has uncertain outcome.

## 2.3 Information Technology Investment in Small and Medium-sized Enterprises

As the small firm grows, the technology investment increases. In a study of 308 small business executives, 92% percent of the decision makers had acquired new hardware for their firms since their firms had first started using computers, and 89.9% had acquired new software. In approximately 90% of the firms, the number of computer users had increased with increased usage in applications such as accounting, human resources, and database applications (Riemenschneider & Mykytyn, 2000). The recent development in service provider applications through the Internet has also offered tremendous opportunities for small firms to invest in IT in order to involve them in e-commerce activities (Arbore & Ordanini, 2006). The data generated from these electronic transactions is necessary for business operations and productivity. In case of systems interruptions, it is imperative to have the technologies to recover and resume the operations in a short time.

The majority of research has proposed a direct causal link between information technology (IT) investment and firm performance (Grandon & Pearson, 2004). IT investments that are focused on meeting business operations needs can have a positive impact on the firm's performance (Gunasekaran et al., 2001). Essentially, the purpose of IT investment is to improve operational efficiency of an organization, reduce costs, and improve profit levels. It has been suggested that small firms do not operate under the same conditions as large firms, for example, in small firms, actions and decision-making behavior are rarely rational because of motives, values, beliefs and perceptions of the owner-manager (Ekanem, 2005). Tallon et al. (2001) suggest that SMEs executives rely on their perceptions in determining whether a particular IT investment is beneficial to the

firm. In addition, it has been difficult for many companies to accept short-term losses in order to reap long-term benefits while trying to make technology investment decisions (Hochstrasser, 1990). For most organizations, the justification of IT investment is a complex issue due to many tangible and intangible benefits which are inherent in the implementation of IT (Irani, 2002). Issues such as constantly trying to identify what the competitors are doing with IT, determining whether or not the firm can remain competitive with or without IT, and evaluating how the adoption of IT can improve the firm's performance are other types of the problems facing decision makers (Gunasekaran et al., 2001).

Existing literature indicates that the strategies and responses of small firms may well be different from those of larger firms since large firms have plenty of resources allowing them to cover their bases (invest in several different technologies allowing for different environmental contingencies), an ability smaller firms do not have (Chesher & Skok, 2000; Kankahill , 2003; Nguyen, 2009; O'Dwyer & Ledwith, 2009; Saleem et al., 2008; Tallon et al., 2001). In addition, studies have shown that IT spending has not benefited smaller firms as it has larger firms, often demonstrating neutral or negative effects on the firm and its owner/manager. A possible explanation for the lack of return for IT spending by small businesses is that smaller firms, compared to larger firms, may lack a strategic decision-making perspective in approaching IT investments (Cleluch et al., 2007). In a study done with Chinese firms, it was shown that SME owners/managers rely heavily on their personal networks for identifying opportunities in the business environment and for information search and advice (Huang, 2009) which will affect their investment decisions.

## 2.4 Information Systems Security

A combination of information handling activities in multiple levels such as technical and operational levels of an organization is considered an information system (Tejay, 2008). An information system usually consists of a combination of hardware and software that work together to collect, process, and store data (Kim & Solomon, 2012). Information system security is defined as measures to minimize risks arising because of inconsistent behavior with respect to the information handling activities within organization (Tejay, 2008). Within organizations, an information system security is the collection of activities that protect the information system and the data stored in it (Kim & Solomon, 2012). The controls and tools to protect the system vary depending on the domains of the system. According to Kim and Solomon (2012), a typical information technology infrastructure has seven domains that need to be secured in order to achieve basic system security. The domains are workstation, users, local area network (LAN), wide area network (WAN), LAN to WAN, remote access, and system/application. In addition, they suggest information can be categorized as secure if it satisfies the three main tenets or properties of information:

1. Availability where information is accessible by authorized users whenever they request information.
2. Integrity where only authorized users can change information.
3. Confidentiality where only authorized users can view information.

In the context of information security, availability is generally expressed as the amount of time users can use a system, application and data. There is a way to calculate availability

by measuring “Uptime” and “Downtime”. Uptime refers to the total amount of time that a system, application, and data are accessible. Downtime refers to the total amount of time that a system, application, and data are not accessible. Therefore, to calculate total availability percentage:

Availability = (Total Uptime) / (Total Uptime +Total Downtime)

According to the Gartner report (2009), few security professionals are familiar with all the controls and supporting tools available to help their organizations to address their information systems security challenges. This lack of understanding of data security controls results in serious gaps in control and risk mitigations. In addition, the report suggests that the traditional approach to information security has failed to focus on data and information contained within. The protection of data as the “crown jewel” must be at the core of a successful security program. The report lists four requirements to address information security:

1. Confidentiality: The need to protect against unauthorized or otherwise inappropriate access to information
2. Integrity: The ability to ensure that information is not improperly modified or deleted.
3. Availability: The ability to provide appropriate access to all stakeholders.
4. Privacy: The assurance that personal information is used for the specific business purpose for which it was collected.

White et al. (1996) suggests multiple approaches to address information system security such as distinguishing between external (pertaining to physical, personnel, and administrative security) and internal security functions (which are implemented as part of

hardware and software), and applying measures to each of these functions. According to Boggs et al. (2009), information system risks fall into three basic categories with internal IT infrastructure; system down time, network outages and security breaches. The article suggests that using appropriate technologies coupled with a rigorous program to standardize and improve IT practices can deliver substantial risk reduction and could reduce total annual outage risk by as much as 85% in SMEs.

As part of the system risk management process, organizations should plan and implement disaster recovery technologies for the availability of mission-critical services and operations. Information systems are vulnerable to a variety of disruptions, ranging from mild incidences such as short-term power interruptions and disk failures, to severe incidences such as equipment destruction, intruder attacks, and natural and man-made disasters (Lennon, 2002). A disaster is any event causing significant disruption to operations, thereby threatening business survival. A disaster also can damage customer relation and compromise business credibility, productivity, and revenue streams (Gibb & Buchanan, 2005). Firms that prepare for such events are able to recover up to three times faster and with significantly less financial and human cost than unprepared businesses (Mitroff, Harrington, & Gai. 1996). The daily cost of downtime due to an interruption varies for different firms, but a basic rule of thumb has been to divide the annual sales by 250. For example, if a firm is projected to have an annual revenue of $6.5 million, then its minimum daily cost of downtime is $65000000/250= $26000 and its minimum hourly cost of downtime is $26000/8= $3250 (Total IT Outsourcing, 2009). Indeed, the true cost of downtime should consider elements such as lost customers, lost opportunities, and loss of other revenue producing processes as well. For example, in January 2001, the

estimated cost of interruptions and data loss of high-tech companies due to a series of electricity failures in Silicon Valley exceeded $100 million (Gibb & Buchana, 2005).

According to the Boston Computing Network consulting firm, 60% of companies that lost their data had shut down within 6 months of the disaster, 93% of companies that lost their data center for 10 days or more had filed for bankruptcy within one year of the disaster, and 50% of businesses that found themselves without data management for this same time period had filed for bankruptcy immediately (Boston Computing, 2009). The estimated cost of data loss and information in 2003 in the United States was $18.1 billion.

To provide the availability of data, one of the main controls is to have a recoverable full copy of data available in case of data loss. Data disaster recovery technologies are internal security control implementations that will help organizations to back up and store their existing critical information into a safe media and be able to restore it back in case of interruptions due to events such as data corruption, data loss, and man-made or natural disasters

To protect the firm's information, the importance of investing in business continuity, disaster recovery, IT security, and business and IT recovery planning have become apparent (Dieter, 1995; Nelson, 2006; Rosenthal & Sheiniuk, 1993; Vijayarman & Rmarkishna, 1993). In large organizations, DRT investment and implementation have been the fundamental approach to protect the firm's IT assets; however, SMEs have been lagging behind in DRT investment (Gereer, 2002).

**2.5 System Risk Perception and Disaster**

According to decision theory, a risk may lead to either positive or negative consequences. However, most of system risk management literature has focused on the

negative consequences associated with a course of action (Keil et al., 2000). A negative consequence or loss is defined as any deprivation of an asset that is possessed (Keil et al., 2000). According to Barki et al. (1993), to assess a risk, the probabilities of undesirable events and their associated losses are determined. Therefore, risk generally can be regarded as the combination of the probability of an undesirable event occurring and the magnitude of the loss that is associated with the event (Keil et al., 2000). Straub and Welke (1998) define the system risk as the likelihood that a firm's information systems are insufficiently protected against certain kind of damage or loss and suggest that managers are not protecting their firms against system risks due to their unawareness of the full range of actions they can take to reduce the risks. Slovic (2000) refers to a flood study by Kates (1962) to explain how protective behavior against risks changes with the person's experience, such as floodplain residents' unwillingness to purchase insurance (despite the multiple warnings) changed when they experienced floods frequently. Another study, Kunruether (1976) discovered that people in earthquake-prone areas often neglected the risk, failing to purchase insurance even when it was subsidized (Michel-Kerjan, 2010). There is some evidence to the effect that difficulties in integrating information may often lead to make irrational decision making (Slovic, 2000). The individual can be aware of ways to reduce risks, but s/he chooses to do nothing. How is situation perceived so that risks are overlooked? It is essential to understand how managers will frame risky decisions within organizations. There are conflicting findings with respect to whether managers pay enough attention to the low probabilities and high consequences. March and Shapira (1987) argue that outcomes with extremely low probabilities seem to be ignored, regardless of their potential significance. Dutton and

Webster (1988) suggest that when uncertainty is high, managers will underestimate the importance of an issue. According to Kunreuther (2010), those at risk often misperceive the likelihood and consequences of extreme events and act as if these disasters "will not happen to me". It seems that those managers are prone to the illusion that they are in control and therefore ignore or downplay the possibility of random or uncontrollable occurrences (Lovallo & Kahneman, 2003; Michel-Kerjan, 2010). Individuals in general overweight low probabilities in risky decision making process (Kahneman and Tversky, 1979), especially when low probabilities are associated with particularly disastrous events (Lichtenstein et al., 1978; Viscusi et al., 1987). While there are many different factors that may affect decision-making, risk perception has been shown to play a central role in decision-making involving risk (Keil et al, 2000; Sitkin and Weingart, 1995). Previous research has shown that perceptions are affected not only by the degree of risk associated with a situation, but also by risk propensity, prior experience, and the individual's frame of reference (Sitkin & Pablo, 1992; Sitkin & Weingart, 1995).

One of the most serious system risks confronting an organization is that mission-critical information systems will become unavailable to process the company's operations. The worst scenario would be that the "disaster" or "catastrophic" events such as hurricane, earthquake, fire, or sabotage cause a total loss of data (Straub & Welke, 1998). Since 2001, hundreds of billions of dollars of economic losses have occurred due to catastrophes such as Hurricanes Hugo and Katrina that have destroyed properties, critical infrastructure, and local businesses (Michel-Kerjan & Slovic, 2010).

Some system risks faced by the firm are either so remote, such as data center destruction or so routinely small such as a corrupted file, that they are minor concerns to managers. Between these two extremes lie risks that pose significant threat and uncertainty, such as mission critical data loss (Lewis et al., 2003). This could be categorized as a disaster if the data is imperative to the livelihood of the firm and cannot be recovered. A disaster or catastrophic event can happen anywhere at any time; therefore, developing a disaster recovery plan for potential systems risks should be a priority. This plan can be formed to focus on determining appropriate levels of risk avoidance, mitigation, and contingency planning.

**2.6 Summary**

SMEs make a significant contribution to the local and state economy and their failure would impact the economy of the country. Studies have shown that eighty percent of the companies that do not recover from a disaster within a month are extremely likely to go out of business (Saleem et al., 2008). Kissel (2009) suggests that many of the SMEs are failing to implement security controls since they are overlooking both Internet and Internet security principles and threats. According to Kankahill (2003), SMEs were found to engage in fewer protective efforts to secure their systems compared to larger organizations. Straub (1990) suggests several explanations for low management deterrent efforts in investing in information systems protection such as the manager's perception of risk, DRT benefits, and lack of knowledge. To better understand the management perception toward investing technologies to protect the firm, the individual's perception, risk propensity, framing, and prior history can be studied in SMEs.

# Chapter 3

# Research Methodology

## 3.1 Introduction

This chapter lays the groundwork for the research proposal, presenting the theoretical basis, research approach, barriers, resources, and milestones.

## 3.2 Theoretical Framework

SMEs lack of investment in protecting the firm is an example of the executive risk-taking behavior. According to normative approach, rational individuals will make the optimal decisions when the facts are known. Firms have lost billions of dollars due to data loss from man-made or natural disasters. It seems that top managers do not always behave rationally. They do not seek to know all possible outcomes, or always assign accurate probabilities to the outcome or consistently select the best payoff from considered alternatives. According to Kahneman and Tversky (1979), individual risk behavior is determined by how a situation is framed. For example, a negatively framed situation leads to a greater risk-taking behavior. However, other research has shown contradictory results where decision maker persist in taking risks if prior risk-related actions were successful even if a situation was positively framed (Osborn & Jackson, 1988). Furthermore, it has been shown that risk propensity and risk perception mediate the effects of framing and final choice (Sitikin & Weingart, 1995).

In order to provide a theoretical background on individual's risk perception, both normative approaches such as "Expected Utility Theory" and descriptive approaches such as "Prospect Theory" will be discussed. Then a mediating model based on award winning research by Sitkin and Weingart (1995) will be presented. This model has been

tested in classrooms based on case studies; the current study applied the model to a real world environment where decision makers are making risky choices to invest or not invest in protective technologies.

### *3.2.1 Expected Utility Theory*

Expected utility theory (EUT) (Von Neumann & Morgenster, 1947) is an extension of classical utility theory for risky choices and suggests that a decision maker is believed to compute the expected utility of the outcomes associated with each decision alternative, and then choose the alternative that maximizes this expected utility.

In case of purchasing insurance premiums, EUT assumes that a risk-averse individual would always make decisions to invest in insurance to maximize the wealth utility. Risk aversion is defined as the tendency to prefer any sure outcome X, over any gamble with an expected value of X. Thus, a risk-averse person would prefer to receive a sure $50 rather than accept a gamble offering fifty-fifty chances to win $100 or win $0 (Slovic, 2000). Therefore, individuals will be willing to buy insurance at a fair price all the time. But field studies of insurance purchases have shown that some aspects of people's insurance behavior run counter to expected utility theory (Slovic, 2000) and investors are not acting rationally. For example, Anderson (1974) showed the failure of individuals to purchase insurance even when the premiums have been highly subsidized. Another study showed a preference for investment in low-deductible policies despite their disproportionately high premiums (Pashigian, Schkade, & Menfee, 1966). In addition, research has shown that most people were aware of the fact that seat belts saved lives, but only a small percentage of motorists wore them prior to becoming a law (Slovic,

Fischhoff, & Lichtenstein, 1978). In these studies, the subjects made decisions that were contrary to EUT.

Another major issue of the EUT model is its inability to account for context effects such as the verbal labels, modes of information presentation, social dimensions, and other circumstances associated with the nature of the decision problem (Schoemaker, 1982). In the case of DRT investment, EUT suggests that the decision maker will invest in technologies to protect the firm if she will know the high cost of downtime to her firm, but SME's DRT investment is lagging behind (Gereer, 2002). It is not an optimum choice to invest in information technology but not invest in DRT to protect the data and firm's information assets.

### *3.2.2 Prospect Theory*

In explaining decision making under uncertainty, an alternative to the normative well-established EUT approach is a descriptive approach called prospect theory (PT). The normative approach suggests what individuals should do rationally, whereas the descriptive approach examines what people actually do. PT takes into consideration the perception of the decision maker and suggests that alternatives are evaluated as gains or losses relative to a reference point rather than as final wealth states (as in EUT). There is evidence that decision makers often do not use precise probability estimates (Shapira, 1995). Instead of applying the rules for estimating probabilities, people replace the laws of chance with intuitive heuristics, which could yield large systematic biases (Slovic, 2000). These intuitive heuristics stem from the individual's perception towards events with risky outcomes. Perception is influenced by the nature of the mental framing of the problem, which is referred to as a "reference point" (Kahnmean & Tversky, 1979). The

reference point is the zero point and each outcome is seen as a gain or loss in comparison to that reference point. The reference point is affected by other factors, which leads the individual to make different decisions for the same problem, depending on how it is presented to her.

In contrast to EUT that describes consumers as risk-averse individuals who will make the optimal decisions under uncertainty, PT argues that individuals evaluate the outcome as changes from a reference point and depending on how a decision is framed; one can make inconsistent and different decisions. This type of behavior is also illustrated in consumer behavior research. Thaler (1980) was able to show that consumers act in a manner that is inconsistent with EUT and he proposed PT as an alternative to explain decisions. He pointed out that a "cash discount" and a "credit card surcharge" are different ways of describing the fact that there are two different prices for cash purchase and credit purchase. However, consumers perceive a 'cash discount' as a gain, compared to the credit card price, and they perceive the "credit card surcharge" as a loss compared to the cash price. The consumers are more willing to use their credit card when they perceive it as giving up a "cash discount" (foregoing a small gain in value) than when they perceive it as accepting a 'credit card surcharge (accepting a large loss) (Baron, 1988).

When choosing between options that appear to be gains relative to that reference point, the individual tends to make risk-averse choices (a sure bet), and when choosing between options that appear to be losses, the individual tends to make risk-seeking choices (the gamble). At the final stage, the individual assigns a value to each of these edited prospects and chooses the one that has the highest value. This sigmoid-shaped (S)

value function that is defined on deviations from the reference point is normally concave for gains, and convex and steeper for losses (see Figure 1).

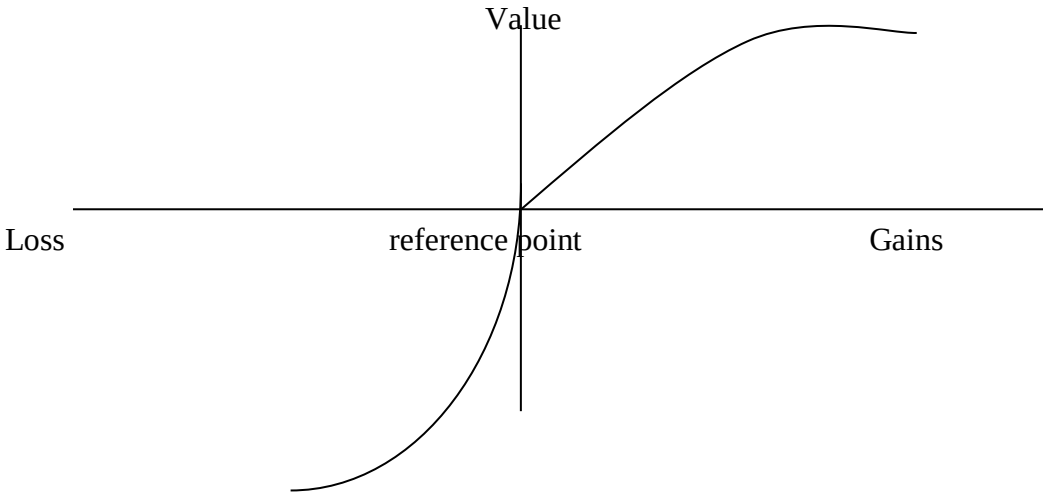



Figure 1. Prospect theory value function

If the decision maker perceives an option as a gain from the reference point, then it will fall into the right of the reference point (concave). Otherwise, it will show at the left of the reference point (convex).

*3.2.3 The Mediated Model of the Determinants of Risky Decision-Making Behavior*

One of the main predictions of PT research suggests that how a situation is framed will determine individual's risk behavior. So framing would have a direct effect in risky choice decision. However, it was shown that past success led to a willingness to take risks which suggests contrary to PT prediction of risk-averse behavior (Osborn & Jackson, 1988; Thaler & Johnson, 1990). In addition, Staw et al. (1981) showed that when individuals are threatened by likely losses, they become risk-averse. This is also

opposite to PT prediction. In an attempt to build upon these direct effects approaches, Sitkin and Pablo (1992) proposed an integrated model of determinants of risky decision making.

Sitikin and Pablo (1992) reviewed a number of potentially relevant individual, organizational, and problem characteristics that have been identified as predictors of risky individual decision making. The result suggested that the effects of a number of previously examined variables on risk taking were not direct but were instead mediated by risk propensity and risk perception. Risk propensity was defined as an individual's current tendency to take or avoid risks and risk perception was defined as an individual's assessment of how risky a situation is in terms of probabilistic estimates of the degree of situational uncertainty, how controllable that uncertainty is, and confidence in those estimate. Later on, Sitkin and Weingart (1995) examined a subset of the original model in which risk propensity and risk perception mediate the effects of framing and outcome history on risky decision-making behavior and suggested future work in different context to provide an opportunity to more efficiently predict individual risk behavior. The present research applied this mediated model of the determinants of risky decision making in the context of DRT investment.

In the following section the mediated model is discussed in the original format, and then hypotheses are formed based on the DRT context to test the model. Figure 2 reflects the model proposed by Sitkin and Weingart (1995) which suggests the inclusion of risk perception and risk propensity as mediators of effects on risky decision making behavior. Risk propensity and risk perceptions were found to significantly reduce the relationships between the antecedent variable and risky decision making. The relationship

between outcome history and decision making was mediated by risk propensity and risk perception in addition to the direct effect of framing on risky decision making behavior. Figure 2 depicts the original format of the model.

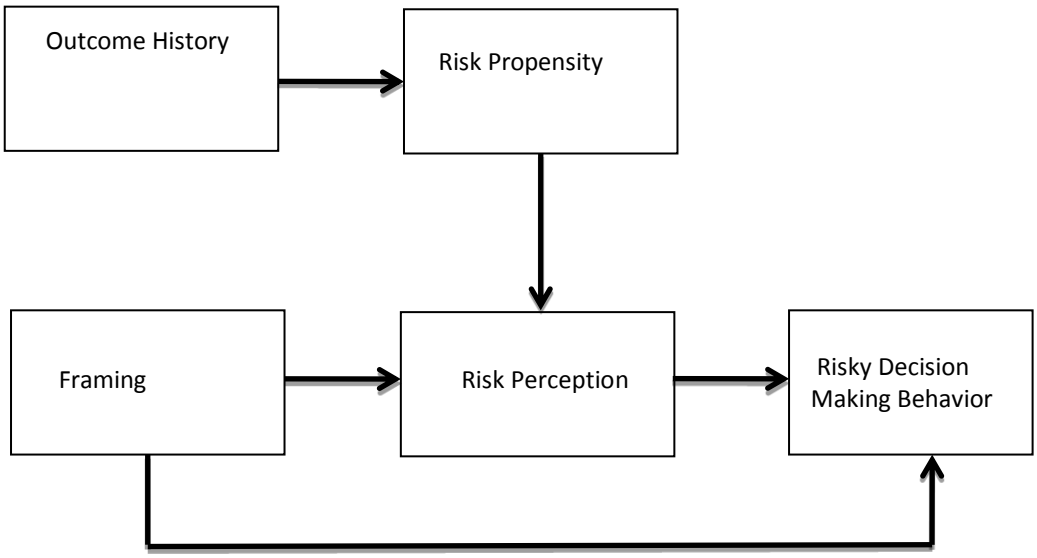



Figure 2. The mediating model of the determinants of risky decision-making behavior. [1]
[1]Adapted from "Determinants of Risky Decision-Making Behavior: A Test of the Mediating Role of Risk Perceptions and Propensity. By S. B. Sitkin and L.R. Weingart, 1995, *The Academy of Management Journal. 38 (6), p 1586.*

According to Sitkin and Weingart (1995), the model suggests that when choosing a risky decision, the effects of outcome history cascade through risk propensity to risk perception and finally from risk perception to risky decision making behavior. Risk-averse decision makers (with a propensity to avoid risk) are hypothesized to attend to and weight potentially negative outcomes more heavily. Risk propensity is a cumulative tendency to take or avoid risks while risk perception is the individual's perception of risks and their related consequences. Outcome history is defined as the degree to which the decision maker believes that previous risk related decisions have resulted in

successful or unsuccessful outcomes. It is an individuals' overall mental representation of how well he or she has fared in the past in similar situations.

In case of framing, Sitkin and Weingart (1995) suggest that problem framing has both a direct and indirect effect on risky decision-making behavior and should be tested in future studies under different contexts to provide an opportunity to more efficiently predict individual risk behavior. Furthermore, the positively framed situations have led to making risk–averse decisions and vice versa (Kahneman & Tversky, 1979). In addition, it has been shown that subtle changes in the way that risks are framed or expressed can have a major impact on perception and decisions. McNeil et al. (1982) asked people to imagine that they had lung cancer and had to choose between surgery or radiation therapy. Both treatments were explained in detail. Some were presented with the probabilities of surviving for varying lengths of time after the treatment and the rest were presented with the probabilities of dying rather than surviving (e.g., instead of being told that 68% of those having surgery will have survived after one year, they were told that 32% will have died). Framing the statistics in terms of dying dropped the percentage of respondent choosing radiation therapy over surgery from 44% to 18%. The effect was as strong for physicians as laypersons (Slovic, 2000).

In study 2 of Sitkin and Weingart (1995) research, framing was manipulated after they had read the case and before they read the first question of the questionnaire. A randomly assigned half of the subjects read a framing paragraph that selectively drew upon information from the case to highlight the potential for losses, and the other half read a framing paragraph that highlighted the potentials for gains. The framing manipulation was found to be effective, subjects in the positively framed condition

reporting a significantly higher concern for opportunity than those in the negatively framed condition. According to Kunreuther (2010), framing is an important factor in making final risky choices since those at risk often misperceive the likelihood and consequence of extreme events and act as if these disasters "will not happen to me".

In summary, the current study applied the revised model of determinants of risky decision-making behavior suggested by Sitkin and Weingart (1995) in a context of DRT investment to the real world environment. The targets were manager/owner/decision makers for SMEs in the northeastern United States who make technology investment in their firms.

*3.2.4 Proposed Research Model and Hypotheses*

In the context of DRT investment, the outcome history is a former data loss experience. The risk propensity is the individuals' tendency to take risk (i.e.: no DRT investment) or avoid risk (i.e.: DRT investment). The risk perception is how the decision maker perceives the probability and consequence of a data loss event to his or her firm. The decision framing is the owner/manager framing of DRT investment such as an opportunity to gain competitive edge or opportunity to lose financial resources when investing in DRT. Figure 3 depicts the mediating model of the determinants of risky decision-making behavior (Sitkin & Weingart, 1995) in the DRT context.

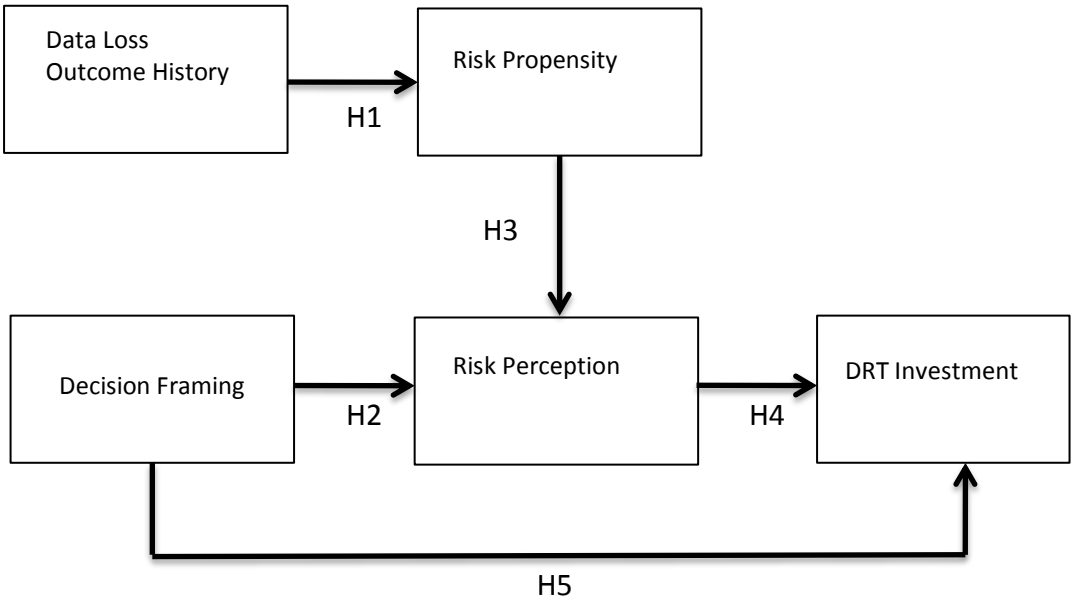



Figure 3. The mediating model of the determinants of risky choice of lack of DRT investment behavior.[2]

[2]Adapted from Sitkin and Weingart (1995) and applied to DRT investment context

Using the above discussions, the following hypotheses were developed to test the model and the relationships between the variables:

H1: A successful data loss recovery outcome history increases a decision maker's propensity to take risk.

H2: A positively framed situation will be perceived as involving higher risk of data loss.

H3: The higher a decision maker's risk propensity, the lower level of perceived risk of data loss.

H4: A decision maker's perception of higher risk will result in greater DRT investment.

H5: A positively framed situation will result in greater DRT investment.

### 3.3 Research Approach

This research was based on a framework of the laboratory experiment to find the determinants of risky decision making behavior by Siktin and Weingart (1995). The current research applied the same model to a real world environment with risky decision making scenario of DRT investment. The research method was a non-experimental survey research design utilizing a survey instrument to produce data that is correlational in nature, and to analyze the data using regression techniques with the purpose of predicting behavior in the real world.

In order to identify and develop the survey, the researcher consulted disaster recovery professionals and IT practitioners prior to this proposal. In addition, the researcher's background in IT and disaster recovery procedures implementations was used in the survey development. The rest of the study was conducted in three phases. During the phase one, a pilot study was performed by providing a pilot instrument to a pre-screened group of SME decision makers who are registered with a local chamber of commerce in the north east region of United States. As a part of the screening process to qualify participants, the listed individuals were contacted via phone to verify their correct contact information and to make sure to include only organizations which were not regulated to have a DRT implementation. A detailed screening script is attached in Appendix A. By the end of phase one, the instrument was refined and validated based on the feedback. The purpose of this phase was to assure that the questions and instructions are clear and meet the purpose of the research.

At phase two, in order to distribute the instrument to the rest of pre-screened participants, an email with the link to the survey location were sent out via electronic

mail. In addition, multiple business organizations posted the survey on their site. Phase three consisted of data collection and analysis.

For the purpose of this study, an investment in DRT is defined as a minimum investment in data backup/recovery software and hardware, existence of a process of backup/recover the data, and conducting periodic testing of backed-up data. If a small firm has invested in the above technologies and procedures, then it will be considered as a DRT investor.

### *3.3.1 Sample*

Since in SMEs, top management or owner-managers make all decisions from daily operations to future investments (Bruque & Moyano, 2007; Nguyen, 2009), the target population is the firm's top management. The role of top management or the owner-manager is crucial to the firm as their decision affect all activities including IT adoption and investment (Nguyen, 2009; Thong, 1999).

The subjects were recruited from SME owners/managers who are either listed with the Career Services and Cooperative Education Center of Suffolk County Community College mailing list or participating members of Long Island Association Group. The center works with more than 2000 small businesses who have registered in order to actively place graduates from the school. Long Island Association (LIA) is the leading business organization in the Long Island region. The LIA's membership is comprised of small and large businesses, technology and manufacturing companies, universities, financial service firms, banks, credit unions, hospitals, media companies and sole proprietors, which together employ two thirds of Long Island's. In addition, local chamber of commerce offices and IT professional organizations such as Contingency

Planning Exchange (CPE) were used in order to have a qualified number of participants. One way to determine the sample size would be to decide the acceptable amount of sampling error and the magnitude of the differences that can be expected to find. To see what margin of error to use, it is acceptable to look at literature describing similar surveys (Bordens & Abbot, 2008). Once the values are determined, then the sample size can be calculated using mathematical equations. Another way to calculate the sample size is to use on-line calculators using estimated means and standard deviations for each group, statistical significant *p*-value and how much power is designated. Power is the probability of finding a statistically significant difference, assuming that a difference exists. The *p*-value refers to the actual probability of making a Type I error given the null hypothesis is true (Bordens & Abbot, 2008).

For the purpose of this research, eighty one complete survey responses were analyzed. This number exceeds the number of Sitkin and Weingart (1995) subjects used in the study where the authors demonstrated sufficient number of subjects with a statically significant *p*-value.

The study was conducted in Long Island of New York area in the United States due to the proximity of the researcher to the area and the availability of the multiple business association groups.

### *3.3.2 Instrument Development*

For the purpose of this study, a self-administered survey was used to gather data to examine the hypothesized roles of outcome history, decision framing, risk propensity, and risk perception in DRT investment decision. Data was collected using an online questionnaire survey.

In order to develop the survey, the researcher had consulted disaster recovery professionals and IT practitioners. In addition, the researcher's background in IT and disaster recovery procedure implementations was used in the survey development. The format and the categories in the survey were developed using the Sitkin and Weingart's (1995) survey; however the questions were modified to reflect the real world SMEs decision maker's experience in DRT investment. In the current study, the survey was conducted in the participant's natural environment and the scenario was his or her firm's real need to make decisions to invest or not invest in DRT. One main advantage of this field study compared to laboratory study is that the results can be easily generalized to the real world (Bordens & Abott, 2008).

The six categories of the survey were specific questions about the firm's demographic information, current implementation of any disaster recovery technologies the decision maker's data loss experience (outcome history), risk propensity, risk perception, and framing. Data loss experience (outcome history), risk perception, risk propensity, and framing were measured in 7-point Likert scale to stay consistent with the original study. Table 1, depicts the constructs and their supporting references for the survey instrument. A detailed survey questionnaire is attached in Appendix B. The validity and reliability of the study is discussed in the following sections.

**Table 1**
The list of variables for the survey instrument

| Variables as shown in the present study | Measuring Criteria | | References |
|---|---|---|---|
| **Independent and Mediating Variables** | | | |
| Data loss experience | Unsuccessful Data Recovery Experience | Successful Data Recovery Experience | Osborn & Jackson, 1988; Sitkin &Pablo, 1992; Sitkin & Weingart , 1995; Thaler & Johnson, 1990; |
| Framing | Positive, Opportunity Gain | Negative Threat Loss | Kanheman &Tversky, 1979, 2000; Kunreuther, 2010; Kunreuther & Pauly, 2004; March & Shapira, 1987; Sitkin &Pablo,1992; Sitkin & Weingart , 1995; Slovic, 2000; Slovic, Fischhoff, & Lichtenstein, 1982; Thaler & Johnson, 1990; |
| Risk propensity | Risk - avoidance | Risk-seeking | Kanheman &Tversky, 1979, 2000; Keil et al., (2000); Kunreuther & Pauly, 2004; March & Shapira, 1987; Sandelands& Dutton, 1981; Sitkin & Pablo, 1992; Sikin & Weingart , 1995; Slovic, 2000; Slovic, Fischhoff, & Lichtenstein, 1982; Thaler & Johnson, 1990; |
| Risk perception | Low Risk Perception | High Risk Perception | Kanheman &Tversky, 1979, 2000; Keil et al. (2000); Kunreuther & Pauly, 2004; March & Shapira, 1987; Sitkin &Pablo,1992;Sikin & Weingart , 1995; Slovic, 2000; Slovic, Fischhoff, & Lichtenstein, 1982; Tallon et al., 2001; Thaler & Johnson, 1990; |
| **Dependent Variable** | | | |
| DRT Investment | Yes (if invested) | No (if not invested) | Gereer, 2002; Irani, 2002; |

### *3.3.3 Validity*

Bordens and Abbot (2008) suggest that a questionnaire must measure content validity to assess whether the questions cover the range of behavior that the research is

measuring. They also refer to construct validity which can be established by showing that questioner's result in observing behavior patterns agrees with the predications based on theoretical patterns. To ensure validity, the questions were drafted in a manner relevant to DRT investment. In addition, the research targeted small to medium-sized enterprises and participants who were the real decision makers; which can lead to a valid test of the model in the real world environment. The convergent and discriminant validity is not considered for the present study since the measures were sufficient for Sitkin and Weingart's (1995) laboratory study and the present study shifts only context.

### *3.3.4 Reliability*

According to Bordens and Abbot (2008), reliability is defined as the ability of a measure to produce the same or highly similar results on repeated administration of a questionnaire. To insure a high level of internal consistency, a Cronbach's alpha value was used. The same value of α that were used for the original study such as α=.75 for risk perception questions and α=.86 for the risk propensity questions (Sitkin & Weingart, 1995) were considered for the current study. Also, by ensuring that questions are clear, and well defined, and appropriate, the reliability was increased. Another step to ensure reliability of data is to set the DRT criteria to a measurable level by setting a minimum investment that includes the data backup/recovery software and hardware and periodic testing (at least once a year) of the backed up data to insure that data can be recovered.

## 3.4 Data Collection

The data was gathered by means of an electronic survey. The process was carried out in three steps. First, the subject's information was identified to include at least the company's name, a contact person, an e-mail address, and a phone number. Second, a

screening call was made to the participant to make sure that the firm is non-regulated in regard to DRT implementation, and also if the e-mail information was accurate in regard to the decision maker for DRT investment. Third, a follow up e-mail was sent to participants to direct them with a script about the study and direction to a website and a location of the survey instrument. The script is attached in Appendix C. In case of survey posted on multiple business groups, the email letter script was posted along with the link to the Survey Monkey web site.

For the purpose of this research, Eighty one complete responses were analyzed. This number exceeds the number of Sitkin and Weingart (1995) subjects used in the study. According to Thomas (2004), an average of web-based response rate of 39.6% was reported by Cook, Health, and Thompson (2000) where a meta-analysis of 49 studies with 68 questionnaires was conducted. Other studies show about the same average but do suggest that the response rate can be increased by factors such as number of contacts, personalized contacts, and incentives (Nutty, 2008; Thomas, 2004). To incorporate low response rate into the current study, the survey were sent electronically to three hundred pre-screened participants. There were a total of twenty eight questions in the survey. Therefore, there were a total of twenty eight data points for each participant.

The unit of analysis for this study was the individual decision maker with the firm. In SMEs, the main investment decision maker is usually the owner or principles of the company (Bruque & Moyano, 2007; Nguyen, 2009; Tallon et al., 2001). The firm had to be a non-regulated organization so that certain security measures such as DRT implementation is a choice of the owner/manager and not a mandatory government policy.

### 3.5 Data Analysis Procedures

A *p*-value is a probability associated with the test statistics. To draw conclusions about the null hypothesis (reject or fail to reject) based on a *p*-value, there is a need to set a predetermined cutoff point where only those *p*-values less than or equal to the cutoff will result in rejecting null hypothesis. This cutoff point is called the alpha level (α) or significance level for the test (Rumsey, 2011). Furthermore, the *p*-value refers to the actual probability of making a Type I error given the null hypothesis is true (Bordens & Abbot, 2008). This study used the cutoff value of 0.05 since it is very popular cutoff value for rejecting the null hypothesis; however, there is still nearly a 5% chance of being wrong in reaching this conclusion (Rumsey, 2011). In the current study, in order to accept the alternative hypothesis and reject each null hypothesis, each one of the hypotheses assumes *p* value of less than 0.05.

The direct effects posited in the study's hypotheses 1 through 5 were examined through bivariate correlational analyses. Bivariate correlation measures the strength of the relationship between two variables (Bordens & Abbot, 2008). The following section will discuss each alternative hypothesis 1 through 5 and the related test to accept or reject it:

Hypothesis 1: A successful data loss recovery outcome history increases a decision maker's propensity to take risk.

Among respondents who indicate a more successful recovery, the researcher expects to see a stronger tendency to take risk in decision making. If there is a significant positive correlation between successful data loss experience and the individual's propensity to take risk, then the alternative hypothesis is accepted and the null hypothesis is rejected.

This type of analysis will be achieved by calculating Pearson r with a $p < .05$ for each of the two outcome history items and risk avoidance average scale score.

Hypothesis 2: A positively framed situation will be perceived as involving higher risk of data loss.

Respondents whose average scale score represents relatively positive framing are expected to perceive a higher risk of data loss. If there is a significant positive correlation between framing and risk perception, then the alternative hypothesis is accepted and the null hypothesis is rejected. This type of analysis is achieved by calculating the Pearson r with $p < .05$ for each of the two average scale score for framing and risk perception.

Hypothesis 3: The higher a decision maker's risk propensity, the lower level of perceived risk of data loss.

Respondents who perceive lower risk of data loss are expected to have higher risk propensity. If there is a significant negative correlation between these two average scale scores, then the alternative hypothesis is accepted and null hypothesis is rejected. This type of analysis is achieved by calculating the Pearson r with $p < .05$ for each of the two risk propensity and risk perception average scale scores.

Hypothesis 4: A decision maker's perception of higher risk will result in greater DRT investment

Respondents who perceive higher risk of data loss are expected to invest in DRT investment. If there is a significant positive correlation between each of the two average scale score for perception of higher risk of data loss and the decision to invest in DRT, then the alternative hypothesis is accepted and the null hypothesis is rejected. This type of analysis is achieved by calculating the point-biserial correlation for the two risk

perception average scale score and DRT investment decision with $p < .05$. Point-biserial correlation is applied when one variable is continuous and the other dichotomous (Bordens & Abbot, 2008). As in all correlations, point-biserial values range from -1.0 to +1.0. For this hypothesis, risk perception will be the continuous variable while DRT investment will be the dichotomous variable (where the "no DRT investment "has a value of 0 and the "DRT investment" has a value of 1).

H5: A positively framed situation will result in greater DRT investment.

Respondents whose average scale scores represent relatively positive framing are expected to invest in DRT investment. If there is a significant positive correlation between positive framing and DRT investment, then the alternative hypothesis is accepted and the null hypothesis is rejected. This type of analysis is achieved by calculating the point-biserial correlation for the two framing average scale score and DRT investment decision with $p < .05$. For this hypothesis, framing will be the continuous variable while DRT investment will be the dichotomous variable (where the "no DRT investment "has a value of 0 and the "DRT investment" has a value of 1).

Since this study was measuring perceptions in response to a real world specific risk scenario based on the prior laboratory research of Sitkin and Weingart (1995), the questions were altered to reflect the real world situation but the measures of Cronbach's alpha stayed consistent with the prior research of Sitkin and Weingart.

SPSS software was used to analyze the data collected In case of missing data which could have several sources such as response refusal, coding error, and data entry errors, SPSS allows to identify specific data values as "missing" and those values will be

recognized as " non-data" and not used in statistical computations (www.ibm.com/spss/rd/students, 2011).

### 3.6 Summary

Although a vast number of scholarly studies (Agarwal & Prasad, 1997; Grandon & Pearson, 2004; Kahneman & Tversky, 2000; Kunreuther & Pauly, 2004; March & Shapira, 1987; Nguyen, 2009; Slovic, 2000; Slovic et al., 1982; Subramanian & Nosek, 2001; Thaler, 1980) have addressed risky decision making behavior within laboratory studies, relatively little work has been done in regard to SMEs' risky decision making behavior, and none for the DRT investment risky choice in the real world. Due to the vitality of small and medium size enterprises to our economy and society, the lack of investment in disaster recovery technologies needs to be investigated. This research focused on advancing the scientific knowledge about the process of risky decision making behavior by studying the lack of DRT investment in the firms that are vital units of our economy. In addition, this study may contribute to the body of knowledge about risky choices and decision framing process. The findings could have many implications for researchers, economists, social behavior scientists, government, and IT security. To study the factors influencing DRT investment, a model of the determinants of risky decision-making behavior (Sitkin & Weingart, 1995) was adapted and applied to the real world environment in DRT context. This chapter reviewed the theoretical background, suggested model, hypotheses, research approach, data collection, data analysis techniques, limitations barriers, and milestones.

# Chapter 4

# Results

## 4.1 Introduction

This chapter lays the groundwork for presenting the results of the study by including descriptive statistics and analysis of the findings of the research. This information is outlined in multiple sections including data analysis, findings, and summary of results.

The goal of this research was to investigate the determinants of disaster recovery technology investment choice in small and medium-sized enterprises. The results have the potential to lay a foundation for further research in applying laboratory research model to a real world context of decision making under uncertainty, in particular, factors that influence disaster recovery technology investment choices in SMEs. To achieve this goal, statistical analyses were performed using the Statistical Package of Social Science (SPSS) software version 22.0 for survey responses.

## 4.2 Data Analysis

A total of 300 survey invitation e-mail letters (see Appendix C) were sent out to small and medium-sized businesses in northeastern US. In addition, the invitation letter with the survey link was posted on multiple business networking sites. A total of 128 participants responded, while only 81 responses were complete. The true average rate of the response is not known since the survey and the email letter were posted on multiple sites. If we just consider the email letters sent out, then the average response rate for all surveys would be 43% and for only completed survey would be 27% which is close to several other studies average response rate (Nutty, 2008; Thomas, 2004). All the

responses were exported to SPSS format and downloaded from the Survey Monkey site. To include only the completed responses, a SPSS software filter was created to exclude any data that is disqualified and incomplete in the SPSS software database. The question labels were changed from the original Survey Monkey labels to a format that identifies the questions in relation to the DRT technology variables. Then descriptive analysis was performed to calculate the means using numerical values with ranges from 1 to 7 utilizing four-item scale for outcome history, three-item scale for positive decision framing, one-item scale for negative decision framing, five-item scale for risk perception, and five-item scale for risk propensity.

In addition, to estimate the total disaster recovery investment value in correlational analysis and linear regression, a new variable called total DRT investment was calculated using survey questions 4-6. The more investment choices were made in DRT technologies, the higher the value of total DRT investment was calculated.

To distinguish between types of decision framing, questions 12-14 were categorized as positive decision framing and question 15 was categorized as negative decision framing. Next, bivariate correlational analysis was performed to investigate the relationships between the constructs. Finally, linear regression was conducted to regress the choice of DRT investment to risk perception and positive and negative decision framing.

*4.2.1 Descriptive Statistics*

The original data files that were exported from the survey site had a total of 128 responses. After using SPSS software filter function to exclude the disqualified and

incomplete surveys, the data base showed 81 complete responses. Table 2 depicts the frequency of responses to the question of if the subject has invested in DRT.

**Table 2**
Descriptive Statistics for DRT investment choice (N=81)

| DRT Investment | Frequency | Percent |
|---|---|---|
| Yes | 56 | 69.1 |
| No | 25 | 30.9 |
| Total | 81 | 100.0 |

The range, mean, and standard deviation for each of the composite variables (i.e., mean of the item measuring each study variable) of the study are depicted in Table 3.

**Table 3**
Descriptive Statistics for composite variables Mean and Standard Deviation (N=81)

| Variables | Minimum | Maximum | Mean | Std. Deviation |
|---|---|---|---|---|
| Successful Recovery Outcome History | 1.00 | 7.00 | 4.9877 | 1.47309 |
| Risk Propensity | 1.00 | 7.00 | 4.5951 | 1.18489 |
| Risk Perception | 1.00 | 6.60 | 4.5093 | 1.25962 |
| Positive Decision Framing | 1.00 | 7.00 | 5.4815 | 1.31656 |
| Negative Decision Framing | 1.00 | 7.00 | 2.9259 | 1.90904 |

The frequencies and percentages for the demographic variables describing the sample are displayed in Table 4 and 5. As shown in Table 5, about forty one percent (40.7%) were from small businesses with less than 10 employees and about twenty six percent (25.9%) were from medium-sized enterprises with more than 250 employees. The highest industry was services with thirty one percent (30.9%). About twenty two percent

(22.2%) of the industry type had chosen other which included construction, education, and other type of services.

**Table 4**
The number of employees for the sample's firm (N=81)

| | Frequency | Percent | Valid Percent |
|---|---|---|---|
| Less than 10 | 33 | 40.7 | 40.7 |
| Between 11 and 49 | 16 | 19.8 | 19.8 |
| Between 50 and 99 | 6 | 7.4 | 7.4 |
| Between 100 and 250 | 5 | 6.2 | 6.2 |
| More than 250 | 21 | 25.9 | 25.9 |
| Total | 81 | 100.0 | 100.0 |

**Table 5**
The type of industry for the sample's firm (N=81)

| | Frequency | Percent | Valid Percent |
|---|---|---|---|
| Services | 25 | 30.9 | 30.9 |
| Retail | 2 | 2.5 | 2.5 |
| Technology | 23 | 28.4 | 28.4 |
| Health | 3 | 3.7 | 3.7 |
| Manufacturing | 9 | 11.1 | 11.1 |
| Government or State | 1 | 1.2 | 1.2 |
| Other | 18 | 22.2 | 22.2 |
| Total | 81 | 100.0 | 100.0 |

*4.2.2 Bivariate Correlation and regression Analysis*

To measure the strength of the linear relationship between two variables, bivariate correlation analysis was performed. There are multiple types of bivariate correlation analysis through SPSS. For the purpose of this study, Pearson r and Point-biserial correlation analysis which is special case of Pearson r analysis were used. In order to reject the null hypothesis, a cutoff value of 0.05 for the *p* was determined. If the *p* value is less than our predetermined cutoff value, then we can reject the null hypothesis. In

addition, the magnitude of correlation coefficient (r) can identify the strength of the relationship. In general, if the value of r or the direct effect is at 1, then there is a perfect relationship. If the value of r is between .5 and 1, then the strength of the correlation is considered significant. If the value is less than .5 but greater than .3, then the strength of correlation is considered moderately significant and if the value is less than .3 to 0 is weakly significant. At r=0, there is no relationship. These relationships are depicted for each hypothesis in the following section:

Hypothesis 1: A successful data loss recovery outcome history increases a decision maker's propensity to take risk.

The average scale score for risk propensity includes the mean of all the values of questions 21 through questions 25 (See Table 6).

**Table 6**

Composite Scores for Successful Recovery Outcome History and Risk Propensity (N=81)

| | Mean | Std. Deviation |
|---|---|---|
| Risk Propensity (Questions 21-25) | 4.5951 | 1.18489 |
| Successful Recovery Outcome History (Questions 9-12) | 4.9877 | 1.47309 |

Pearson r correlation and linear regression analysis were conducted between Risk Propensity and Successful Recovery Outcome History. The correlation showed significance ($p$<.001) and an r of .517 showed a large effect (See Table 7).

**Table 7**

Pearson r Correlation between Successful Recovery Outcome History and Risk Propensity

| | Successful Recovery Outcome History |
|---|---|
| Risk Propensity | .517* |

* $p$<.001

The regression analysis showed a coefficient determination of .287 ( $R^2$ = .287) indicating the model was a moderate to low fit with a beta of .416, therefore, only 28.7 percent of the variation in risk propensity is explained by successful recovery outcome (See Table 8).

**Table 8**

Regression Coefficients of Successful Recovery outcome History

| | B | Std. Error | β |
|---|---|---|---|
| Constant | 2.522 | .403 | |
| Successful Recovery Outcome History | .416 | .077 | .517* |

$R^2$ = .287 *$p$<.001

There was a significant positive correlation between successful data loss recovery experience and risk propensity. Therefore, among respondents who indicated a more successful recovery, there was a stronger tendency to take risks in decision making. There was a significant positive correlation between successful data loss experience and the individual's propensity to take risk. Therefore, the hypothesis was confirmed. This result agrees with the original Sitkin and Weingart study (1995) results.

Hypothesis 2: A positively framed situation will be perceived as involving higher risk of data loss. The average scale score for positive decision framing includes the mean of all values of questions 12 through question 14. The average scale score of risk perception includes the mean of all values of questions 16 through question 20 (See Table 9).

**Table 9**

Composite Scores for Positive Decision Framing and Risk Perception (N=81

| | Mean | Std. Deviation |
|---|---|---|
| Positive Decision Framing (Questions 12-14) | 5.4815 | 1.31656 |
| Risk Perception (Questions 16-20) | 4.5093 | 1.25962 |

Pearson r correlation and regression analysis were conducted between Positive Decision Framing and Risk Perception. The correlations showed significance ($p$<0.01) and an r of .592 showed a large effect (See Table 10)

**Table 10**

Pearson r Correlation for Positive Decision Framing and Risk Perception

| | Positive Decision Framing |
|---|---|
| Risk Perception | .592* |

* $p$ <.001

The regression showed a coefficient determination of .351 ($R^2$ =.351) indicating the model was a moderate fit with a beta of .567, therefore, about 35.1 percent of variation in risk perception is explained by positive decision framing. (See Table 11)

**Table 11**

Regression Coefficients for Positive Decision Framing and Risk Perception

| | B | Std. Error | β |
|---|---|---|---|
| Constant | 1.404 | 489 | |
| Positive Decision Framing | .567 | .087 | .592* |

$R^2$ = .351 * $p$ <.001

There was a significant positive correlation between positive framing and risk perception; therefore, among respondents who average scale score represents relatively positive framing scored higher risk perception of data loss. Therefore, the hypothesis was confirmed.

Hypothesis 3: The higher a decision maker's risk propensity, the lower level of perceived risk of data loss.

In the original Sitkin and Weingart study (1995), when subjects reported higher levels of risk propensity (risk taking propensity), they also reported that they perceived less risk in the situation. In the present study, a significant negative relationship was only shown between risk avoidance propensity and risk perception using Pearson r correlation analysis (See Table 12). The value for risk avoidance propensity was calculated by subtracting the mean of total score of five-item scale of risk propensity from the value 7.

**Table 12**

Composite Scores for Risk Avoidance Propensity and Risk Perception (N=81)

| | Mean | Std. Deviation |
|---|---|---|
| Risk Avoidance Propensity | 2.4049 | 1.18489 |
| Risk Perception | 4.5093 | 1.25962 |

Pearson r correlation analysis was conducted between Risk Avoidance Propensity and Risk Perception. The correlation showed significance ($p$ <0.01) and an r of -.536 showing a large negative effect (See Table 13).

**Table 13**

Pearson r Correlation for Risk Avoidance Propensity and Risk Perception

| | Risk Avoidance Propensity |
|---|---|
| Risk Perception | -.536* |

* $p$ <.001

On the other hand, between Risk Propensity (risk taking propensity) and Risk Perception, the correlation showed significance ($p$ <0.01) and an r of .536 showing a large positive effect (See Table 14 and 15 for Composite scores and correlation).

**Table 14**

Composite Scores for Risk Propensity and Risk Perception (N=81)

| | Mean | Std. Deviation |
|---|---|---|
| Risk Propensity | 4.5951 | 1.18489 |
| Risk Perception | 4.5093 | 1.25962 |

**Table 15**

Pearson r Correlation for Risk Propensity and Risk Perception

| | Risk Propensity |
|---|---|
| Risk Perception | .536* |

* $p$ <.001

The regression showed an $R^2$ of .536 indicating the model was a Strong fit with a beta of .569. (See Table 16)

**Table 16**

Regression Coefficients for Risk Propensity and Risk Perception

| | B | Std. Error | β |
|---|---|---|---|
| Constant | 1.893 | .479 | |
| Risk Propensity | .569 | .101 | .536* |

$R^2$ = .536 * $p$ <.001

Respondents who had a higher risk taking propensity, perceived a higher risk of data loss. Therefore, the results show a disagreement with what the hypothesis had expected and the findings did not support this hypothesis.

Hypothesis 4: A decision maker's perception of higher risk will result in greater DRT investment. There were two analysis approaches for this hypothesis. First, to measure the strength of the relationship between total DRT investment and risk perception, a Pearson r correlation analysis was conducted. The correlation showed strong significance ($p$ = .005) and an r of .971 (See Table 17 and Table 18 for the composite scores and Pearson r correlation).

**Table 17**

Composite Scores for Risk Perception and Total DRT Investment ( Valid N=56)

| | Mean | Std. Deviation |
|---|---|---|
| Total DRT Investment | 5.9683 | 2.22136 |
| Risk Perception | 4.7042 | 1.10228 |

**Table 18**

Pearson r Correlation for Risk Perception and Total DRT Investment

| | Total DRT Investment |
|---|---|
| Risk Perception | .971* |

* $p$ =.005

However, the linear regression showed $R^2$ =.000 indicating the model as a low fit. Therefore, the findings using the degree of DRT investment did not support the hypothesis. Second, to measure the strength of the relationship between those decision makers who chose to invest in DRT and risk perception, a point-biserial correlation analysis was conducted. The correlation showed significance ($p$ =.035) and r of -.234 showing a small effect (See Table 19 for Composite scores and Table 20 for point-biserial correlation), this negative correlation indicates that lower level of risk perception is associated with higher level of DRT investment choice (Yes =1 and No=2). Therefore, among respondents who perceived less risk in data loss, there was stronger chance to not to invest in DRT. Therefore, the findings using the choice of DRT investment did support this hypothesis.

**Table 19**

Composite Scores for Risk Perception and DRT Investment Choice

| | Mean | Std. Deviation |
|---|---|---|
| Risk Perception for DRT Investment choice =Yes (N=56) | 4.7042 | 1.12725 |
| Risk Perception for DRT Investment Choice = No (N=25) | 4.0700 | 1.44431 |

**Table 20**

Point-biserial Correlation for Risk Perception and DRT Investment Choice

| | DRT Investment Choice |
|---|---|
| Risk Perception | .234* |

* $p$ =.035

Hypothesis 5: A positively framed situation will result in greater DRT investment. There were two analysis approaches for this hypothesis. First, to measure the strength of the relationship between Total DRT investment and Positive Decision Framing, a Pearson r correlation analysis was conducted. The correlation showed no significance ($p$ = .054) and an r of .250. In addition, the linear regression showed $R^2$ =.062 indicating the model is very low fit. (See Table 21).

**Table 21**

Pearson r Correlation for Positive Decision Framing and Total DRT Investment

| | Total DRT Investment |
|---|---|
| Positive Decision Framing | .250* |

* $p$ =.054

Second, to measure the strength of the relationship between those decision makers who chose to invest in DRT and positive decision framing, a point-biserial correlation analysis was conducted. The correlation showed significance ($p$ =.023) and r of -.253 showing a small effect (See Table 23 for point-biserial correlation), this negative correlation indicates that lower level of Positive Decision Framing is associated with higher level of DRT investment choice (Yes =1 and No=2). Therefore, among respondents who framed less positive situation (loss frame), there will be stronger chance not to invest in DRT. Therefore, the hypothesis was confirmed. Table 22 depicts the point-biserial correlation.

**Table 22**

Point-biserial Correlation for Positive Decision Framing and DRT Investment Choice

| | DRT Investment Choice |
|---|---|
| Positive Decision Framing | -.253* |

* $p$ =.023

In addition, Figure 4 shows this relationship in a scatter graph which depicts the negative slope.

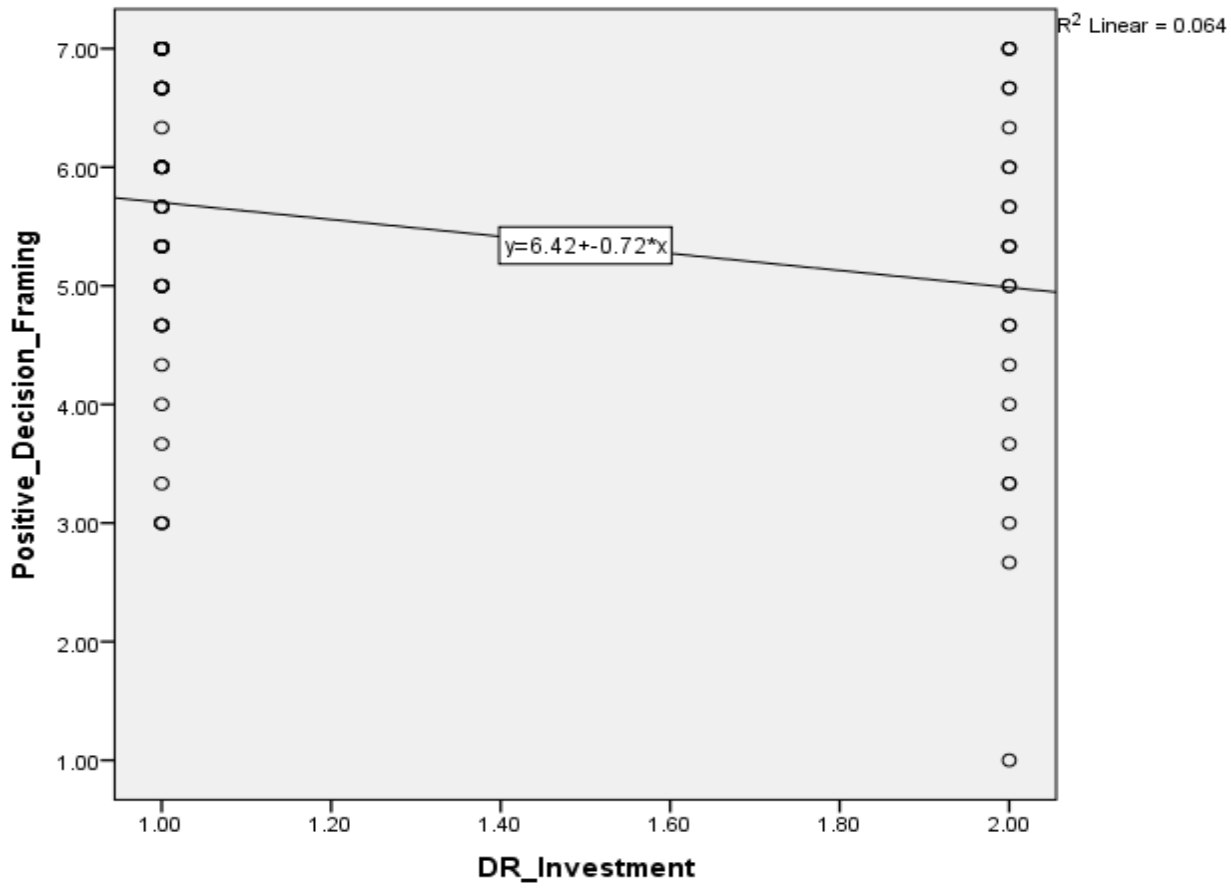



Figure 4, scattered graph for positive decision framing and DRT investment

*4.2.3 Reliability of Measures*

The study cases and Cronbach's alpha assessing the internal consistency of the study's measures of .80 is displayed in Table 23 and Table 24. The alpha level of .80 is high and above the accepted threshold of .70, suggesting adequate reliability.

**Table 23**

Case Processing Summary

| | | N | % |
|---|---|---|---|
| Cases | Valid | 81 | 100.0 |
| | Excluded | 0 | .0 |
| | Total | 81 | 100.0 |

**Table 24**

Reliability Statistics

| Cronbach's Alpha | N of Items |
|---|---|
| .800 | 4 |

*4.2.4 Measures of Validity*

The convergent and discriminant validity is not considered for the present study since the measures were sufficient for Sitkin and Weingart's (1995) laboratory study and the present study shifts only context.

**4.3 Findings**

The results of data analysis suggested that Hypothesis 1 and 2 and 3 were confirmed and supported. Hypothesis 4 and 5 were partially supported.

Hypothesis 1: A successful data loss recovery outcome history increases a decision maker's propensity to take risk. There was a significant positive correlation and relation between successful data loss recovery outcome history and risk propensity. The

respondents, who indicated a more successful recovery, did show strong tendency to take risks in decision making. Therefore, this hypothesis is fully supported.

Hypothesis 2: A positively framed situation will be perceived as involving higher risk of data loss. There was a significant positive correlation and relation between positively framed situation and risk perception. The respondents, who indicated data recovery and DRT investment as a positive gain, did perceive higher risk in data loss. Therefore, this hypothesis is fully supported.

Hypothesis 3: The higher a decision maker's risk propensity, the lower level of perceived risk of data loss. Respondents who perceive higher risk of data loss are expected to have higher risk avoidance propensity. There was a significant negative correlation between risk perception and risk propensity to avoid risk and there was a significant positive correlation and relation between risk perception and risk propensity to take risks. The findings were in disagreement with what the alternate hypothesis expected and therefore, not supported.

Hypothesis 4: A decision maker's perception of higher risk will result in greater DRT investment. In case of the amount of DRT investment and risk perception, there was no significant correlation between these two variables. However, in case of the choice of DRT investment and risk perception, there was a negative weak correlation between the risk perception and the lack of DRT investment (the choice not to invest) Therefore, this hypothesis is partially supported.

Hypothesis 5: A positively framed situation will result in greater DRT investment. In case of the amount of DRT investment and positively framed situation, there was a moderate positive significance. Therefore, hypothesis was supported. However, in case of

the lack of DRT investment and positively framed situation, there was a weak negative relationship between these variables. Therefore, this hypothesis is partially supported. A result of the modified model is shown in Figure 5.

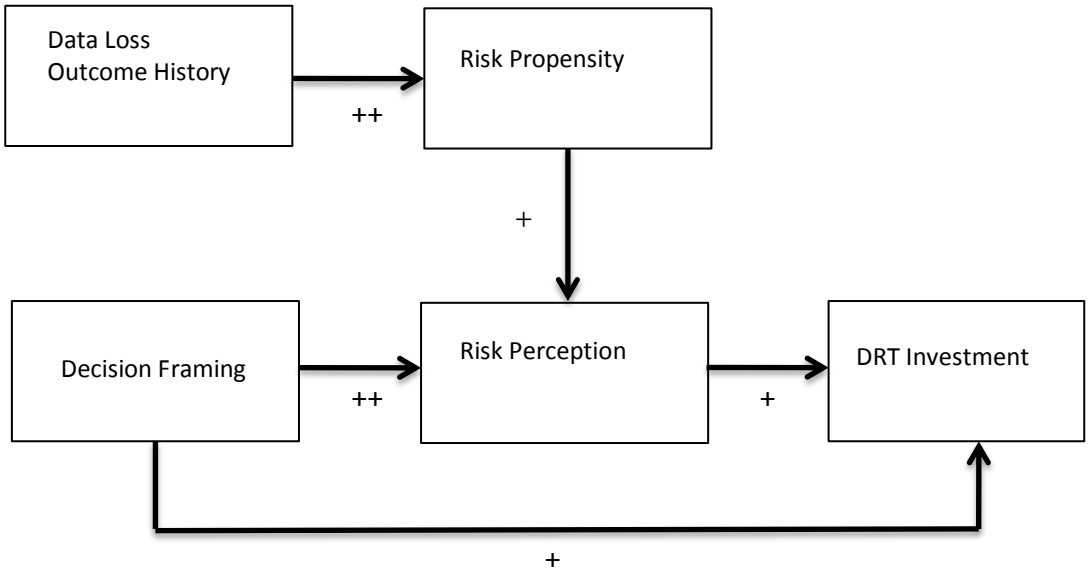



Figure5. Revised model of the determinants of risky choice of lack of DRT investment behavior.[2]

[2]Adapted from Sitkin and Weingart (1995) and applied to DRT investment context
The significant relationships are shown. The strength of the results is indicated by the number of plus or minus signs shown; "+" or "-"indicates the significance of $p<.005$, whereas "++" or "—"indicates significance of $p<.001$.

### 4.4 Summary of Results

The descriptive statistics, bivariate correlation, and regression analysis confirmed the direct effects and relationship between the variables of a laboratory model that had been applied to real world context of DRT investment behavior. Hypothesis 1, 2 and 3 showed a significant correlation and relation while hypothesis 4 and 5 showed a weak correlation. The Cronbach's alpha of .80 suggested an adequate reliability. The convergent and discriminant validity was not considered for the present study since the measures were sufficient for Sitkin and Weingart's (1995) laboratory study. The findings

support the original model (Sitkin and Weingart, 1995) which can be applied to the real world situations.

# Chapter 5

## Conclusions, Implications, Recommendations, and Summary

### 5.1 Conclusions

The purpose of this study was to investigate the determinants of disaster recovery investment choice in SMEs by applying a revised model of determinants of risky decision-making behavior suggested by Sitkin and Weingart (1995) to a context of DRT investment in the real world. The model was empirically tested using survey data collected from a list of SMEs decision makers located in the northeastern United States. Four independent and mediating variables and one dependent variable were initially identified through a literature review and expert interviews. The independent and mediating variables were data loss outcome history, risk propensity, risk perception, and decision framing. The dependent variable was the choice to invest in DRT. One set of questionnaire, which consisted of 28 questions within six categories were used for a survey instrument. Eighty one valid samples were collected for the data analysis through the Survey Monkey site. The six categories of the survey were the firm's demographic information, current implementation of any disaster recovery technologies, the decision maker's data loss outcome history (past experience), risk propensity, risks perception, and framing. Descriptive statistics, bivariate correlation, and linear regression analysis were used to examine the construct's relationship significance of the applied model. The results of hypotheses tests were:

Hypothesis 1: It was hypothesized that a successful data loss recovery outcome history increases a decision maker's propensity to take risk. This hypothesis was confirmed and fully supported.

Hypothesis 2: It was hypothesized that a positively framed situation will be perceived as involving higher risk of data loss. This hypothesis was confirmed and fully supported.

Hypothesis 3: It was hypothesized that the higher a decision maker's risk propensity, the lower level of perceived risk of data loss. This hypothesis was not supported.

Hypothesis 4: It was hypothesized that a decision maker's perception of higher risk will result in greater DRT investment. In case of the amount of DRT investment and risk perception, this was not confirmed. However, in case of the choice of DRT and risk perception, the hypothesis was partially supported.

Hypothesis 5: It was hypothesized that a positively framed situation will result in greater DRT investment. In case of the amount of DRT investment and positively framed situation, the hypothesis was supported. However, in case of the lack of DRT investment and positively framed situation, the hypothesis was partially supported.

The results from the bivariate correlation analysis indicated that successful data loss experience influences the risk propensity. In addition, positive decision framing influences the individual's risk perception. Furthermore, risk taking propensity influences the risk perception positively while risk avoidance propensity influences the risk perception negatively. The risk perception and positively framed situation influences the decision maker's choice to a limited degree. The results of the present study provided support for the original model (Sitkin and Weingart, 1995) which can be applied to a real world context.

## 5.2 Implications

### *5.2.1 Academic Implications*

This research offers several contributions to IS literature. First, it was shown that a laboratory model can be applied to a real world context. The results support the validity and reliability of the study by close similarity of the relationships between the current researches constructs. The use of bivariate correlation was found effective in discovering the relationships.

Second, it sheds light on the relationship between risk perception and framing to decision making under uncertainty in a real world context. Both of these constructs had an influence on the choice of DRT investment. In order to understand the lack of DRT investment, risk perception and framing can be studied further since there are scales now available to measure them in quantitative research.

Third, the research model and questionnaire provide a map to investigate the relationship between outcome history to risk propensity and risk propensity to risk perception. Finding a map or a way to measure the relationship between these constructs in a real world context can make the future research of this type less complex.

### *5.2.2 Practical Implications*

The present study offers multiple contributions to our economy and small and medium-sized enterprises research. First, it validates that many SME decision makers are still not investing in DRT. The lack of DRT investment affects their ability to recover data in case of a disaster. Second, it adds to the knowledge base of the factors to investigate when examining the lack of DRT investment choice which is a decision under

uncertainty. In operating any business, there will come a time to decide if one should invest in processes and technologies intended to increase profitability. Decision makers need to know which factors could influence their choice under uncertainty to make the right decision. Finally, the current study could assist many entities such as non-profit contingency planning organizations, government, and vendors to concentrate on key factors to be able to help SMEs to make the most beneficial decision.

## 5.3 Recommendations

Since the current research is based on the individual's characteristics and decision making behavior, many different contexts can be used to test the model. Real world contexts such as decisions to protect the firm through crisis management and business continuity procedures are examples of the future research. In addition, the research model can be applied to other firms which are not categorized as SMEs. Many larger companies are regulated to have disaster recovery plans and technologies, it would be interesting to investigate the executive's risk characteristics with any other type of decision making under uncertainty.

SMEs are the livelihood of the global economy. It would be beneficial to extend this research to other countries and economies to study the similarities and differences in the individual's decision making.

### *5.3.1 Limitations and Future Research*

The limitations for this research that could present future research opportunities include examining the effects of mediating variables and other variables that are known to have potential effects on decision making under uncertainty. Variables such as the firm's cultural orientation, policies, leadership styles, and decision maker's tendency

toward using a trusted advisor to make risky choices are among important factors that have shown to effect decision making (Osborn & Jackson, 1988; Sitkin & Pablo, 1992; Sitkin &Weingart, 1995). Examining other variables such as firm's revenues or decision maker's gender would also be beneficial for this type of research.

In addition, SMEs are defined with the firms less than 500 employees (United States Business Administration, 2006); however, this research had forty one percent (40.7%) of the respondents from small businesses with less than 10 employees. This phenomenon might be due to the process of selecting the samples from a list through business center for small businesses in a community college. A future study with the firm size that is more evenly distributed to include larger firms might be a better representation of the population. Furthermore, since there was no other similar study in the context of DRT, the instrument was based on a laboratory research in the context of risky choices for car racing decisions. For further research, the instrument can be designed to have more focused questions to the organizational issues and policies.

Another limitation on of this study is the sensitive nature of the questions in regard to data security and recovery. Many executives are reluctant to complete a survey that might reveal sensitive information of their operations. Although, the researcher had emphasized the anonymity of the survey, there is always suspicion of misusage of the data and not willing to share the information by the samples. Furthermore, due to the sensitivity of the survey topic, the response rate was low. Research has shown that sensitivity of the survey topic is likely to affect response rates in web surveys (Fan & Yan, 2010). The researcher had to participate in multiple networking events and go through several legal procedures in order to post the survey and the email letter to

multiple business networking sites. According to Fan and Yan (2010), one of the factors to increase response rate is to focus on survey delivery by providing a better way to contact the respondents. One suggestion would be to have networking strategy to approach and contact the executives in their own social networking events.

**5.4 Summary**

In today's growing economy, information systems and networks have become a vital part of the organization. An important part of the systems is the data that are generated by the applications and software used in operating the business. To safeguard and protect the data is no longer a luxury but a basic requirement (Hecht, 2002). However, SMEs lag behind in investing in technologies such as disaster recovery tools to protect their firm (Prekumar, 2003). SMEs make a significant contribution to the local and state economy and their failure would impact the economy of the country. Studies have shown that eighty percent of the companies that do not recover from a disaster within a month are extremely likely to go out of business (Saleem, et al., 2008).To investigate the factors that are influencing the decision to not invest in DRT, a study based on a existing model in a laboratory research of investigating determinants of risky decision-making behavior was proposed.

The main goals of this research were to (a) identify the factors that could affect DRT investment choice through expert interviews and literature review, (b) test and validate the relationship between factors and the DRT investment choice, and (c) determine the key factors that contribute significantly to DRT investment, based on applying an existing laboratory model to a real world context.

In the original study (Sitkin & Weingart, 1995), four different categories were measured as independent variables using multiple-item scales. In the present study, the researcher followed the same categories and scale, but changed a number of the questions to reflect the situation in a real world context of data recovery scenario where the decision maker has decided to invest or not invest in DRT. The four independent variables were data loss outcome history, risk propensity, risk perception, and decision framing. The dependent variable was the choice to invest or not to invest. The measuring objectives were to find the relationships between these independent variables and the dependent variable. The following model was proposed, see figure 6:

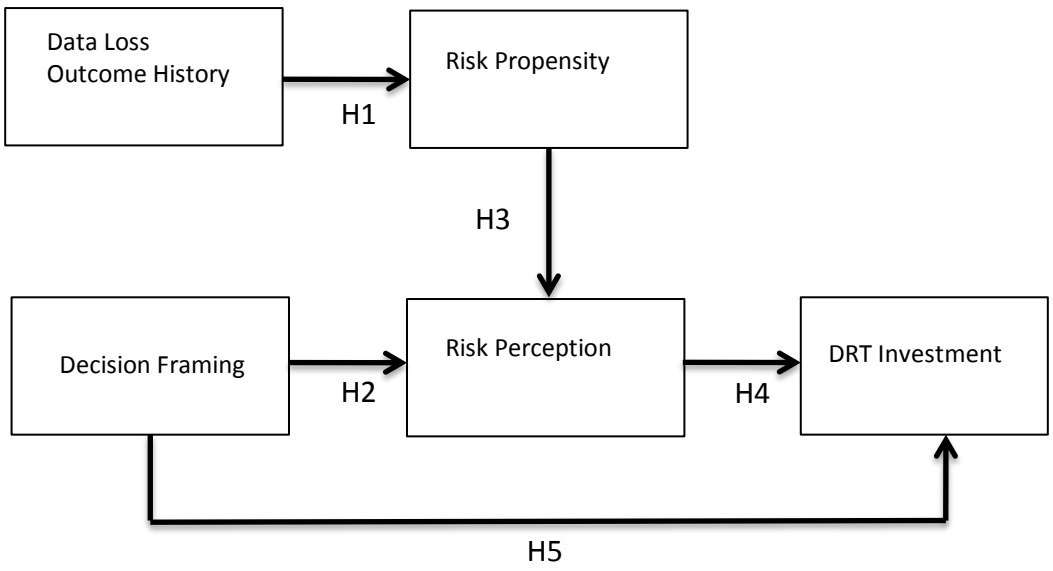



Figure 6. The mediating model of the determinants of risky choice of lack of DRT investment behavior.[2]

[2]Adapted from Sitkin and Weingart (1995) and applied to DRT investment context

Using the proposed model in figure 6, the following hypotheses were developed:

H1: A successful data loss recovery outcome history increases a decision maker's propensity to take risk.

H2: A positively framed situation will be perceived as involving higher risk of data loss.

H3: The higher a decision maker's risk propensity, the higher level of perceived risk of data loss.

H4: A decision maker's perception of higher risk will result in greater DRT investment.

H5: A positively framed situation will result in greater DRT investment.

A survey instrument was used to collect data online. A total of 300 survey invitation e-mail letters were sent out to business and IT executives. In addition, the email letter and the survey link were posted on multiple networking sites. Through the online survey questionnaire, 128 responses were returned. A total of 81 responses were complete and used in the data analysis.

Bivariate correlation and linear regression were used to examine the relationship between the variables. The results of data analysis suggested that Hypothesis 1 and 2 and 3 were confirmed and supported. Hypothesis 4 and 5 were partially supported.

Hypothesis 1: it was hypothesized that a successful data loss recovery outcome history will increase a decision maker's propensity to take risk. This hypothesis was confirmed and fully supported.

Hypothesis 2: It was hypothesized that a positively framed situation will be perceived as involving higher risk of data loss. This hypothesis was confirmed and fully supported.

Hypothesis 3: It was hypothesized that the higher a decision maker's risk propensity, the lower level of perceived risk of data loss. This hypothesis was not supported.

Hypothesis 4: It was hypothesized that a decision maker's perception of higher risk will result in greater DRT investment. In case of the amount of DRT investment and risk perception, this was not confirmed. However, in case of the choice of DRT and risk perception, the hypothesis was partially supported.

Hypothesis 5: It was hypothesized that a positively framed situation will result in greater DRT investment. In case of the amount of DRT investment and positively framed situation, the hypothesis was supported. However, in case of the lack of DRT investment and positively framed situation, the hypothesis was partially supported.

The results of the analysis indicated that risk propensity is affected by outcome history and risk perception is affected by decision framing. In addition, risk propensity affects risk perception and risk perception affects the choice of DRT investment. Furthermore, decision framing has moderate effect on DRT investment. In conclusion, risk perception and decision framing have direct effect on DRT investment, where risk propensity and outcome history have mediating effect on DRT investment.

## Appendix A: Screening Call

As a part of the screening process, each name on the list will be contacted via phone in order to qualify the individual who should be receiving the email to take the survey online.

The script will be:

Hello, my name is Fara Afshar. I am a PhD candidate with Nova Southeastern University. I am doing a study of understanding management's approach in making risky choice decisions. You have been invited to participate in a short survey. Could I ask you couple of questions to make sure we have the right individual?

1. Is your name and email address…….
2. Is your organization regulated with government data storage policies?
   Yes or No
   Could I email you the survey?

## Appendix B: Survey Instrument

Thank you for taking the time to participate in this survey.
Based on your experience with disaster recovery technologies (DRT) investment decisions, please answer all the questions to the best of your ability.

**Part 1: Qualifying the Respondent:**

1. Are you the individual who makes the decision whether or not to invest in information technologies? Yes or No

Yes
No

**Part 2: DRT Experience**

2. How much experience have you had making this type of decisions?

No Experience
Little Experience
Some Experience
Extensive Experience

**Part 3: DRT Investment**

3. Have you invested in any disaster recovery technologies?

Yes
No

4. Please check the disaster recovery technologies that you have invested in:

-Data Backup software
-Backup devices such as tape drives, cd drives, external storage
-Backup media such as tapes, CDs, USBs, or any other removable media to back up data
-Cold offsite data backup (offsite storage facility for the data backup media)
-On-line data backup (such as using cloud or remote backup)
-None of the above

5. How often is your critical data backed up? (please check all that apply)

Hourly
Daily
Weekly
Yearly
None of the above

6. How often do you test your backed up data to make sure it can be recovered in case of disaster?

Weekly
Semi-annual
annual
Once every 5 years

Never

**Part 4: Outcome History**

7. Have you had any experience with data loss incidents in the past?
Yes
No

8. About how many times in past two years, have you experienced data disruptions or data loss incident?
1=Very Low 2 3 4 5 6 7=Very High

9. On a scale of 1 to 7, how would you data rate recovery experience?
1=Very Low 2 3 4 5 6 7=Very High

10. On a scale of 1 to 7, to what degree do you feel your prior decisions regarding information technology investment have been successful?
1=Very Low 2 3 4 5 6 7=Very High

11. On a scale of 1 to 7, how confident do you feel about future decisions regarding disaster recovery technology investments in view of your investment decisions made in the past?
1=Very Unsure 2 3 4 5 6 7=Very Confident

**Part 5: Decision Framing**

On a scale of 1 to 7, for the next five questions, please indicate to what extent does each of the following statements influence your disaster recovery investment decision?

Please note: Data integrity refers to overall completeness, accuracy and consistency of data.

12. Future ability to recover data is the key, even though data loss is not a sure thing.
1=Very Little 2 3 4 5 6 7=Very Much

13. Investing in Disaster recovery technologies is a huge opportunity to safe guard our data integrity.
1=Very Little 2 3 4 5 6 7=Very Much

14. We needed to invest in disaster recovery technologies; you cannot gain competitive edge by refusing to spend resources on disaster recovery technologies.
1=Very Little 2 3 4 5 6 7=Very Much

15. Disaster recovery technology investment is a financial loss since data loss might never happen.
1=Very Little 2 3 4 5 6 7=Very Much

**Part 6: Risk Perception**

16. On a scale of 1 to 7, what is the likelihood of a data loss incident in organizations similar to your own?
1=Very Unlikely 2 3 4 5 6 7=Very Likely

17. On a scale of 1 to 7, what is the likelihood of a data loss incident in your organization?
1=Very Unlikely 2 3 4 5 6 7=Very Likely

18. On a scale of 1 to 7, what is the financial consequence of data loss in your organization?
1=Very Unlikely 2 3 4 5 6 7=Very Likely

19. On a scale of 1 to 7, what is the likelihood of recovering data successfully in case of data loss in your organization?
1=Very Unlikely 2 3 4 5 6 7=Very Likely

20. On a scale of 1 to 7, what is the likelihood of damaging your organization's excellent reputation if data is lost and cannot be recovered?
1=Very Unlikely 2 3 4 5 6 7=Very Likely

**Part 6: Risk Propensity**

As a decision maker, you face risky choices that can affect your organization's financial future. In making such decisions, how would you rate your confidence in making the following choices?

21. Making decisions based on the assessment of others on whom you must rely?
1=Very Unsure 2 3 4 5 6 7=Very Sure

22. Making decisions which rely upon highly technical analyses?
1=Very Unsure 2 3 4 5 6 7=Very Sure

23. Making decisions which could have a major impact on the strategic direction of your organization?
1=Very Unsure 2 3 4 5 6 7=Very Sure

24. Initiate a strategic corporate action which has the potential to backfire?
1=Very Unsure 2 3 4 5 6 7=Very Sure

25. Support a decision while being aware that relevant analyses were done while missing several pieces of information?
1=Very Unsure 2 3 4 5 6 7=Very Sure

**Part 7: Demographic Information**

26. Please choose the number of employees in your company:
Less than 10
Between 11 and 49
Between 50 and 99
Between 100 and 250
More than 250

27. Please choose the industry corresponding to your company:
Services
Retail
Technology
Health
Manufacturing
Government or State
Other

28. What is your gender?
Female
Male

## Appendix C: Email Letter

Dear Professional,

My name is Fara Afshar-DeStefano. I am a doctoral candidate of information systems in Nova Southeastern University. You are invited to participate in an online questionnaire of investigating the determinants of disaster recovery technology (DRT) investment choice in small and Medium-sized enterprises. It will take you approximately 15-20 minutes to complete this questionnaire. Participants will have the option of entering a random drawing to receive one of ten $25 gift cards.

Your participation will not only further my study, but also it is an important step toward helping businesses to understand the process of investing in protective measures from the decision maker's frame of reference.

If you would like to participate in this survey, click on this link: https://www.surveymonkey.com

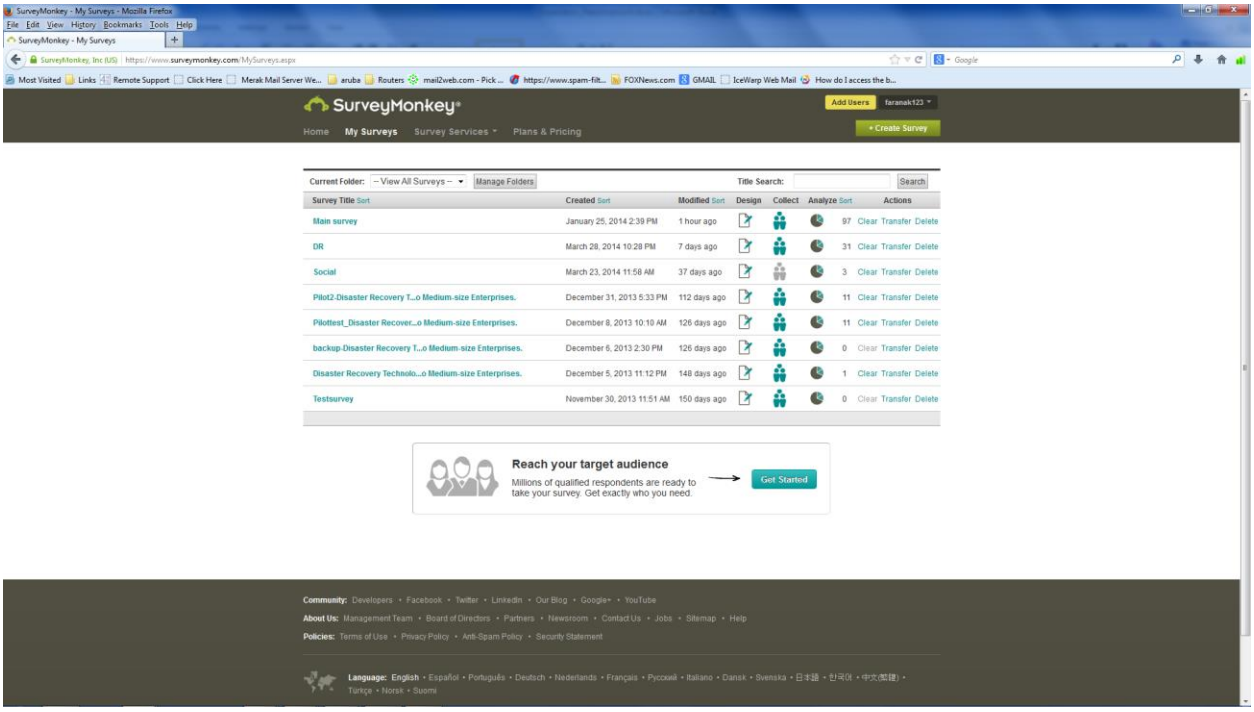
If you choose to participate in the drawing, you will need to provide your email address on the questionnaire. This information will be kept separately from the survey information, and it will be deleted once the drawing is completed. You will be contacted for your mailing address if you are selected as one of the gift card winners. This information will be deleted after gift cards are mailed.

Please email or call me if you have questions on participating in or learning more about this dissertation study. I may be reached at afshar@nova.edu or 516-641-1780.

Sincerely,

Fara Afshar-DeStefano
Doctoral Candidate
Nova Southeastern University
Fort Lauderdale, FL.

# Appendix D: Survey Instrument Site Sample



## Appendix E: NSU IRB Approval Letter

**MEMORANDUM**

To: Faranak Afshar
From: Ling Wang, Ph.D.
Institutional Review Board **Date:** Nov. 19, 2013

**Re:** *Investigating the Determinants of Disaster Recovery Technology Investment Choice in Small and Medium-sized Enterprises*

**IRB Approval Number:** wang11151301

I have reviewed the above-referenced research protocol at the center level. Based on the information provided, I have determined that this study is exempt from further IRB review. You may proceed with your study as described to the IRB. As principal investigator, you must adhere to the following requirements:

1) CONSENT: If recruitment procedures include consent forms these must be obtained in such a manner that they are clearly understood by the subjects and the process affords subjects the opportunity to ask questions, obtain detailed answers from those directly involved in the research, and have sufficient time to consider their participation after they have been provided this information. The subjects must be given a copy of the signed consent document, and a copy must be placed in a secure file separate from de-identified participant information. Record of informed consent must be retained for a minimum of three years from the conclusion of the study.
2) ADVERSE REACTIONS: The principal investigator is required to notify the IRB chair and me (954-262-5369 and 954-262-2020 respectively) of any adverse reactions or unanticipated events that may develop as a result of this study. Reactions or events may include, but are not limited to, injury, depression as a result of participation in the study, life-threatening situation, death, or loss of confidentiality/anonymity of subject. Approval may be withdrawn if the problem is serious.
3) AMENDMENTS: Any changes in the study (e.g., procedures, number or types of subjects, consent forms, investigators, etc.) must be approved by the IRB prior to implementation. Please be advised that changes in a study may require further review depending on the nature of the change. Please contact me with any questions regarding amendments or changes to your study.

The NSU IRB is in compliance with the requirements for the protection of human subjects prescribed in Part 46 of Title 45 of the Code of Federal Regulations (45 CFR 46) revised June 18, 1991.

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