AN EMPIRICAL EXAMINATION OF FACTORS AFFECTING ADOPTION OF AN ONLINE DIRECT SALES CHANNEL BY SMALL AND MEDIUM-SIZED ENTERPRISES

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Table of Contents

List of Figures

List of Tables

1. Introduction

1.1 Economic Contributions of Small and Medium-Sized Enterprises

Small and medium-sized enterprises (SMEs) are major contributors to national economies. By SMEs, most countries define them as firms with relatively fewer employees or lower annual sales revenues, but no universal standard exists. European Union defines an SME as an independent company with fewer than 250 employees and either an annual turnover not exceeding €40 million or a balance sheet not exceeding €27 million (EU, 2007). A small firm has a maximum of 50 employees, and maximum turnover of 7 million ECU or balance sheet total of 5 million ECU. A micro enterprise has a maximum of ten employees.

However, in the United States, the Small Business Administration (SBA) defines small businesses as firms with less than 500 employees (SBA Office of Advocacy, 2006a). Recently, the SBA has revised its size standards to match those with industries as defined by the North American Industrial Classification System (NAICS), as well as to establish criteria based on revenue. But the maximum size for almost all sectors remains to be 500 employees.

Different researchers have chosen their own focus of firm size for SMEs. For instance, Santarelli and D'Altri (2003) focus on a group of firms with fewer than 100 employees for their SME Internet diffusion study. But Johnston and Wright (2004) use a working definition of SMEs as having fewer than 500 people. Because my sample has been taken in the US and 500 has been used in many other studies, I focus my study on firms with fewer than 500 employees.

SMEs have become increasingly important contributors to nearly every economy. In the United Kingdom, SMEs employ 70% of the workforce (Notman, 1998). In Ireland, SMEs

(companies with fewer than 250 employees) make up 99.4% of all enterprises (Foras, 1999). In European Union (EU) as a whole, more than 90% of all businesses are comprised of small enterprises, accounting for 25% of EU turnover. More than 90% of the total European enterprise population (16 million businesses) is of very small size employing fewer than 10 people (Dutta & Evrard, 1999).

In China, 158,234 (87%) of 181,557 industrial enterprises are small-scale enterprises. Those enterprises produced 4.5 trillion Yuan (41%) of 11.1 trillion Yuan total gross output (National Bureau of Statistics of China, 2003). In the Asia-Pacific region as a whole, nearly 72% of all private sector enterprises are micro-enterprises representing 20% of private sector employment. The Asia-Pacific Economic Cooperation (APEC) describes SMEs as "a seed bed for entrepreneurship and growth," "an alternative to unemployment," and "a means of alleviating poverty" (APEC, 2002). According to the United Nations (1992), SMEs account for more than 90% of all jobs, sales, and value-added in developing countries and over 50% of these measures in developed countries.

In the US, SMEs play a crucial role in the American economy. While emphasizing the importance of small businesses, the Small Business Administration Office of Advocacy cites the following statistics (SBA Office of Advocacy, 2006a).

Small firms:

- Represent 99.7 percent of all employer firms.
- Employ half of all private sector employees.
- Pay more than 45 percent of total U.S. private payroll.
- Have generated 60 to 80 percent of net new jobs annually over the last decade.
- Create more than 50 percent of nonfarm private gross domestic product (GDP).

- Supplied more than 23 percent of the total value of federal prime contracts in FY 2005.
- Produce 13 to 14 times more patents per employee than large patenting firms. These patents are twice as likely as large firm patents to be among the one percent most cited.
- Are employers of 41 percent of high tech workers (such as scientists, engineers, and computer workers).
- Are 53 percent home-based and 3 percent franchises.
- Made up 97 percent of all identified exporters and produced 28.6 percent of the known export value in FY 2004.

In spite of their substantial contribution to economies, SMEs have been ironically neglected in the literature (Tambunan, 2005). While there is an ample literature examining the adoption and diffusion of IS innovations for larger firms, studies focusing on small firms are underrepresented and they rarely appear in major IS journals. However, understanding the drivers and barriers underlying the adoption and diffusion of IS innovation among SMEs remains important, considering the benefits such innovations may bring to SMEs. This study intends to contribute to the literature by investigating the factors that affect SMEs' adoption and use of Internet-based selling activities.

1.2 E-commerce and Its Impact on SMEs

In recent years, one of the most fundamental shifts in the way companies conduct businesses is the increased use of the Internet (Gale Group, 2005). This type of business, usually known as e-business, e-commerce, or I-commerce (for Internet commerce), refers to buying,

selling, and supporting products and services on the Internet (Gibbs, Kraemer, & Dedrick., 2003). Based on the parties involved, E-commerce can be categorized into B2B (Business to Business), B2C (Business to Consumer), and C2C (Consumer to Consumer). Companies across almost all industries and business sectors have tried to explore the potential of the increasingly globalized E-business technologies in order to gain customer base, integrate business processes and improve relationships with suppliers, resellers and customers. "If they do not," as Kaefer and Bendoly (2003) argue, "those competitors that do make use of such technologies threaten to outpace them in efficiency gains and hence jeopardize their market position" (p. 529).

This dissertation focuses on the selling aspect of Internet-based e-commerce, whose complete process includes online advertising, online order processing, online order tracking, online payment, and online post-purchase customer service. A firm is considered to be selling online if it carries out at least the first two activities online, that is, advertising and online order processing. I include advertising as a part of the definition because online order processing is naturally accompanied by at least a minimum amount of online advertising of the goods. Using off-the-net advertising alone but processing sales transactions online is unlikely because if an e-commerce website already has sales transaction functionalities such as a shopping cart, advertising on the same website will incur minimum expenses. Also, without basic online advertising such as an online product catalogue, online shopping and online sales transactions will almost be impossible. In the present study I do not differentiate B2B and B2C; instead, I am interested only in whether firms use or intend to use the Internet as their sales channels.

In spite of the fact that the potential impact of e-commerce on firms' marketing strategies may become even more important in years to come (Santarelli & D'Altri, 2003), the bursting of the Internet bubble has led some to question the very value of the Internet (Barua, Konana, Whinston, & Yin, 2001). Researchers have consistently argued that E-commerce is likely to

contribute to sustained competitive advantages through extended market reach (Barua et al., 2001; Porter, 2001), enhanced differentiation (Porter, 2001) and cost efficiency (Barnes et al. 2003; Boyer & Olson, 2002; Frohlich & Westbrook, 2002; Porter, 1985, 2001; Power and Sohal, 2002; Presutti, 2003; Quayle, 2003; Soliman & Janz, 2004; Zank & Vokurka, 2003).

Recent work has also demonstrated the use of Internet and e-commerce technologies improves a firm's supply chain management (SCM). Examples include improved lead times (Hauguel & Jackson, 2001; Power & Sohal, 2002; Quayle, 2003; Zank & Vokurka, 2003), speedier deliveries (Barnes et al., 2003; Boyer & Olson, 2002; Frohlich & Westbrook, 2002), and improved communication and coordination among supply chain members (Zank & Vokurka, 2003).

The Internet and e-Commerce technologies have provided SMEs with further opportunities to overcome their constraints in size, resources and competitive scope (such as product segments and geographic areas served) and to compete with larger firms across the world. These technologies have offered SMEs an affordable way to communicate with customers and business partners, access local, national, and even global markets, take and track orders electronically, accept electronic payments, and provide online-based customer service. As pointed out by Barua et al. (2001), Internet's far greater geographic reach makes it possible for SMEs to find new customers without being constrained by geography, size of the customer, and financial limit of the firm. Essentially, such technologies have leveled off the playing field for SMEs to compete with larger firms.

The literature has revealed a variety of advantages that e-commerce may bring to SMEs. Santarelli and D'Altri, (2003) demonstrates how SMEs can adopt and use e-commerce as a way to reduce distributive costs and to increase the number of potential customers. Dewan (2000) suggests that e-commerce technologies enable SMEs to gather information about buyers'

preferences and to customize their products and prices accordingly with limited costs. Lohrke, Franz, Franklin, and Frownfelter-Lohrke (2006) find that an SME can enhance its market position through strategic use of e-Commerce to improve its relationships with customers through Internet-mediated communication and customer service.

By selling on the Internet, SMEs can establish direct customer contact and reduce reliance on channel intermediaries for product distribution or customer support. Some researchers (Hamill & Gregory, 1997; Lituchy & Rail, 2000; Nieto, & Fernández, 2006) argue that the use of the Internet can even enhance an SME's global competitiveness.

Caskey, Hunt and Browne (2001) use two general business trends to explain the opportunities brought to SMEs by e-Commerce. The two trends are: (1) concentration upon core competencies, and (2) tighter cooperation among the firms within a supply chain. The first trend reflects a shift in the balance between the cost of controlling economic activity within a firm and the cost of coordinating activities between firms, usually referred to as "hierarchy costs" and "transaction costs" (Coase, 1937). The emerging Internet and e-commerce technologies have more effectively addressed the costs of cooperation between firms (transaction costs), and thus have made outsourcing more attractive. Such technologies have shifted the equilibrium between coordination costs and transaction costs in favor of SME participation as the costs of cooperation decrease in relation to the costs of coordination activities within a large firm, buying from outside firms becomes more attractive (Caskey et al., 2001).

The second trend impacts cooperation and coordination between producers and suppliers after their relationship is established. With better information, producers can produce goods that better serve customers' needs at lower costs and thus benefit both suppliers and producers.

The two business trends have helped bring SMEs more outsourced business opportunities as well as an easy and affordable channel to find and cooperate with customers, suppliers, and

business partners. Nevertheless, given the benefits brought to SMEs by the Internet and the fact that adoption of e-commerce technologies remains at a rudimentary level, it is very important to examine factors underlying the adoption and use of the Internet among SMEs ((Lohrke, Franklin, & Frownfelter-Lohrke, 2006).

1.3 Rationales of the Study

Innovation adoption is a process that includes activities leading to a decision to adopt and to facilitate the use and continual use of the innovation (Damanpour, 1991). During the last few decades, Information Systems (IS) researchers studying the adoption and diffusion of information technologies have proposed dozens of adoption factors. The coexistence of an overwhelmingly large number of factors in multiple influential theories without a common structure has limited the usefulness of innovation adoption research. Furthermore, existing information technology (IT) innovation adoption theories tend to focus on factors of a specific adoption dimension while neglecting factors of other dimensions.

Building upon Rogers' Paradigm of the Adoption of an Innovation by an Individual within a Social System (Rogers, 1962), this dissertation proposes a simple but comprehensive theoretical adoption framework, which classifies adoption factors into three dimensions: Decision Entity (DE: an individual or an organization), Decision Object (DO: the information technology to be adopted), and Decision Context (DC: the environment where a decision is made). An adoption process is essentially a decision-making process. The outcome of such a process is a decision (to adopt or not to adopt), which is made by a DE on a specific DO in a particular DC. Factors within any of the three dimensions may impact the adoption decision that the DE makes.

I operationalize the adoption classification framework through an empirical investigation of critical factors underlying the adoption and use of the online direct sales channel (ODSC) by small and medium-sized enterprises (SMEs). I focus my study on SMEs because: (1) systematical and empirical examination of factors underlying SMEs' adoption and use of ODSC is lacking; (2) such examination is critical for understanding SMEs' organizational behavior toward the use of the Internet as a distribution channel.

Despite the opportunities that e-commerce technologies have brought to SMEs, they have not necessarily rushed into the adoption of online sales channel (To & Ngai, 2006). The extent of adoption of the Internet varies from those embracing e-commerce and using it strategically to transform their businesses, to those unwilling to adopt even the most basic e-commerce technologies (Hawkins & Prencipe, 2000). While some SMEs have adopted minimal E-commerce technologies, many others have started connecting to the Internet, to build company web sites, and to advertise their products and services online. Only a small portion of those firms have moved further to adopt more advanced E-commerce technologies for real-time online trade and transactions. Kula and Tatoglu (2003) find that most SMEs use the Internet only for the purpose of gathering business information and product search. More recent studies (e.g., Fisher, Craig, & Bentley, 2007) suggest that SME's use of websites is still limited to advertising and very few of them are ready for moving to e-Commerce.

Dholakia and Kshetri (2004) examined Internet adoption using a three-stage model – pre-adoption, adoption (web site ownership) and routinization (use web for e-commerce applications). Their study demonstrated that, although approximately 51% of SMEs own business websites, only about 15% of SMEs sell on the Internet. Houghton and Winklhofer (2004) pointed out that, despite widespread website adoption within SMEs, the number offering e-commerce activities is still declining or remains static.

According to a report from the Gale Group (2005), a leader of e-research, 60% of the firms selling directly online reported an average 45% increase in Internet sales from 2003 to 2004. However, the same report revealed that, although nearly all firms have a Web presence today, many, particularly SMEs, are still not selling over the Internet. Examining factors that drive some SMEs to adopt ODSC while leaves others unaffected will be useful for both business managers and researchers.

Despite the contribution of SMEs to an economy and the potential impact of e-commerce on SMEs, attention to SMEs' use of e-commerce technologies are underrepresented in existing innovation adoption and diffusion studies. Moreover, almost all existing studies in the literature on SMEs' use of e-commerce are conceptual papers or case studies. Quantitative empirical studies that establish prediction models for e-commerce adoption among SMEs are lacking (To & Ngai, 2006).

This paper intends to bridge the gap. Building upon and synthesizing major existing IT adoption and diffusion theories, I propose that DO factors (including perceived relative advantage and perceived ease of use), DE factors (including risk propensity, resource slack, and expertise in the Internet), and an important DC factor, perceived competitive pressure, significantly impact, directly or indirectly, an SME's intention to adopt or to continue utilizing ODSC. To test the model of ODSC adoption by SMEs, I have developed and administered a survey to a sample of SMEs within the State of Ohio in the United States. Structural Equation Modeling (SEM) has been used to test the goodness of fit of the model, obtain parameter estimates, and test hypotheses associated with the research model.

1.4 Research Objectives

The main objectives of this dissertation are:

1. To examine the overall level of adoption and usage of ODSC among SMEs.
2. To propose a theoretical classification model of factors affecting IS adoption. The model suggests that IS adoption factors can be classified in three categories: Decision Entity (DE) factors, Decision Object (DO) factors, and Decision Context (DC) factors. The model is not merely useful for the classification of existing factors identified in the literature, but also helpful in identifying factors in future IS adoption studies.
3. To propose and empirically test a behavioral model of ODSC adoption by SMEs, which is an operationalized case of the classification framework. The model identifies three DE factors--expertise, resource slack, and risk propensity, two DO factors--perceived relative advantage and perceived ease of use, and one DC factor—perceived competitive pressure, that affect the adoption of ODSC among SMEs.
4. To discuss the academic and managerial implications of findings of the research.

1.5 Implications of the study

This dissertation contributes to the IT adoption literature in the following ways: First, the classification model provides a simple but robust framework for categorizing existing factors identified in previous IS adoption studies. It is also useful for guiding the identification of new factors in future IS adoption studies.

Second, the research model for the adoption of ODSC by SMEs, which is proposed and empirically tested in this dissertation, will not only enhance our knowledge of the pattern of

SMEs' adoption of ODSC, but will also improve our understanding of SMEs' adoption and use of IS innovations in general. Most influential frameworks for technology adoption and diffusion, such as the Technology Acceptance Model (TAM), Unified Theory of Acceptance and Use of Technology (UTAUT), and Innovation Diffusion Theory (IDT), tend to emphasize primarily on technology factors (or DO factors) and are commonly used in explaining individual adoption of technologies. The SMEs' ODSC adoption model proposed in this study contributes to the literature by incorporating adoption factors from all three adoption dimensions--DE, DO and DC; also, it focuses on organizational (as opposed to individual) adoption behavior.

Third, the measures that I have developed and validated for this dissertation may be useful for future studies on the adoption and diffusion of IS innovation, particularly the adoption of Internet related technologies among SMEs.

This dissertation has significant implications for practice as well. The examination of ODSC adoption among SMEs provides empirical evidence regarding what drives the adoption and use of ODSC among SMEs, which in turn, helps facilitate better decision-making by managers of electronic market service providers, e-commerce system developers, and policy-makers of relevant governmental agencies to stimulate the use of ODSC among SMEs. The study also enhances SMEs' knowledge of what other SMEs are thinking about and doing with ODSC, which will eventually influence their own future decisions on the use of ODSC.

The rest of the dissertation is structured as follows: chapter two provides the theory development, literature review, and hypothesis development. Chapter three includes the instrument development and data collection process as well as statistical method to be used. In chapter four, I present major results of the study in terms of descriptive statistics, goodness of fit, parameter estimates and hypothesis testing. The dissertation concludes with chapter five, which discusses the implications, limitations of the future research associated with the study.

2. Literature Review

2.1 Theory Development

2.1.1 Adoption Factor Classification Model

In the past two decades, IS researchers studying the adoption and diffusion of information technologies have proposed numerous adoption factors. The coexistence of an overwhelmingly large number of factors in multiple influential theories without a common structure has limited the usefulness of innovation adoption research. Some researchers have realized the problem and have attempted to categorize those factors. For example, Lefebvre and Lefebvre (1996) classified their adoption factors into two types: internal factors and external factors. Wang and Cheung (2004) categorized the Internet adoption factors that they identified into three categories: environmental factors, organizational factors, and managerial factors. Damanpour (1991) indicated that organizational innovation was subjected to influences from three categories of factors-- individual, organizational, and environmental factors. While those categorization schemes somehow help organize the factors that researchers identified for particular studies, few of them were able to embrace all factors proposed in the literature.

The Paradigm of the Adoption of an Innovation by an Individual within a Social System, which was proposed by Rogers (1962), encompasses a robust adoption factor classification model. The paradigm states that the adoption of an innovation by an individual contains three divisions: Antecedents (factors present in the situation prior to the introduction of an innovation), Process (information sources as stimuli), and Results (adoption or rejection of the

innovation). Antecedents include factors pertaining to Actor's Identity and Perceptions of The Situation while Process covers factors related to Perceived Characteristics of the Innovation (Figure 1).

Rogers' paradigm was not intended as an adoption factor classification model. Instead, it was a complex paradigm emphasizing factors in different stages of adoption—factors prior to adoption, factors as stimuli during the adoption process, and the consequences (accept/reject) of the adoption process.

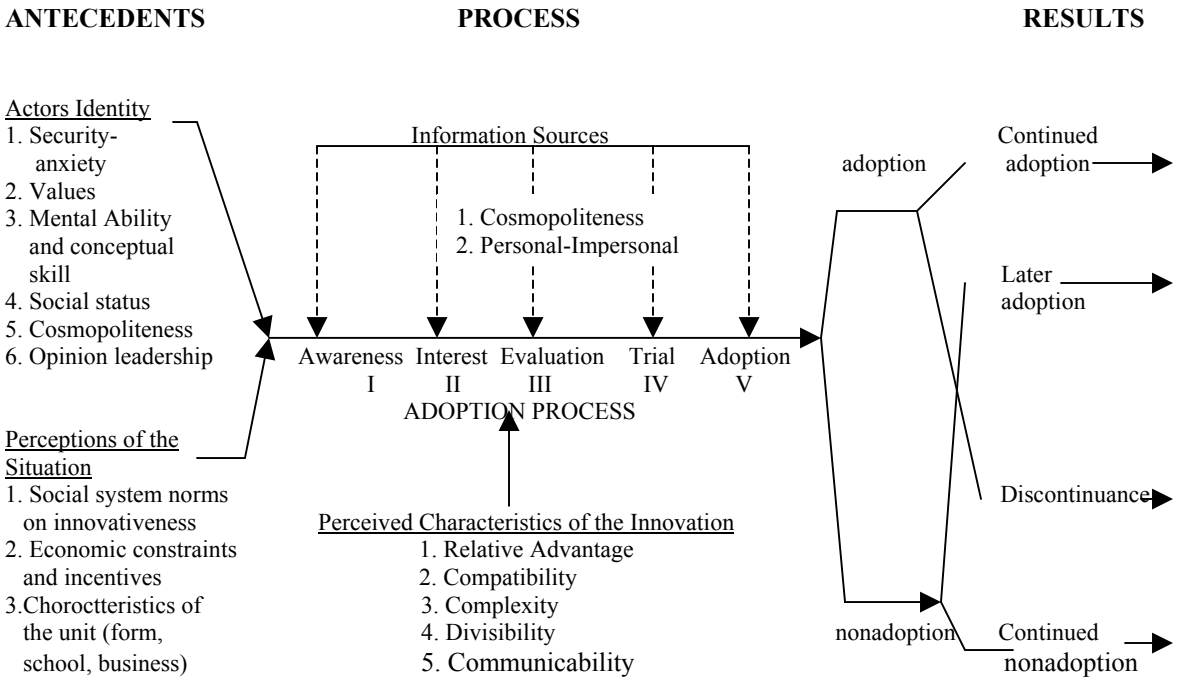

Figure 1: Rogers' Paradigm of Adoption of An Innovation

Source: Based on Rogers, 1962, p. 306

Building upon Rogers' paradigm, this dissertation proposes an adoption factor classification model (Figure 2), which classifies adoption factors into three dimensions: Decision Entity (DE: an individual or an organization), Decision Object (DO: the information technology to be adopted), and Decision Context (DC: the situation where a decision is made). An innovation adoption process is essentially a decision-making process. The outcome of such a process is a decision (to adopt or not to adopt), which is made by a DE on a specific DO in a particular DC. Factors in any of the three dimensions may impact the adoption decision that the DE makes.

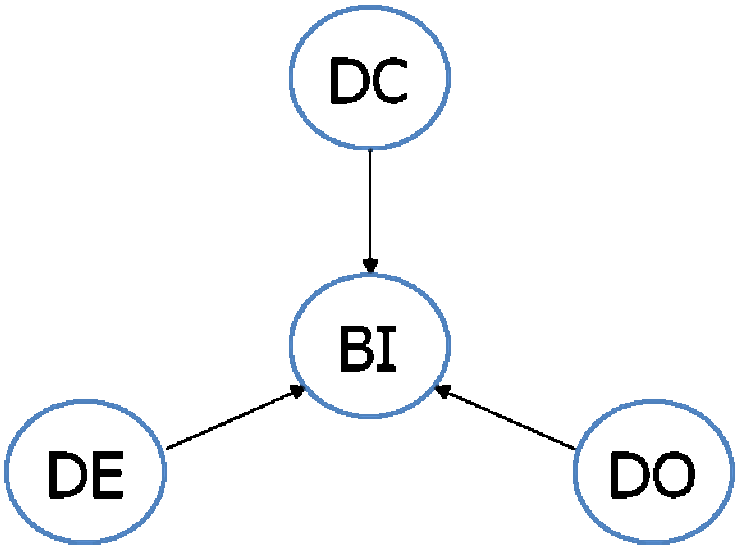

Figure 2: The Classification Model

DE: Decision Entity
DO: Decision Object
DC: Decision Context
BI: Behavioral Intention to Adopt

While acknowledging major credit to Rogers' paradigm, the adoption factor classification model proposed in this study has the following original contributions.

- First, Rogers' paradigm emphasizes the overall stages and sequence of adoption, but my classification model is intended primarily to establish a classification model that is simple but robust enough to embrace the adoption factors identified in the past few decades.
- Secondly, while Rogers' paradigm is limited to the adoption of an innovation by an individual, the classification model proposed in the present study extends Rogers' paradigm to the adoption of innovations by organizations. Factors related to the organization's adoption of innovation, such as DE factors like firm size, industry, resources, organizational expertise, organizational risk propensity, DC factors like reseller influence, competitor pressure, customer pressure, are now all important parts of the model.
- Finally, the present study contributes to Rogers' theory by providing the paradigm with empirical evidence. Although a lot of empirical studies have been conducted over the past few decades to validate the Innovation Diffusion Theory (IDT), most of such studies have focused on IDT's five categories of individual innovativeness—innovators, early adopters, early majority, late majority (e.g., Beatty, Shim, & Jones, 2001; Dos Santos & Peffers, 1998; Park & Yoon, 2005) —or five innovation adoption factors—relative advantage, compatibility, trialability, observability, and complexity (e.g., Agarwal & Prasad, 1997; Chen, Gillenson, & Sherrell, 2002; Hardgrave, Davis, & Riemenschneider, 2003; Hung, Ku, & Chang, 2003; Tan & Teo, 2000). Little empirical evidence exists for the Paradigm of The Adoption of An Innovation by an Individual within a Social System (Rogers, 1962).

2.1.1.1 Decision Object--What It Offers Determines Your Intention to Use It

Attributes of the decision object, or the technology under consideration for adoption, undoubtedly determine whether a decision entity, either an individual or an organization, will adopt and use it. Commonly discussed attributes of the decision object include usefulness, ease of use, relative advantage, risks, security, cost, and so on. Although in many studies, such attributes are measured via the DE's perceptions, the focus of them is still on the DO.

Multiple DOs may fall into a class of DOs. For example, if cell phone or Bluetooth is treated as a DO in an adoption decision, then wireless technologies is the class they fall into. Wireless technologies can also be treated as a DO, which is in the class of telecommunication technologies. DOs in the same class are likely to have some attributes in common, and thus, they may share similar sets of adoption factors.

In an IS adoption study, researchers need to decide precisely what is the decision object. Once the DO (a technology or a group of technologies) is determined, only the attributes of the DO (not of its class or another technology in the same class) should be examined. For instance, if online payment systems are the decision object, then attributes of online ordering systems should not be included in the study, though both of them are e-commerce technologies.

2.1.1.2 Decision Entity--What You Are Determines What You Do

Decision entity (DE) refers to an individual or an organization that is faced with an innovation adoption decision. Given the same situation, DEs different in industry, age, firm size, expertise, experience, resources, attitude toward the DO (Ajzen, 1991; Fishbein & Ajzen, 1975;

Kahneman & Tversky, 1979), risk propensity, innovativeness, leadership, globalization orientation, and so on, may make totally different adoption decisions on the same technology.

2.1.1.3 Decision Context—Where You Are Determines What You Do

The decision context (DC) in this dissertation refers to the situation in which an adoption decision is made. Specifically, it is a context or situation shaped by the convergent influences of different players, which encourage or discourage a DE to make a particular adoption decision. DC overlaps heavily with a commonly used term, "environment." I use DC in this dissertation because I believe it clearly emphasizes the situation shaped by decision-relevant factors; yet "environment" is a more generic term that denotes all factors, whether relevant to the decision or not. The common factors that shape an organization's adoption decision context include institutional influence, competitive pressure, and pressure from various business partners in a value chain, such as the suppliers, resellers, and customers.

2.1.1.4 Influence of Decision Object, Entity, and Context Factors on Adoption

In any given adoption setting, a different set of DE, DO, and DC factors influences the adoption of the given technology (Figure 2). That is consistent with existing propositions in the literature that the nature and importance of antecedents of adoption are expected to vary across different adoption settings (Plouffe, Hulland, & Vandenbosch, 2001; Rogers, 1995).

2.2 The Classification Model and Existing IS Adoption Theories

The Adoption Factor Classification Model is a simple but comprehensive classification framework that builds upon, synthesizes, and covers factors of existing technology adoption and diffusion theories. The following are a few examples (Table 1):

Theory of Reasoned Actions and Theory of Planned Behavior: Theory of Reasoned Actions (TRA) focuses on the impact of a DE factor, attitude, and a DC factor, subjective norm, on the DE's behavioral intention to adopt the DO (Fishbein & Ajzen, 1975). Attitude toward the behavior is defined as the individual's positive or negative feelings about performing a behavior. It is determined through an assessment of one's beliefs regarding the consequences arising from a behavior and an evaluation of the desirability of those consequences.

Subjective norm is defined as an individual's perception of whether people important to that individual think the behavior should be performed. The contribution of the opinion of any given referent is weighted by the motivation that an individual has to comply with the wishes of that referent. Hence, overall subjective norm can be expressed as the sum of the individual perception multiplying motivation assessments for all relevant referents.

Ajzen (1991) extended TRA and proposed the theory of planned behavior (TPB) by introducing an additional factor, behavior control, which refers to the DE's perception of the difficulty of performing a behavior. Behavior control is a factor that can potentially stem from attributes of each of the three elements, DE, DO, and DC. Exploring the effect of relevant attributes of each of the three elements can yield more detailed information. For instance, a DE's perception of behavior control may be linked to the DE's personality, the effect of DC, or directly to the difficulty level of the DO. Overall, both TRA and TPB emphasize the importance of DE and DC but downplay the importance of DO attributes in the intention toward DO.

Technology Acceptance Model: Technology Acceptance Model (TAM) is among the most influential models of adoption of IT innovations. It is essentially the adaptation of Theory of Reasoned Actions to be used in the IS field. TAM maintains that two DO factors, perceived usefulness and perceived ease of use, are the direct determinants of user behavioral intention to adopt a system, which is a mediator to actual adoption of the system (Davis, 1989). Perceived usefulness is also directly affected by perceived ease of use. While the two key constructs proposed in TAM--perceived usefulness and perceived ease of use--have been repeatedly validated in a series of empirical studies, the model has its limitation when explaining the adoption of specific technologies in specific situations. Thus, many attempts have been made to extend the model to fit into different technologies and different situations, by introducing factors from related models, by introducing additional or alternative belief factors, or by examining antecedents and moderators of perceived usefulness and perceived ease of use (Wixom & Todd, 2005).

In 2000, Venkatesh and Davis published their TAM2 in *Management Science*. TAM2 extended TAM by including a few DC factors such as subjective norm and several DO factors, including job relevance, output quality, result demonstrability, and perceived ease of use as determinants of perceived usefulness.

The Unified Theory of Acceptance and Use of Technology (UTAUT), which was developed in 2003 by Venkatesh, Morris, Davis, and Davis, maintain that performance expectancy and effort expectancy (DO factors), social influence (DC factor) and facilitating conditions (DE factor) are direct determinants of usage intention and behavior (Venkatesh et. al., 2003). A few DE factors including gender, age, experience, and voluntariness of use are posited to mediate the impact of the four key constructs on usage intention and behavior (Venkatesh et. al., 2003). The theory is developed through a review and consolidation of the constructs of eight

models that earlier research had employed to explain IS usage behavior (theory of reasoned action, technology acceptance model, motivational model, theory of planned behavior, a combined theory of planned behavior/technology acceptance model, model of PC utilization, innovation diffusion theory (IDT), and social cognitive theory). Subsequent validation of UTAUT in a longitudinal study found it to account for 70% of the variance in usage intention (Venkatesh et. al., 2003).

Motivational Model, based on Motivational Theory (Davis, Bagozzi, & Warshaw, 1992), states that the DE's motivation, including extrinsic motivation and intrinsic motivation, drive the DE's use of computer technologies. Extrinsic motivation is a motivation where performing a specific activity (e.g., the use of computers) is for some external motive(s), such as increased job performance, pay raise, or promotion. On the other hand, intrinsic motivation is a motivation in which one performs an activity simply because of the activity itself, such as the individual's enjoyment of the activity.

Innovation Diffusion Theory (IDT) segregates individuals into five categories in terms of their individual innovativeness and earliness in the adoption of a technology: innovators, early adopters, early majority, late majority, laggards (Rogers, 1995). The theory also proposes five factors of adoption of an innovation, all of which are all essentially DO attributes: relative advantage, compatibility, trialability, observability, and complexity (Rogers, 1995). Moore and Benbasat (1991) were the first that applied IDT to an IS context. They added some DO attributes, such as image and voluntariness, to Roger's IDT theory and developed an eight-factor model on IS innovation adoption, which articulates that voluntariness, relative advantage, compatibility, image, ease of use, result demonstrability, visibility, and trialability are the key determinants of the adoption of computer technologies.

Social Cognitive Theory and Self-Efficacy Theory: Social cognitive theory provides a framework of relationships between an individual (DE), the environment (DC), and human behavior. The theory identifies human behavior as an interaction of personal factors (e.g., demographic factors, cognitive factors, and other personal factors), environment (such as social pressures and particular situational characteristics) and behavior (Bandura, 1977). An individual chooses an environment and is influenced by the environment. Behavior in a given situation is affected by the environment and in turn affect environment. Behavior is affected by personal factors and at the same time affects those factors. Compeau and Higgins (1995) applied Social Cognitive Theory to the context of computer utilization. They hypothesized and tested a series of relationships between environmental factors (others' encouragement, others' use, and others' support), personal factors (computer self-efficacy and outcome expectations) and behavior (affect, anxiety, and usage).

Model of PC Utilization: Thompson and Higgins (1991) adapted the theory of interpersonal behavior proposed by Triandis (1980) to the context of PC use by knowledge workers in an optional use environment, where knowledge workers can voluntarily choose to use or to not use a PC. This theory suggests that perceived consequences (complexity, job fit, and long-term consequences), affect, social factors, and facilitating conditions, are the primary determinants of utilization of personal computers. All those factors fall in the three dimensions of the classification model proposed in this dissertation.

	Decision Entity Factors								
	Age	Gender	Attitude	Experience	Abilities (Resources)	Voluntariness of use	Affect	Anxiety	Image
Expected Utility Theory									
Prospect Theory									
Innovation Diffusion Theory									
Theory of Reasoned Actions			Attitude						
Theory of Planned Behavior			Attitude						
TAM									
TAM2				Experience		Voluntariness of Use			
Motivational Model									
Model of PC Utilization					Facilitating Conditions		Affect		
Self-Efficacy Theory					Self-efficacy		Affect	Anxiety	Image
UTAUT	Age	Gender		Experience	Facilitating Conditions	Voluntariness of use			
TAM&TPB			Attitude						

	Decision Object Factors							Decision Context Factors
	Benefits	Ease of Use	Complexity	Compatibility	Visibility	Trialability	Result Demonstrability	Social Influences
Expected Utility Theory								
Prospect Theory								
Innovation Diffusion Theory	Relative advantage	Perceived ease of use	Complexity	Compatibility	Visibility	Trialability	Result demonstrability	
Theory of Reasoned Actions								Subjective Norm
Theory of Planned Behavior		Perceived behavior control						Subjective Norm
TAM	Perceived usefulness	Perceived ease of use						
TAM2	Perceived usefulness, Output Quality, Result demonstrability	Perceived ease of use						
Motivational Model								
Model of PC Utilization	Job fit, long-term consequences		Complexity					Social factors
Self-Efficacy Theory								Others Support, Use & Encouragement
UTAUT	Performance Expectancy	Effort expectancy						Social influences
TAM&TPB	Perceived Usefulness	Perceived Behavior control						Subjective Norms

Table 1: The Classification Model & IS Adoption Theories

The major IS theories that are discussed above identify a variety of factors affecting the adoption of IS innovations, either from an individual's or an organization's perspective. Most of those theories emphasize factors of specific dimensions of the classification model while neglecting those of others. The classification model proposed in this dissertation can help synthesize multiple theories and establish a holistic view of adoption of a particular technology.

2.3 Review of Studies on SMEs' Adoption of E-commerce

Extant research in e-commerce adoption among SMEs has formed a foundation for the research model I propose on the adoption of ODSC. As early as 1995, Iacovou, Izak and Dexter proposed and tested a framework of electronic data interchange (EDI) adoption by small businesses, which identified three major factors that influence the EDI adoption practices of small firms. These factors include a DE factor, organizational readiness, which is related to the low levels of IT sophistication and resource availability of small firms, a DC factor, external pressures to adopt, which is associated with the weak market positions of small firms and the network nature of the technology, and a DO factor, perceived benefits, which concerns the limited impact of IT on small firms because of under-utilization and lack of integration.

Dandridge and Levenburg (2000) investigated the Internet use by 195 US micro enterprises (firms with fewer than 25 employees) and found that several DE factors, such as firm size, intentions for growth in the next six months, including sales change, employment change and export plans influence those firms' use of the Internet.

Based on multiple-case research, Levy, Powell, and Yetton (2001) developed and tested a model of strategic information systems (IS) investment in small and medium-sized enterprises (SMEs). Their study revealed that IS investment of an SME was a function of its strategic

context, consisting of its strategic focus (cost reduction versus value added), and its market positioning (few versus many customers), both of which were essentially DE factors emphasizing the characteristics of the SME.

Sadowski, Maitland, and van Dongen (2002) applied a modified strategic use model to examine the extent of strategic use, which refers to the ability of businesses to recognize the strategic elements in the use of the Internet and then relate them to network formation in the specific user environment. The authors proposed that the extent of strategic use of the Internet by SMEs was linked to a DE factor, communication requirements, a DC factor, competitive pressure and a mixture of DE and DO factor, the support and incentives in the adoption process. Their empirical analysis based on data from 264 Dutch SMEs suggested that, while the communication requirements have driven SMEs to adopt the Internet, other strategic determinants proposed, such as competitive pressure or support and incentives for adoption, hardly affects SMEs in their adoption of the Internet. Daniel and Grimshaw (2002) found that the use of e-commerce for responding to competitors (a DC factor), enhancing customer services, and improving relations with suppliers (a DO oriented factor) was driving the uptake by smaller businesses to a greater extent than by their larger counterparts. They also demonstrated that SMEs believed they had achieved greater benefits from their e-commerce services than had the larger firms.

Building upon the innovation adoption, organizations, and information systems (IS) implementation literature, Pflughoeft, Ramamurthy, Soofi, Yasai-Ardekani and Zahedi (2003) developed three models—partial-mediator, reduced partial-mediator, and mediator--on the relationships between "context-IT-use-benefit" (CIUB). These models propose that the extent of Web use by small businesses is driven primarily by organizations' contextual characteristics and their IT infrastructure, all of which are essentially DE factors. Levy and Powell (2003) conducted

a case study of twelve SME cases, which indicates that SMEs' recognition of the business value of the Internet (DO factor) and their attitude to business growth (DE factor) are key factors in determining Internet adoption strategies. Stunsfield and Granl (2003) identify three major factors affecting adoption of networked processes, which include a DO factor, perceived benefits, a DE factor, organizational readiness, and a DC factor, external pressure.

Based on data from 94 SMEs, Karakaya and Khalil (2004) found that three DE factors, namely company size, financial condition, and technological readiness, influence Internet adoption within SMEs. In another study, Grandon and Pearson (2004) identified four factors--a DE factor, organizational readiness, a DC factor, external pressure, and two DO factors, perceived ease of use and perceived usefulness—as determinants of electronic commerce adoption among SMEs.

A recent study (Levy, Powell, & Worrall, 2005) revealed that a DE factor, strategic intent, affected decisions on e-business investment among SMEs. Those SMEs remaining in their existing markets were found the least likely to invest e-commerce, because Internet is not perceived as necessary for business growth. The study also demonstrated that product innovation rather than market penetration drives e-business.

More recently, To and Ngai (2006) proposed a prediction model on adoption of online retailing. The study revealed that a DO factor, relative advantage, two DC factors, competitive pressure and channel conflict and a DE factor, technical resource competence, are the key factors that affect an organization's adoption of e-tailing. Using focus group methodology, Al-Qirim (2006) studied technological innovation factors affecting e-commerce adoption in small businesses (SMEs) in New Zealand. The study indicated that SMEs tended not to invest their scant resources on perceived risky advanced e-commerce initiatives. While DO factors like cost and compatibility were found not to hinder SMEs' adoption of simple e-commerce technologies

such as Web pages and e-mail, those factors had more significant effect on SMEs' advancing e-commerce initiatives, such as adopting full-blown and interactive Websites.

2.4 Model of Determinants of ODSC Adoption by SMEs

The decision on what variables should be included in a regression model should be based on existing literature and theoretical frameworks (Schumacker & Lomax, 1996). Based on the literature I have reviewed above and the characteristics of ODSC, I propose that DE factors, including perceived relative advantage and perceived ease of use, DO factors, including resource slack, expertise, and risk propensity, and a DC factor, perceived competitive pressure, will influence SMEs' intention to adopt or continue to use ODSC.

2.4.1 DE Factors

Drawn upon earlier studies (Damanpour, 1987; Kim, 1980; Kimberly & Evanisko, 1981), Damanpour (1991) pointed out that organizational variables have been the most widely studied, and in many cases such variables are found to be primary determinants of innovation adoption.

While studying the relationships between organization attributes, Ein-Dor and Segev (1978) categorized organizational variables into three broad categories: 1) controllable variables, which include variables about size of organizations such as annual sales, work force, assets and market share, and Extra-organizational situation variables such as availability of trained manpower, availability of hardware, availability of software, and availability of decision techniques; 2) partially controllable variables, which include the psychological climate variables such as attitudes to information systems, perceptions of information systems, expectations from information systems and organizational resource variables such as size of budget and liquidity;

and 3) fully controllable variables such as responsible executive. In this dissertation, I focus on the examination of the impact of three organizational attributes, including expertise, resource slack, and risk propensity, on SMEs' behavioral intention to embrace ODSC.

2.4.1.1 Resource Slack

The availability of resources that are required for establishing an ODSC, such as monetary resources, IT infrastructure, and IT personnel, may affect SMEs' behavioral intention to embrace ODSC. Resource slack of an organization refers to the excess of resources that an organization has possessed that is not committed to an existing business operation and can be used in a discretionary manner (Dimick & Murray, 1978). Earlier studies (e.g., Bourgeois, 1981; Singh, 1986) have demonstrated that slack resources enable organizations to act more boldly and thus positively impact the organization's willingness to adopt and invest in risky innovations. Slack resources may also encourage business managers to take risks because such resources allow the organization to absorb the costs associated with failures (Rosner, 1968; Singh, 1986).

Numerous studies (e.g., Aiken & Hage, 1971; Damanpour, 1991) have found that resource slack was positively associated with the adoption and diffusion of innovations. Some of those studies (Cragg & King, 1993; Lee, 2004) demonstrated that an organization's resource slack positively affects the adoption and diffusion of Internet related technologies.

Compared with larger organizations, SMEs have limited resources and thus resource slack may play an even more crucial role in their adoption of relatively risky innovations. Resource slack may also influence SMEs' expertise, which in turn, impacts the SMEs' perceived ease of use of an innovation (Cragg & King, 1993). In addition, resource slack may have a positive impact on an SME's perception of advantages of the ODSC because, when an excess of

resources is available, attention tends to be focused on potential advantages rather than risks of the innovation.

Based on the above analysis, I posit:

Hypothesis 1a: Resource slack will positively affect an SME's perceived ease of use of the ODSC.

Hypothesis 1b: Resource slack will positively affect an SME's perceived advantage of the ODSC.

Hypothesis 1c: Resource slack will positively affect an SME's behavioral intention to adopt or continue to use the ODSC.

2.4.1.2 Expertise

An organization's knowledge about e-business or about information systems in general impacts its adoption of computer related technologies (Dubelaar, Sohal, & Savic, 2005). Numerous studies in the literature have linked knowledge and expertise to the adoption of innovations. For instance, a study conducted by Lucchetti and Sterlacchini (2004) indicated that a highly educated workforce was a key factor affecting the adoption of information and communication technologies. Dewar and Dutton (1986) found that technical knowledge was positively associated with innovation adoption: the greater the technical knowledge resources, the more easily and more rapidly can an organization capture new technical ideas and formulate procedures for their development and implementation.

Some more recent studies also found positive relationship between knowledge or expertise and e-commerce adoption among SMEs. Teo and Ranganathan (2004) demonstrated that SMEs tended to have difficulty developing expertise among their staff in e-commerce, which eventually affected their intention to adopt e-commerce. Olson and Boyer (2003) revealed that education level of and annual training received by employees, both closely related to the knowledge or expertise of a small organization, impacted its adoption of Internet purchasing.

An SME's expertise is naturally linked to perceived ease of use of the ODSC. A higher level of expertise in the Internet and e-commerce will positively influence an SME's perception of ease of use of an ODSC. Also, perceived expertise may have a positive effect on perceived relative advantage because an SME with higher expertise tends to have more confidence in running an e-commerce website effectively and thus may be more likely to see the advantages of the ODSC.

Based on the above analysis, I posit:

Hypothesis 2a: Perceived expertise in the Internet positively affects an SME's perceived ease of use of the ODSC.

Hypothesis 2b: Perceived expertise in the Internet positively affects an SME's perceived advantage of the ODSC.

Hypothesis 2c: Perceived expertise in the Internet positively affects an SME's perceived behavioral intention to embrace the ODSC.

2.4.1.3 Risk Propensity

Risk refers to the probability of the occurrence of an undesirable event as well as the magnitude of loss associated with the event (Boehm, 1991; Collins & Ruefli, 1992; Haimes, 1991; Mellers & Chang, 1994; Sherer, 1994; Sjoberg, 1980; Yates & Stone, 1992). In an ODSC, businesses are conducted on the Internet, which is a virtual environment that involves more risks. Such risks are usually reflected in undesirable actions of a business party (e.g., the seller may send an inferior product and the buyer may default on payment) as well as the likelihood of an unauthorized access, retrieval, and modification of customer data, commercial transaction data, and payment transaction data.

Decision theory articulates that risks may lead to either positive or negative effects on decisions (Arrow, 1970). Overall, two risk-related factors are likely to impact an organization's decisions, which are perceived risks and risk propensity. Perceived risk refers to a decision maker's assessment of the risk inherent in a decision alternative (Sitkin & Pablo, 1992). Perceived risk is essentially a DO factor because it emphasizes an attribute of the decision object—"risks." Risk propensity is defined as a consistent tendency of a decision maker to take or avoid choices that it believes is risky (Harnett & Cummings, 1980; Kogan & Wallach, 1964; Sitkin & Pablo, 1992). Risk propensity is essentially a DE factor because it emphasizes a characteristic of the decision entity—"the decision maker's propensity."

Perceived risks and risk propensity tend to overlap and interact with each other and that may be why the majority of studies have focused on the effect of one of the two factors on decision-making (Keil & Wallace, 2000). In this study I focus on the risk propensity because existing research has not only found risk propensity to be a key determinant of decision-making under risk in general (e.g., Sitkin & Pablo, 1992), but also has demonstrated a positive

relationship between risk propensity and organizational decisions on IT related projects (e.g., Keil & Wallace, 2000).

Risk propensity may also have an indirect effect on an organization's decision to embrace a risky alternative, through the mediation of DO factors including perceived relative advantages and perceived ease of use. Risk propensity impacts perceived relative advantages. An organization with higher risk propensity is more likely to recognize and weigh positive outcomes and thus overestimating the probability of a gain relative to the probability of a loss (Brockhaus, 1980; Vlek & Stallen, 1980). In contrast, a risk-averse decision maker tends to weigh negative outcomes more highly, which in turn, results in a lower perception of relative advantage of the alternative (Schneider & Lopes, 1986).

In addition, risk propensity of an organization may also influence its perceived ease of use of a risky alternative like ODSC. An organization with higher level of risk propensity tends to proactively approach the risky alternative and gain knowledge about it, which in turn, influences its perceived ease of use of the alternative. Also, as in its influence on perceived relative advantage, risk propensity may result in consistent recognition of the positive side of the risky alternative—for instance, a SME with higher risk propensity may be more likely to underestimate the efforts that are needed to implement and use an ODSC.

With the analysis above, I hypothesize that risk propensity will affect, both directly and indirectly, the adoption of ODSC among SMEs.

Hypothesis 3a: An SME's risk propensity will positively affect its perceived ease of use of the ODSC.

Hypothesis 3b: An SME's risk propensity will positively affect its perception of relative advantage of the ODSC.

Hypothesis 3c: An SME's risk propensity will positively affect its intention to adopt the ODSC.

2.4.2 DO Factors

2.4.2.1 Perceived Relative Advantage

Relative advantage is defined as "the degree to which an innovation is perceived as being better than the idea it supersedes" (Rogers, 1983, p. 15). The degree of relative advantage is usually described in economic terms, such as economic profitability, low cost, a decrease in discomfort, a savings in time and efforts, and timeliness of benefits (Cragg & King, 1993; Rogers, 1983). It is the perception of relative advantage rather than the objective advantage that matters in the adoption and diffusion of an innovation (Rogers, 1983).

Perceived relative advantage is one of the best predictors of the rate of adoption of an innovation, because it signals the potential benefits and losses resulting from the adoption of the innovation (Rogers, 1983). A Meta-analysis of 75 articles by Tornatzky & Klein (1985) indicates that relative advantage is among few factors that are consistently related to innovation adoption.

The purpose of adopting an innovation is generally to improve the effectiveness and performance of the organization (Damanpour, 1991). Prior to making an adoption decision, a potential adopter would inevitably assess the degree to which an innovation is better than an existing practice. The expansion of use of e-commerce among SMEs, therefore, can only be stimulated by the realization of long-term benefits by SMEs (Poon & Swatman, 1999).

Technologies must create values to prevail. For e-business, such values are created by the ways in which transactions are enabled: efficiency, complementarities, lock-in, and novelty, and so on (Amit & Zott, 2001). Like any other technology, an e-Business technology is not for technology's sake. Instead, practical business considerations, such as profitability and cost savings are usually the principal drivers behind E-commerce adoption (Porter, 2001; Tang et al., 2003; Thatcher, 2002), because a rational business understands that adopting E-commerce by simply reacting to emerging technological opportunities without a focus on the added values as the basis of strategy does not help it achieve competitive advantages (Tang et al, 2003).

Since perceived relative advantage was proposed by Rogers (1962, 1983, and 1995) in his Innovation Diffusion Theory as a key factor affecting the adoption and diffusion of innovations, the variable has been consistently found to have a significant influence on the adoption of E-Commerce technologies. Many studies were conducted among SMEs. For instance, Cragg and King (1993) found that an SME's value proposition of an information technology determined its intention to adopt it. Numerous recent studies (e.g., Cao, Gruca, & Klemz , 2007; Lee, 2004; Lau & Voon, 2004; Looi, 2005; Sandy and Graham, 2007) have also demonstrated the impact of perceived relative advantage on the adoption of e-Commerce technologies among SMEs.

With the analysis above, I posit,

Hypothesis 4: Perceived relative advantage of an ODSC will positively affect an SME's behavioral intention to embrace the ODSC.

2.4.2.2 Perceived Ease of Use

Perceived ease of use refers to how hard a decision entity is willing to try and how much of an effort it is planning to exert in order to perform the behavior (Davis, 1989). Since perceived ease of use was proposed in the technology acceptance model (Davis, 1989), an influential IS adoption theory, as a key determinant of IS adoption, it has been well examined in many studies. While research has consistently demonstrated that the other key determinant of IS adoption proposed in TAM, perceived usefulness, directly affects behavioral intention, it has yielded inconsistent results regarding perceived ease of use (Gefen & Straub, 2000). Latest studies (e.g., Lee, 2004; Mollenkopf, Rabinovich, Laseter, & Boyer, 2007; Yu, Ha, Choi, & Rho, 2005) have demonstrated that perceived ease of use or effort expectancy tend to have an indirect effect on behavioral intention, mediated by perceived usefulness or relative advantage. In this study, I hypothesize both direct and indirect effects of perceived ease of use on an SME's behavioral intention to embrace the ODSC.

Hypothesis 5a: Perceived ease of use positively affects an SME's perception of relative advantage of the ODSC.

Hypothesis 5b: Perceived ease of use positively affects an SME's behavioral intention to embrace the ODSC.

2.4.3 DC Factors

The decision context (DC) refers to the context or situation in which an adoption decision is made. In particular, the present study refers to it as a situation shaped by the influence of

different players (e.g., customers, suppliers, business partners, and rivals), who (or whose activities) encourage or discourage an organization to make a specific adoption choice. The common influences that shape an organization's adoption context may include governmental influence (e.g., tax incentives), institutional influence, competitive pressure, and pressure from various business partners in a value chain, such as the suppliers, resellers, and customers.

Abrahamson and Rosenkopf (1993) described two commonly cited pressures, institutional pressure and competitive pressure, as "bandwagon pressure":

> "The sheer number of organizations adopting an innovation can cause a bandwagon pressure, prompting other organizations to adopt this innovation. Institutional pressures occur because nonadopters fear appearing different from many adopters. Competitive bandwagon pressures occur because many nonadopters fear below-average performance if many competitors profit from adopting" (p. 487).

Institutional pressure is related to a DE's pursuit for "legitimacy" (DiMaggio & Powell, 1983). Institutional theorists have found that innovation adoption may not necessarily be totally benefit-driven; instead, it may be just the result of pursuit of conformity with a firm's social and relational environment (DiMaggio & Powell, 1983). Through the pursuit of alikeness, or "Mimetic Isomorphism" (DiMaggio & Powell, 1983), an organization may choose to or be compelled to adopt a technology that others in the institution (or community) have adopted. While institutional pressures, which are concerned about the influence of what other SMEs are doing with e-commerce, may affect an SME's adoption of Internet related technologies,

competitive pressures appear to be the factor that ultimately shapes the decision context of ODSC adoption among SMEs.

2.4.3.1 Perceived Competitive Pressure

A firm can either proactively adopt a new technology to establish competitive advantage or reactively adopt it under certain pressures (Beach, 2004). Proactive approach is associated with a firm's strategic and tactical objectives and thus is believed to be more likely to contribute to an SME's sustained competitive advantage.

However, e-commerce adoption among SMEs appears to be driven more by reactive factors such as competitors' pressure or pressure from more technologically advanced and commercially powerful customers (Beach, 2004). As Santarelli and D'Altri (2003) suggest, when it comes to the adoption of Internet related technologies, SMEs tend to follow a "wait-and-see" attitude, and mostly focus on the implementation of a defensive strategy; that is, if the decision context does not exert sufficient pressure, they simply live without e-commerce. When the decision context exerts adequate pressure, SMEs will adopt e-commerce, not in order to gain competitive advantage, but in order to compete effectively (Cragg & King , 1993).

Competitive pressure is the pressure on an organization arising from the threat of losing its competitive advantage (Abrahamson & Rosenkopf, 1993). Such a pressure arises when the adoption and diffusion of a new innovation within the industry causes a firm to adopt the innovation to maintain its competitive position (Forman, 2005; Iacovou et al. 1995). Extant adoption literature has repeatedly found competitive pressure to be a driver behind SMEs' adoption of Internet related technologies. For instance, Dubelaar, Sohal, and Savic (2005) found that an SME's decision regarding adoption of e-business related technologies were influenced by

its competitors' activities. Barnes, Hinton, and Mieczkowska (2003) suggested that e-commerce adoption and investments were driven mainly by a fear of being left behind by competitors rather than by a desire to improve business process performance. Zhu, Kraemer, Xu, & Dedrick (2004) also pointed out that pressure from competitors could force a SME to adopt E-commerce. Dos Santos and Peffers (1998) found competitive pressure to have a significant influence on the adoption of innovative applications in e-Commerce.

Dholakia and Kshetri (2004) conducted an empirical investigation on the factors that impacted small and medium-sized enterprises (SMEs') involvement with the Internet, in terms of ownership of a web site and use of the Internet for selling purposes. The study demonstrated that competitive pressure influenced both stages of Internet adoption. Caskey et al. (2001) revealed that competition from new e-businesses as well as existing businesses was one of the key driving forces for SMEs in the food industry to invest in e-business. Sandy and Graham (2007) also found that competitive pressure to be a major factor affecting the deployment of E-commerce among SMEs.

Competitive pressure can directly affect SMEs' intention to embrace ODSC; it may also indirectly impact SMEs' intention through the mediation of perceived relative advantage. The reasoning for the indirect effect is: when a serious competitive pressure exists, an SME will view ODSC useful in gaining or maintaining its competitiveness, and thus intends to adopt it. In contrast, if little or no competitive pressure exists, the SME will not see ODSC as necessary (or useful) in gaining or maintaining its competitiveness; that is, without competitive pressure, the SME is going to do fine anyway, with or without ODSC. Based on the above analyses, I formulate the following hypotheses:

Hypothesis 6a: Perceived competitive pressure positively affects an SME's perception of relative advantage of the ODSC.

Hypothesis 6b: Perceived competitive pressure positively affects an SME's behavioral intention to adopt or to continue to use the ODSC.

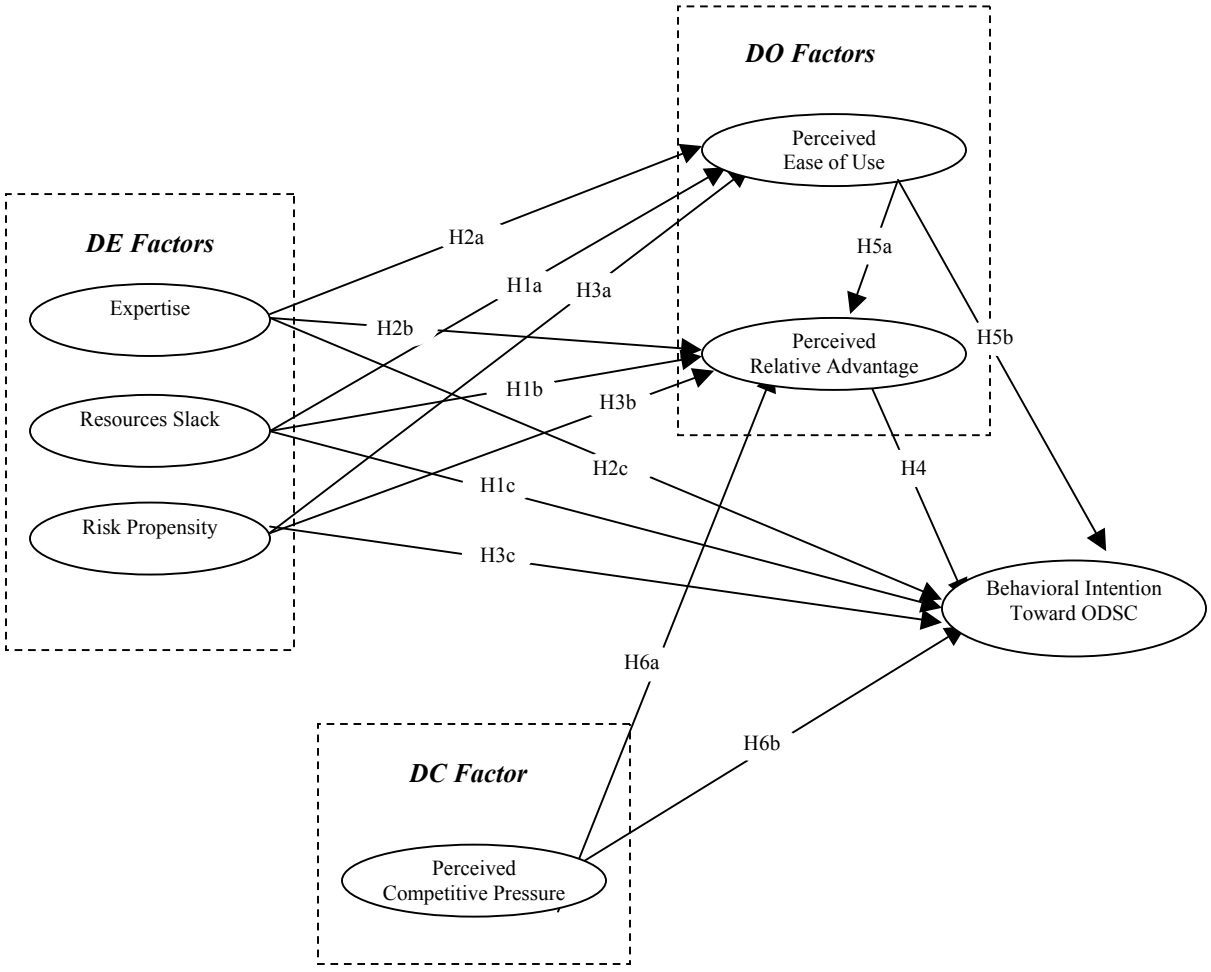

Figure 3: Model of Determinants of ODSC Adoption by SMEs

Summarizing the hypotheses above, I propose a research model on the adoption of ODSC by SMEs (Figure 3). I hypothesize that three DE factors including expertise, resource slack, two DO factors including perceived relative advantage and perceived ease of use, and one DC factor,

perceived competitive pressure, will influence, directly and/or indirectly, SMEs' behavioral intention to embrace ODSC.

3. Research Methods

A web survey has been used to collect data for this dissertation. The reasons for choosing a web survey are threefold: first, compared with other forms of survey, such as mail survey, a web survey is less expensive. Second, a web survey is an increasingly important data collection mechanism with demonstrated effectiveness. Andrews, Nonnecke, and Preece (2003) suggested that web surveys were superior to email surveys in many aspects. While combined with email and offline media, they argued, a web survey was an even more effective vehicle for data collection. Finally, web surveying has grown mature. Commercial web surveying software with sophisticated skip logics capable of handling complex survey questionnaires is readily available. Web surveying guidelines are abundant in the research methodology literature, which help researchers maximize the strength and minimize the weaknesses of a web survey.

3.1 Instrument Development

I followed Churchill's "procedure for developing better measures" (1979) as a guideline for the development of my survey instrument. The procedure includes two broad stages: Instrument Creation & Refinement Phase and Pilot Phase (Figure 4). The Instrument Creation and Refinement Phase consists of four sub-stages: Specifying construct domains and dimensions, generating item pool under dimensions, purifying survey items, pre-testing and revision of the online version of the instrument. The Pilot Phase includes the pilot study and the revision of the instrument based on the feedback from the pilot study.

3.1.1 Instrument Creation and Refinement

3.1.1.1 Specifying Construct Domain & Dimensions

I conducted an extensive review of e-commerce literature, literature of IS innovation adoption and diffusion, and literature related to SMEs' use of innovations to determine the constructs to be included in the research model. The review revealed that perceived relative advantage, perceived ease of use, perceived competitive pressure, and expertise, resource slack, and risk propensity of SMEs were the key variables that impacted SMEs' adoption of IS innovation--in particular, e-commerce related technologies. In-depth literature review also allowed me to identify the major dimensions of each construct, which formed the basis for the generation of my survey question items.

3.1.1.2 Generating Item Pool under Dimensions

Initial survey questions are developed based on the findings of the literature review. A pool of questions for each construct is generated based on the dimensions of the construct. In order to increase the validity of the measurement instrument, some of the questions are adapted directly from survey questionnaires in earlier studies. For instance, the behavioral intention scales are adapted from Davis et al.'s TAM study (1989).

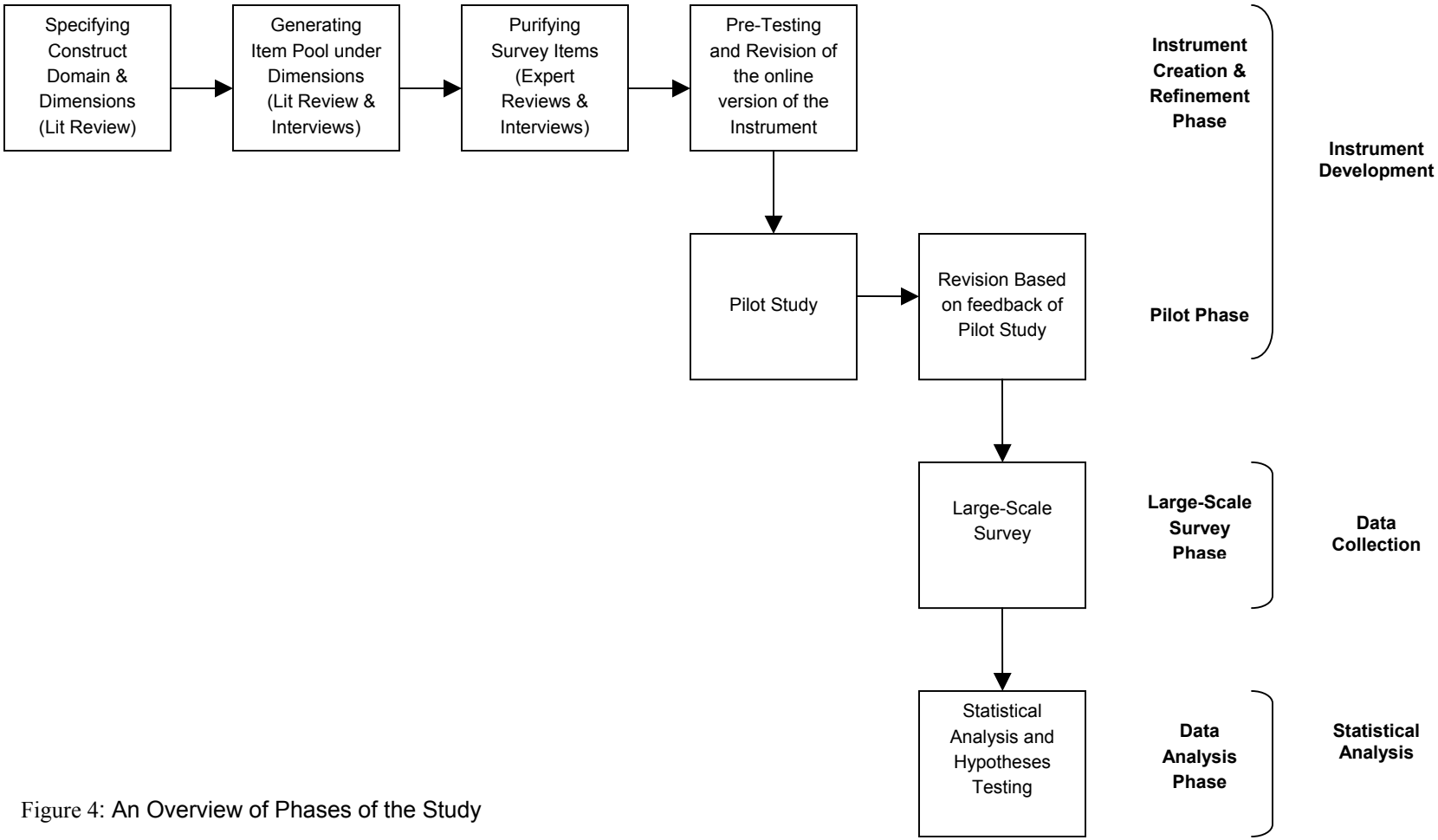

Figure 4: An Overview of Phases of the Study

3.1.1.3 Purifying Survey Items

After the initial survey questionnaire is developed, a multi-stage guideline proposed by Andrews, Nonnecke, and Preece (2003) is followed to refine the instrument. The guideline includes four stages: Stage One involves a thorough review by knowledgeable experts to ensure question completeness, efficiency, relevancy, and format appropriateness. Stage Two involves a pre-test, which helps to ensure wording comprehensibility, interpretation consistency, logical sequencing, and overall positive impression from the look and feel of the survey. Stage Three consists of a small pilot study that emulates all the procedures proposed by the main study. In Stage Four, researchers conduct one last check using people who have no connection to the survey. The objective is to catch typos and errors that may have been inadvertently introduced during the last revision process.

In my study, I first conducted a series of expert reviews involving nine knowledgeable experts from different areas related to the survey questions. The qualitative expert review, according to Carmines and Zeller (1979), is a common approach for establishing content validity, which is the extent to which a measurement instrument captures the different aspects or dimensions of a construct (Rungtusanatham, 1998). Those experts participating in the present study included:

- Two Information Systems professors specializing in technology adoption
- One Operations Management professor specializing in decision theory
- One Marketing professor specializing in online marketing
- One General Management professor

- Two small business experts--a director and a senior researcher from a Small Business Development Center (SBDC), both of whom had extensive experience working with small and medium-sized enterprises
- Two doctoral students majoring in Information Systems

The experts were asked to examine each question of the survey carefully and to provide a critique of its content relevancy, wording, and structure. They were also asked to provide some feedback on the survey as a whole regarding the completeness of its contents, order of question items, and its overall structure. The whole review and iteration process lasted five months, from May to October 2006, during which a total of twenty-four discussion sessions were held and a total of forty-nine revisions of the questionnaire were generated until the final version was finalized for a pilot study.

3.1.1.4 Structure and Contents of Survey Questionnaire

The resulted instrument starts with a survey instruction (Appendix 4), followed by the questionnaire, which was comprised of three sub-questionnaires intended for three different types of SMEs.

- Questionnaire A: for SMEs that have never sold their products or/and services on the Internet (Appendix 5)
- Questionnaire B: for SMEs that sold on the Internet in the past but have abandoned the online sales channel (Appendix 6)
- Questionnaire C: for SMEs that are currently selling their products or/and services on the Internet (Appendix 7)

The three sub-questionnaires included slightly differently formatted (e.g., using different tenses where necessary) questions for the same constructs, which included behavioral intention to embrace ODSC, perceived relative advantage, perceived ease of use, perceived competitive pressure, resource slack, expertise, and risk propensity. To reduce participants' effort and frustration level and to ensure completion rate, I generally placed questions under the same constructs together. However, in order to prevent participants from responding to the same block of questions with the same or similar answers, I intentionally shuffled some questions across constructs and reverse-scored some scales. Also, to verify consistencies of the participants' responses, I intentionally included some redundant questions in the survey.

The survey was conducted on Websurveyor, an enterprise-level online data collection system. At the beginning of the survey, a general section was used to cover questions shared by all the three sub-questionnaires. The section included questions on industry, geographic distance of customers, experience and expertise in Internet, and an index question on the firm's e-commerce profile (never sold online, sold online in the past but has abandoned the online sales channel, currently selling online). Based on the response to the index question the survey system would take the participant to an appropriate sub-questionnaire. I also implemented skip logics in the survey system to make sure that every SME would be asked only questions relevant to it. Irrelevant questions were skipped. For instance, if an SME indicated in an earlier question that it did not have a website of its own, then any questions about selling on its own website would be skipped.

The survey concluded with a few questions about general information of the participating SME such as its size in terms of number of employees and the year it was founded and some information about the informant, such as his/her job title and email address, which was optional

and only necessary if the participating SME was willing to receive a summary of findings of the study.

3.1.1.5 Pre-testing of Survey Instrument

After the questionnaire was finalized it was loaded on the Websurveyor system. In order to make sure the survey was implemented appropriately on the survey system, four people (two professors in business administrations and two IS doctoral students) were invited to test-take the survey online. They were requested to report the time it took to finish the survey and the appropriateness of the arrangement of questions (e.g., number of questions per page); they were also requested to pay some special attention to the index logics, skip logics and submission function of the survey.

The pre-testing proved useful. The reports from the four participants provided me with information about the approximate time the survey would take—which was about ten to fifteen minutes. That assured me that the length of the survey was appropriate. The pre-testing feedback also helped me locate and fix several errors with the skip logics and improve the look of the survey by rearranging the order and clustering of some of the questions.

3.1.2 Pilot Study

Survey piloting is the process of conceptualizing and re-conceptualizing the goals of the study, which ensures that the actual survey will go smoothly and important aspects are not left out (Oppenheim, 1992). In order to gain feedback from SMEs on the questionnaire prior to the general survey, I conducted a small-scale pilot study in November 2006. The contents and procedure of the pilot study were identical with the general survey carried out later, except that, in

addition to the survey questions on the research, the pilot survey questionnaire included questions exploring participants' comments on the questionnaire, such as their opinions about the length of the survey, the time it took to complete the survey, the relevance of the contents, and the clarity and understandability of the questions. The participants were also encouraged to suggest any other important questions that the survey failed to include (Refer to Appendix 7 for details).

In the pilot study, thirty SMEs were randomly selected from the clients of one SBDC. An invitation email message was emailed to each SME in the sample. The invitation message was the same as the one used in the general survey, except that the participating SMEs were informed that they were participating the pilot study of the research. One week later, a reminder email message was emailed to the same sample of firms. The pilot study ended one week after the reminder message was sent out. The results of the pilot study revealed the following information:

- Expected response rate: The invitation email was sent to 30 SME contacts. Five completed surveys were received, which yielded a response rate of 17%. While the small sample could not provide a reliable prediction of the response rate of the general survey, it at least offered an estimate.
- Length of time it took to complete the survey: according to feedback from the pilot study, it took an average of 10.6 minutes to complete the survey questionnaire, with a minimum of 5 minutes and a maximum of 15 minutes. Thus, the length seemed reasonable. But when asked whether they felt the length of the survey was reasonable, two of the respondents said "No." The structure of the survey might have made it appear longer. Therefore, in the revision of the questionnaire, some blocks of questions were rearranged.
- Comprehensibility of the questions: When asked whether the questions were easy to understand, informants of two SMEs complained about the redundant questions, which

were intentionally included in the survey to examine consistency of informants' responses. Thus, I slightly reworded and relocated the redundant questions to make them look less redundant.

- Internal consistency reliability: Duplicated questions worded slightly differently were embedded throughout the survey to check the internal consistency reliability. Close examination of the responses demonstrated consistency in responses to those questions, but statistical analysis, such as Cronbach's Alpha, could not be calculated until the general survey because of the small size of pilot sample.
- Content validity: When asked whether the questions were relevant to SMEs' decisions on selling online, three-fifths said "yes," one-fifth said "no," and one-fifth raised concerns that firms that were already selling online would have to answer irrelevant questions. As a matter of fact, my survey had several sub-surveys. For firms that were already selling online, the systems would direct them to a different set of questions. The pilot study as well as the expert reviews has assured the content validity of the survey instrument (Carmines & Zeller, 1979).

The results from the small-scale pilot study also lead to several minor modifications of wording and order of the question items. I also dropped a few intentionally embedded redundant questions due to the complaints from the participants in the pilot study in the final questionnaire.

3.2 Data Collection

After the questionnaire was revised based on the feedback from the pilot study, the study entered its general survey phase, which was intended to collect data from a larger sample of

SMEs to test the validity and reliability of the instrument and to test the research model and associated hypotheses proposed in the study.

The major data collection procedures were:

1. First, I conducted a Google search using keywords "small business Ohio," "SMEs Ohio," "Chamber of Commerce Ohio," and "small business association Ohio." Through the search, I generated a list of business organizations in Ohio whose main clients or members were primarily SMEs.
2. I telephoned the leadership of the organizations--usually executive director, chairperson or president--and asked for their assistance to send in their own names an email invitation message to their clients or members. I asked them to email the invitation message in the hope of leveraging their influence on their members so as to enhance the response rate.
3. Then, I emailed those who agreed to help an invitation message that they must use to invite their clients to the survey. The invitation message was formulated and phrased following the guidelines proposed by Dillman (2007). The messages (Appendix 1) concisely articulated the importance and focus of the research project and then provided a hyperlink to the survey. A one-week deadline was set for the participants to complete the survey.
4. Two days later, I either telephoned or emailed the business organizations again to check whether they had emailed the invitation message. If not, I made every effort to contact them again to make sure they send the invitation.
5. One week after an organization sent out the invitation message, I emailed it a pre-composed reminder email message (Appendix 2) intended to remind those SMEs that had not taken the survey to do so. The reminder message gave the participants one more week

to complete the survey. A few hours later, I followed up with a telephone call to the organization to confirm whether it had received my email and to request its help in sending the message.

6. Two months later, I asked the organizations to send a second reminder message (Appendix 3) to their clients. The major purpose of this reminder message was to trigger some survey responses from late respondents. Such responses would be compared with earlier responses to test whether non-response bias existed in the study. Non-response bias will be discussed further in a later section of this dissertation.

3.2.1 Sample

The sample of the study is a collection of small and medium-sized enterprises in the state of Ohio of the United States. Since SMEs associated with different types of organizations may have different characteristics and in order to obtain a less biased and more widely representative sample, I intentionally chose several types of organizations rather than use only SBDCs to send the invitation message. The business organizations that I chose to email the survey invitations include several Ohio Small Business Development Centers (SBDCs) and a few Ohio Chambers of Commerce and Economic Development Centers.

Table 2 is a summary of the profiles of the informants who responded to the survey. The informants of the participating SMEs that completed the survey were mostly owners or high-rank employees of the firms who, I assume were relatively more knowledgeable about their firms and thus were likely to provide relatively more reliable and accurate responses to the survey.

Position	No. of Informants	Percent	Cumulative Percent
President or/and CEO	52	27.1	27.1
VP	19	9.9	37.0
Owner	45	23.4	60.4
CFO/CIO	2	1.0	61.5
Controller	4	2.1	63.5
Director	14	7.3	70.8
Manager	23	12.0	82.8
Treasurer	2	1.0	83.9
Advisor/consultant/analyst	3	1.6	85.4
Engineer	8	4.2	89.6
Sales Rep	6	3.1	92.7
Customer Service Rep	2	1.0	93.8
Secretary/Administrator	6	3.1	96.9
Others	6	3.1	100.0
Total No. of Responses	192		
Undeclared	10		
Total	202		

Table 2: Profiles of Informants

Survey email invitations were sent from the Ohio Small Business Development Centers, Chambers of Commerce, and Economic Development Centers to 2,004 firms in June and July, 2007. A total of 213 (10.6%) responses were received. While the response rate is not very high, it is comparable to the rate of similar studies. I also conducted a Wave Analysis, which indicated that no non-response bias existed. Details about non-response bias and the Wave Analysis are presented in a later section of this dissertation.

Among the 213 responses, eight turned out to be from non-SMEs (firms with more than 500 employees) and thus were dropped from the sample. In the remaining 205 firms, which were all SMEs, three failed to provide responses in several fields and were deemed unusable, and thus, were dropped as well. In the final data set of 202 SMEs, 120 (59%) SMEs reported to have never sold on the Internet; 78 (39%) claimed to be selling online currently, and the remaining four

SMEs (about 2%) reported to have sold on the Internet in the past but have abandoned such practice (Table 3).

Among those that are currently selling online, an overwhelming majority claimed to have their own e-commerce websites. Only three (about 4%) reported to be selling on a third party's website. With such a small number of firms using a third party's website, my sample does not allow me to conduct any further analysis to compare those that adopt ODSC by establishing their own e-commerce websites and those that adopt the online sales channel by using a third party's e-commerce website. Besides, such analysis is not essential for the current study because the focus of the study is SMEs' adoption of Internet-based sales channel. Whether such adoption involves an SME's own e-commerce website or a third party's website is less relevant.

The four SMEs that abandoned the ODSC used it for an average of 1.5 years before abandoning it. The major causes for such abandoning, based on their responses, seemed to lie in factors related to benefits (average score: 4.75; 50% scores at least 5), ease of use (average score: 45; 25% scores at least 5), and lack of resources (average score 3.5; 25% scores at least 5).

Type of SMEs	Number of SMEs	Percent
Never adopted ODSC	120	59%
Adopted ODSC but abandoned it	4	2%
Currently using ODSC	78	39%
Total	202	100%

Table 3: ODSC Adoption among SMEs

The size distribution of the participating firms is shown in Table 4. The distribution is consistent with the data from the United States Small Business Administration. For instance, my data, just like those of SBA, show that approximately 95% of all employer firms have fewer than 100 employees. Such consistency is an indication that my sample is an unbiased sample, in terms of size distribution.

Size Classification	No. of SMEs	Percent	Cumulative Percent
>500	8	3.8	3.8
>200 but <=500	6	2.8	6.6
>100 but <=200	11	5.2	11.7
>0 but <=100	176	82.6	94.4
Undeclared	12	5.6	100.0
Total	213	100.0	

Table 4: Size Distribution of the Participating Firms

The sample also has a good representation of different industries of SMEs. Refer to Table 5. The industries that are well represented in the sample include manufacturing, services, retail trade, wholesales trade, finance, insurance and real estate, construction, transportation, and so on. The broad representation of different sizes and industries of SMEs increase the generalizability of findings of the study.

Industry	No. of SMEs	%	Cumulative %
Manufacturing	27	13.4	13.4
Services	95	47.0	60.7
Wholesale Trade	6	3.0	63.7
Retail Trade	21	10.4	74.1
Finance, Insurance, And Real Estate	14	6.9	81.1
Agriculture, Forestry, And Fishing	4	2.0	83.1
Construction	19	9.4	92.5
Transportation, Communications, Electric, Gas, And Sanitary Services	9	4.5	97.0
Public Administration	6	3.0	100.0
Total	201	99.5	
Undeclared	1	0.5	
Grand Total	202	100.0	

Table 5: Industry Distribution of the Participating SMEs

3.2.2 Missing Data

I dropped several returned questionnaires because of a large number of incomplete responses. All the remaining retuned questionnaires have provided responses to all or most of the survey questions. To keep those questionnaires that have missed a small number of questions, I followed the mean-person imputation procedures proposed by Hair, Andersen, Tatham, and Black (1995) and Roth, Switzer, and Switzer (1999), in which, the mean value of a measure was used for a missing value. Researchers, including Roth et al. (1999), have demonstrated that mean-person imputation procedure does not significantly bias subsequent data analysis. Table 6 lists the number and percentage of items imputed in each variable.

Variable	Items Affected	Percentage Affected
ADVTG1	7	3.5%
ADVTG 2	6	2.9%
ADVTG 3	8	3.9%
EASE1	5	2.5%
EASE2	6	2.9%
EASE3	7	3.5%
RESO1	2	1%
RESO2	3	1.5%
RESO	3	1.5%
RP1	3	1.5%
RP2	3	1.5%
COMP1	8	3.9%
COMP2	5	2.5%
COMP3	4	2.0%
EXPTM	2	1.0%
EXPTE	8	3.9%
INT1	6	2.9%
INT2	3	1.5%
INT3	5	2.5%
Overall	94	2.4%

Table 6: Mean-Person Imputation

3.2.3 Non-Response Bias

Non-response bias, or non-response error, refers to the bias that is caused by the differences in demographic or attitudinal variables between those who responded and those who did not respond (Sax, Gilmartin, & Bryant, 2003). Non-response bias may jeopardize the external validity of a survey, because when non-response bias exists, survey results can produce misleading conclusions that cannot be generalized to the entire population (Rogelberg & Luong, 1998).

A low response rate does not automatically signify that the data obtained from a survey are biased (Dillman, 1991; Krosnick, 1999; Rogelberg & Stanton, 2007; Sax et al., 2003). Researchers must analyze whether their low response rates truly have a significant impact on conclusions drawn from the data; if no impact exists (Rogelberg & Stanton, 2007), or if respondent characteristics are representative of non-respondents (Sax et al., 2003), then no non-response bias exists.

Non-response bias is likely to be an important issue when all of the following three problems occur (Dillman, 2007): 1) a significant number of participants in the survey sample do not respond to the survey questionnaire; 2) the participants that do not respond have different characteristics from those that respond; 3) the different characteristics are important in the study; in particular, they are related either to the dependent variable or to a variable that is correlated with the dependent variable.

Wave Analysis is a standard technique for examining the differences between respondents and non-respondents (Yip & Dempster, 2005). In Wave Analysis, respondents who returned responses near the end of the survey, usually after significant coaxing, are used as a proxy of non-respondents. Late responses are compared with responses of early respondents to determine whether differences in key variables exist (Johnson, Beaton, Murphy, & Pike, 2000; Smith, 1983; Stinchcombe, Jones, & Sheatsley, 1981). By noting whether each survey is completed before the deadline, after an initial reminder message, after a second reminder message, and so on, responses from pre-deadline surveys can be compared with the late responders on the actual survey variables. If responses of late responders differ significantly from those of earlier responders, then it signifies the existence of some level of non-response bias (Rogelberg & Stanton, 2007); otherwise, there is no indication of non-response bias.

I followed the Wave Analysis procedure proposed by Armstrong and Overton (1977), through which I examined whether participating SMEs were significantly different from non-responding ones by: 1) comparing survey responses received after the initial invitation email message was sent but before the first reminder message was sent (Group 1, n=121) with those received after the first reminder but before the second reminder (Group 2, n=48); 2) comparing Group 2 responses with those received after the second reminder was sent (Group 3, n=33). Because the second reminder message was sent out two months after the initial invitation and the first reminder, characteristics of SMEs that responded after the second reminder may be arguably similar to non-respondents.

Therefore, if a t-test reveals significant differences in any of the key attributes between the groups then there may be a response bias; otherwise, no evidence of non-response bias exists. The results of wave analysis in this study reveal no difference in any variable between Group 1 and Group 2 and between Group 2 and Group 3. However, two of the nineteen variables—ADVTG3 (an observed variable for perceived relative advantage) and COMP2 (an observed variable for perceived competitive pressure)--are found to be significantly different between Group 1 and Group 3. Therefore, possibility of non-response bias cannot be totally eliminated.

Nevertheless, serious non-response bias in this study is not likely. First, if severe non-response bias does exist, the wave analysis is more likely to show significant differences in a fairly large number of variables. But the wave analysis actually results in significant differences only in two (about 10%) of the nineteen observed variables. The differences in such a small number of variables may be caused by the relatively small sample size of Group 3.

Moreover, if serious non-response bias exists, then the highly correlated observed variables that measure the same latent construct are very likely to yield significant differences across the groups at the same time. However, that does not happen. For instance, if non-response

bias has caused the difference in ADVTG3 ("Selling online will help improve our ordering process.") between Group 1 and Group 3, then ADVTG1 ("Selling online will increase our overall sales revenues.") and ADVTG2 ("Selling online will bring us additional profits.") are very likely to be significantly different across the two groups as well. But neither ADVTG1 nor ADVTG2 is found to be significantly different. Similarly, if the difference in COMP2 ("Our main competitors are already selling successfully online.") between Group 1 and Group 2 is caused by non-response bias, then a similar item, COMP3 ('Our main competitors are seizing our market share.") is expected to be significantly different as well; but the wave analysis does not reveal a difference in COMP3 across the two groups.

Based on the analysis above, I believe that, while I cannot totally eliminate the possibility of non-response bias, severe non-response bias is unlikely.

3.2.4 Common Method Bias

Common method bias, sometimes known as methodological artifact, occurs when the research method used affects the accuracy of measurements, leading to incorrect relationships between constructs. According to Cote and Buckley (1987), about 26% of the variance in a typical research measure might be caused by systematic sources of measurement error like common method biases. Common method bias can either inflate or deflate observed relationships between constructs and therefore lead to Type I or Type II error (Podsakoff, MacKenzie, Lee, & Podsakoff, 2003).

A variety of sources my cause common method biases, which include having a common rater, a common measurement context, a common item context, and some characteristics of the items such as reverse-scoring (Podsakoff et al., 2003). In the present study, I have tried to control the following potential sources of common method bias,

- *Item ambiguity*-- Tourangeau et al. (2000) suggested that item complexity and ambiguity is among the major causes of common method bias. To reduce survey item complexity and/or ambiguity, I have each survey item carefully reviewed during the instrument development process, through expert panel review, pre-testing, and pilot study. Participants in those processes are specifically asked to evaluate the clarity and simplicity of each survey item and their feedbacks are used as basis for revision of the survey item.
- *Consistency motif* — This is by far the most common source of common method bias in a survey study. A survey respondent tends to have a desire to maintain consistency in their responses to different items, which results in relationships that would not otherwise exist at the same level in real-life settings (Podsakoff et al., 2003). To reduce this source of bias, I have placed multiple measures of the criterion variable--perceived behavioral intention--in different sections of the survey, sometimes before a predictor variable measure and sometimes after a predictor variable. This reduces the respondent's ability and motivation to use his/her prior responses about a predictor variable to answer subsequent questions about measures of the criterion variable, thus reducing consistency motifs (Podsakoff et al., 2003).
- *Item social desirability (or item demand characteristics)*--A respondent tends to respond to a survey question in a culturally acceptable and appropriate manner (Podsakoff et al., 2003). Earlier research (e.g., Thomas and Kilmann, 1975, Nederhof, 1985) has also demonstrated that respondents' responses are significantly affected by item social desirability. In the present study, I am concerned that respondents may regard a firm's behavioral intention to embrace the ODSC as something desirable and respond accordingly. In order to reduce this potential source of common method bias, I emphasize

in the survey instruction that there is no right or wrong answer to any of the question in the survey. Whether the respondent's SME is intending to use the Internet as a sales channel or not, his/her responses will be of equal importance for the research, and that that all responses are anonymous.

In spite of these procedures and precautions that are implemented to control the common method variance, common method bias will not be totally eliminated. To evaluate whether serious common method bias still exists, I have conducted Harman's single-factor test, which is one of the most commonly used techniques to address the issue of common method bias (Podsakoff et al., 2003). Traditionally, researchers using this technique (e.g., Andersson & Bateman, 1997; Aulakh & Gencturk, 2000; Greene & Organ, 1973; Organ & Greene, 1981; Schriesheim, 1979) conduct an exploratory factor analysis on all variables in their studies. Significant common method bias will be determined to exist if: (a) a single factor emerges from the factor analysis or (b) one factor accounts for the majority of the covariance among the measures (Podsakoff et al., 2003).

Table 7 shows the results of exploratory factor analysis of the 19 observed variables in the present study. The results demonstrate that neither a single factor emerges from the analysis nor a general factor accounts for the majority of the covariance among the measures. Therefore, there is no evidence that a significant amount of common method variance exists.

	Component	Initial Eigenvalues(a)			Extraction Sums of Squared Loadings		
		Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %
Raw	1	28.473	37.706	37.706	28.473	37.706	37.706
	2	12.543	16.610	54.316	12.543	16.610	54.316
	3	6.360	8.423	62.738	6.360	8.423	62.738
	4	4.663	6.176	68.914	4.663	6.176	68.914
	5	3.999	5.296	74.210	3.999	5.296	74.210
	6	3.935	5.211	79.421			
	7	2.512	3.326	82.747			
	8	1.946	2.576	85.324			
	9	1.896	2.511	87.834			
	10	1.536	2.034	89.868			
	11	1.439	1.905	91.773			
	12	1.317	1.744	93.517			
	13	1.104	1.462	94.979			
	14	.850	1.126	96.105			
	15	.685	.906	97.012			
	16	.652	.864	97.875			
	17	.588	.778	98.653			
	18	.581	.769	99.422			
	19	.436	.578	100.000			
Rescaled	1	28.473	37.706	37.706	6.435	33.866	33.866
	2	12.543	16.610	54.316	2.959	15.574	49.440
	3	6.360	8.423	62.738	1.774	9.339	58.779
	4	4.663	6.176	68.914	1.075	5.659	64.439
	5	3.999	5.296	74.210	1.136	5.982	70.420
	6	3.935	5.211	79.421			
	7	2.512	3.326	82.747			
	8	1.946	2.576	85.324			
	9	1.896	2.511	87.834			
	10	1.536	2.034	89.868			
	11	1.439	1.905	91.773			
	12	1.317	1.744	93.517			
	13	1.104	1.462	94.979			
	14	.850	1.126	96.105			
	15	.685	.906	97.012			
	16	.652	.864	97.875			
	17	.588	.778	98.653			
	18	.581	.769	99.422			
	19	.436	.578	100.000			

Extraction Method: Principal Component Analysis using the covariance matrix

Table 7: Harman's single-factor test

3.2.5 Scales and Measures

To ensure the validity and reliability, my scales were all built upon prior research. Some of the scales were adapted directly from existing measures. Others were formulated based on literature. Refer to Appendix A for a complete list of the constructs and scales.

Perceived Relative Advantage: Unlike an individual who may adopt a technology for reasons other than economic reasons such as hedonic reasons, an organization adopts a technology ultimately in order to enhance its productivity and efficiency and eventually to increase its profitability. I used three items to measure perceived relative advantage of ODSC. The first one was the perceived potential of ODSC to help increase the company's overall revenue, the second was its potential to enhance the firm's profitability, and the last item focused on the ability of ODSC to improve commercial transaction efficiency, in particular, the efficiency of the ordering process.

Perceived Ease of Use: Adapted from Davis (1989), the construct was measured using three scales: The first scale measured perceived ease of obtaining an e-commerce website, the second scale captured perceived ease of training competent personnel to support an e-commerce system, and the last scale focused on the perception of effort needed to maintain an e-commerce website.

Perceived Competitive Pressure: The level of competitive pressure is reflected in three aspects: 1) competitors sell online, 2) online competitors are successful in selling online, and 3) competitors are seizing market share. Therefore, I used three scales based upon the three aspects to measure perceived competitive pressure.

Perceived Expertise in the Internet: An organization's expertise is reflected in the expertise of its employees. Therefore, I used the expertise of an SME's employees as the proxy of

the expertise of the SME. Because the expertise of managers of an organization, in particular, of an SME, may have more influence on the organization's decision, including its ODSC adoption decision, I used two separate items to measure the expertise of managers and the expertise of other employees. The respondents of the survey were asked to rate the level of expertise of managers and other employees. Severn point Likert-Type scales were used in the rating: 1 represents "novice," the middle scale, 4, represents "competent," and 7 represents "experts."

Risk Propensity: two scales were used to measure an SME's willingness to take risks. The items were straightforward: one item stated that the firm was usually willing to take risks, and the other item stated that senior managers of the firm were willing to take risks. Seven point Likert-Type scales were used: 1 indicates "strongly disagree" and 7 indicates "strongly agree." Participants were asked to rate the extent to which they agreed with the statements.

Resource Slack: A variety of resources are needed to adopt and use an ODSC. I measured an SME's capacity and sufficiency in several resources: the availability of a good business website, the sufficiency of human resources to maintain an e-commerce website, and the sufficiency of general resources, which may include financial resources and any other resources needed for the establishment and management of an e-commerce website. The scales were measured in seven-point Likert-Type scale. Participants were asked about the extent to which they agreed with the given statements.

Behavioral Intention: the measures for behavioral intention were adapted from Davis et al.'s TAM study (1989). Participants were asked whether their firm would/intended/planned to embrace (adopt or continue to use) ODSC within the next two years. The scales were measured in seven-point Likert-Type scale: 1 indicates "strongly disagree" and 7 indicates "strongly agree."

3.3 Statistical Analysis Methodology

3.3.1 Structural Equation Modeling

Structural Equation Modeling (SEM) was used for data analysis. SEM is an analytical tool that combines several statistical techniques, including factor analysis, path analysis, and multiple regression. It is more powerful than multiple regression because it takes into account the modeling of interactions, nonlinearities, correlated independent variables, measurement error, correlated error terms, multiple latent independent variables, each measured by multiple indicators, and one or more latent dependent variables also each with multiple indicators (Garson, 2007).

The use of structural equation modeling has been rapidly growing in psychology, social and behavioral sciences (Anderson 1987; Bollen & Ting, 1991; Fassinger, 1987; Saris & Stronkhorst, 1984; Segars and Grover, 1993). SEM's ability to simultaneously estimate multiple relationships among observed and unobserved variables makes it very helpful in data analysis involving complex models. Compared with other multivariate procedures, SEM has at least two other important advantages (Byrne, 2001): (1) it takes a confirmatory rather than an exploratory approach to data analysis. That means the research model is built on theory, and then data are analyzed to estimate its fit to the model. (2) Unlike other multivariate procedures that are unable to assess and correct for measurement errors, SEM provides explicit analysis of error variance parameters.

3.3.2 Measurement and Structural Models

A structural equation model consists of two components: the measurement model, also known as the confirmatory factor model, and the structural model. The measurement model is concerned with relationships between unobserved measures and their latent constructs while the structural model specifies the causal relationships between the latent constructs, which are hypothesized based upon theories. The measurement model provides an assessment of convergent and discriminant validities while the structural model provides an assessment of predictive validity (Anderson & Gerbing, 1988). The complete model (measurement model and structural model) I propose is presented in Figure 4.

Because using a single variable for a latent variable does not allow for the estimation of errors through structural equation modeling, multiple observed variables should be used for any latent variable, except when there are accepted approaches to boost validity and reliability or when only one observed variable is available Schumacker and Lomax, 1996, p. 80). In the present study, at least two observed variables were used for any latent variable; most latent variables had three observed measures.

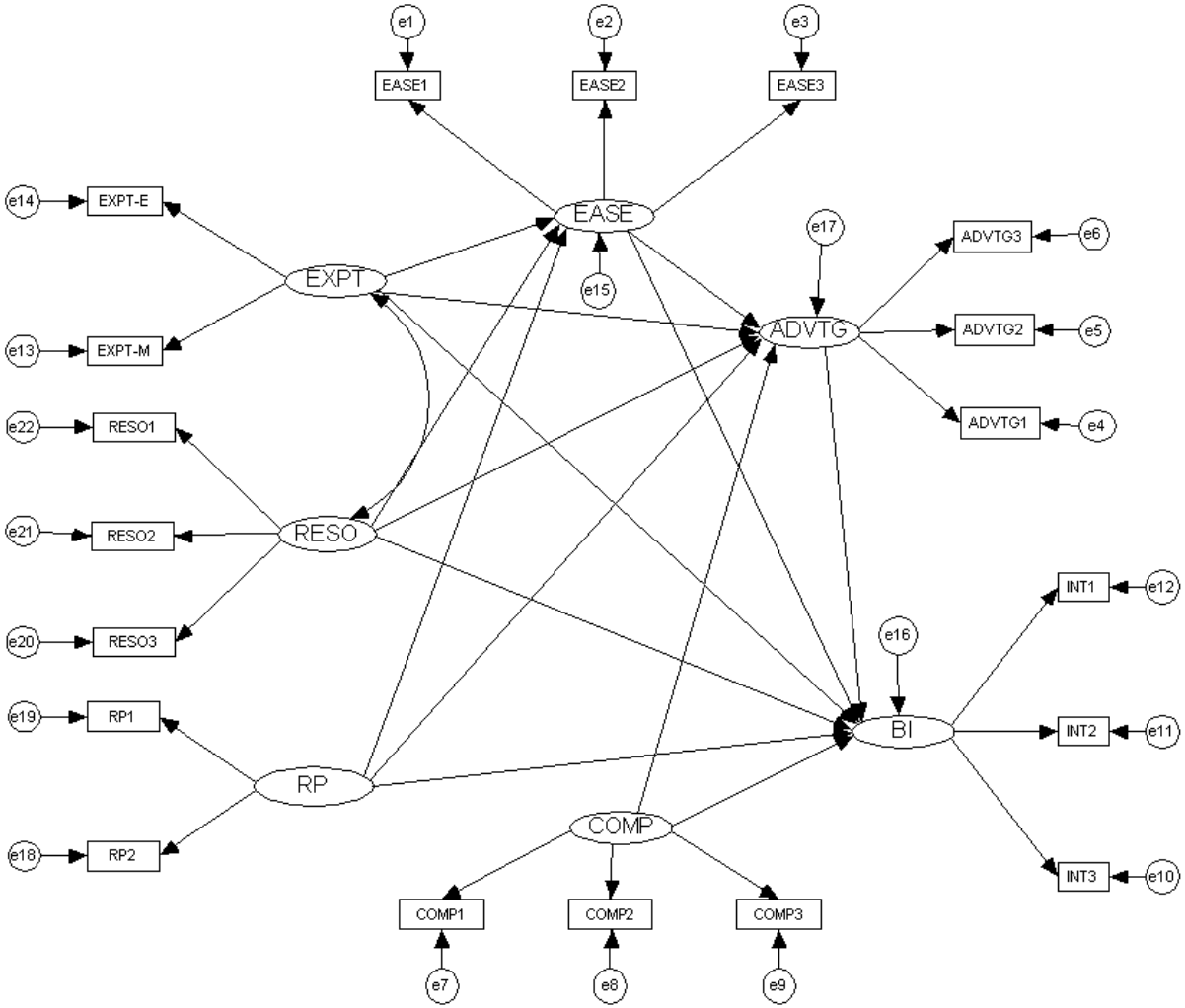

Figure 5: The Complete Model: SME's Intention to Adopt ODSC

Several statistical software packages are available for structural equation modeling. I used Analysis of Moments Structures (AMOS) for the data analysis in the present study. I chose maximum likelihood (ML) as the method to estimate parameters and assess model fit. Because of the departure from multivariate normality (details are provided in a later section about multivariate normality), I also ran a bootstrap procedure to test the stability and reliability of the ML estimates. In addition, I conducted a Bollen-Stine Bootstrap procedure to obtain an adjusted p-value, which corrected the chi-square test p-value. Details about the bootstrap procedures and results are included in a later section of this dissertation.

3.4 Validity and Reliability

In addition to the content validity of the survey instrument, which I have evaluated through interviews with experts during the instrument development stage, construct validities, including convergent validity and discriminant validity, and reliability must be examined to determine the adequacy of the survey instrument and the measurement model.

3.4.1 Construct Validity

Construct validity refers to whether a scale measures the unobservable construct it intends to measure. Construct validity can be broken down into two sub-categories: convergent validity and discriminant validity. Convergent validity is the extent to which a measure correlates (converges) with other measuring methods that it should theoretically be correlated with. Discriminant validity is the extent to which a measure differs from (or diverges from) other measures that it should theoretically be not correlated with (Kerlinger & Lee, 2000).

Although the main concern of working with a full model is to assess the relationships among latent variables, it is critical that the measurement of each latent variable is psychometrically sound. Therefore, it is important to test the validity of the measurement model prior to evaluating the structural model (Byrne, 2001).

The assessment of the construct validity of an instrument is usually achieved through a confirmatory factor analysis. Common factor analysis, also known as principal factor analysis (PFA) or principal axis factoring (PAF) is a commonly used confirmatory factor analytic procedure. Unlike the exploratory data reduction technique--principal components analysis (PCA), which accounts for the total variance (both common and unique variance) of a set of variables, PFA keeps the least number of factors that account for the common variance or covariation of the variables (Garson, 2007). Because of such difference, it is possible under common factor analysis but not under PCA to add variables to a model without affecting the factor loadings of the original variables in the model (Garson, 2007).

PFA is a better approach than PCA for the purpose of modeling, as in structural equation modeling (SEM). As Widaman (1993) suggested, PFA instead of PCA should be used if a researcher wishes to obtain relationships among latent constructs or factors.

An important decision in factor analysis is to determine the number of factors to extract. There are a variety of approaches to determining the number of factors to retain. For example, a researcher can choose to retain factors with eigenvalue of one or above, to retain factors that account for a specific pre-determined level of variance, to extract factors until all residual values are 0.1 or below, or to generate a scree plot and retain the factors up to the bend of the curve. Using different methods may lead to conflictive results. When conflicts occur, researchers should use existing theory as first guideline and other rules of thumb as additional guidance. Researchers should not follow any of the rules too strictly, but instead, they should evaluate the solution as a

complete picture and assess how it is consistent with prior findings and theoretical models in the current study (The University of Texas at Austin, 2004).

Refer to Table 8. In the present study, factors 1 through 6 all have eigenvalues of 1 or above. Factor 7 has an eigenvalue very close to 1. To determine whether to retain or drop factor 7, I produced the Scree Plot (Figure 5). It is clear that the big "elbow" or bend is between factor 7 and 8. Factor 7 goes smoothly along with factors 4, 5, and 6, which all have eigenvalues of 1 or above; but the eigenvalue drops sharply from factor 7 to factor 8. In addition, the seven-factor model is consistent with the existing theories (Refer to Literature Review section). Therefore, it is advisable to retain seven factors. The seven factors explain nearly 72% of variance (Refer to Table 8).

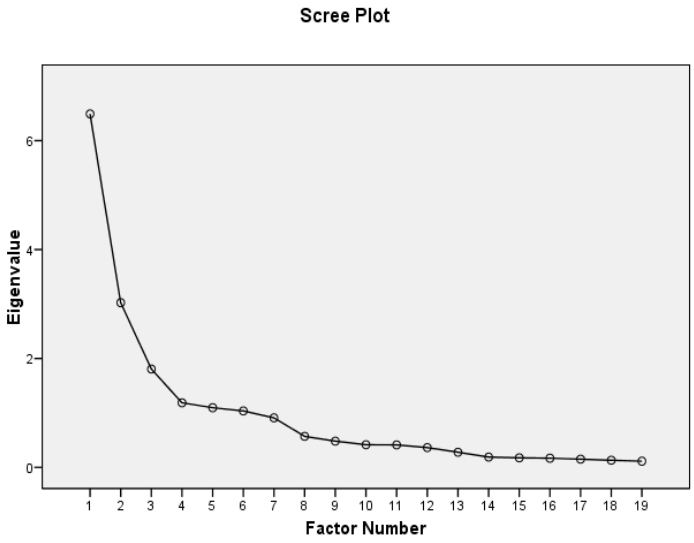

Figure 6: Scree Plot

Factor	Initial Eigenvalues			Rotation Sums of Squared Loadings		
	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %
1	6.491	34.164	34.164	2.376	12.504	12.504
2	3.024	15.918	50.082	2.258	11.886	24.390
3	1.806	9.506	59.587	2.137	11.247	35.636
4	1.186	6.243	65.831	2.115	11.132	46.769
5	1.096	5.766	71.596	1.961	10.323	57.092
6	1.036	5.454	77.051	1.718	9.041	66.133
7	.909	4.784	81.835	1.069	5.628	71.761
8	.569	2.997	84.832			
9	.482	2.535	87.367			
10	.416	2.191	89.558			
11	.413	2.173	91.731			
12	.364	1.915	93.646			
13	.278	1.464	95.110			
14	.189	.995	96.105			
15	.176	.926	97.031			
16	.169	.887	97.918			
17	.151	.795	98.713			
18	.131	.689	99.402			
19	.114	.598	100.000			

Table 8: Total Variance Explained

Extraction Method: Principal Axis Factoring

Factor loadings and purity of loadings (loadings on single constructs) are usually used to assess the convergent and discriminant validities. Different researchers have recommended different cutoff values of factor loadings. Some authors, such as Lederer and Sethi (1991) recommended 0.35. Hair et al. (1995) recommended that factor loadings should be greater than 0.3 in order to meet the minimum level; factor loadings of 0.4 or greater are considered more important; factor loadings of 0.5 or greater are considered practically significant.

In this study, the loadings on all factors exceed 0.6 and most of the loadings are above 0.7 (Table 9). That demonstrates a practically significant convergent validity of the survey instrument. In addition, the loadings are all loaded quite purely on single factors, indicating an acceptable level of discriminant validity.

3.4.2 Internal Consistency Reliability

Reliability is the extent to which a measure can yield consistent results in repeated trials. In variance terms, it is the proportion of the "true" variance to the total variance of the data yielded by the test. Reliability does not imply validity (Kerlinger & Lee, 2000). That is, just because a measure is measuring something consistently does not necessarily mean it is measuring what it intends to measure. However, a valid test must be reliable (Kerlinger & Lee, 2000).

Cronbach's α (alpha) is a commonly used test for assessing the internal consistency reliability of an instrument. It measures the level of correlation among a set of test items and indicates the extent to which they can be treated as measuring a single latent variable (Kerlinger & Lee, 2000). The Cronbach's α of the survey instrument in this study is 0.889, indicating very good internal consistency reliability. The Cronbach's α values for all constructs except Expertise are above 0.8, which demonstrates good internal consistency reliability. However, the α value of Expertise (0.65) is a little low. The construct will eventually be dropped in the revised model because all hypotheses associated with it are not supported in the initially hypothesized model.

Latent Variables	Observed Variables	Alpha	Factor						
			1	2	3	4	5	6	7
Expertise	EXPT-E	**0.65**	.010	.027	.090	.043	.100	.089	**.647**
	EXPT-M		.075	-.015	.188	.039	.187	.068	**.673**
Resource Slack	RESO1	**0.82**	.058	.085	.161	.028	**.687**	.078	.051
	RESO2		.095	.039	.260	.111	**.802**	.101	.185
	RESO3		.078	-.039	.316	.013	**.686**	-.018	.191
Risk Propensity	RP1	**0.90**	.196	-.049	.137	.091	.089	**.817**	.116
	RP2		.108	.011	.065	.104	.062	**.943**	.086
Perceived Advantage	ADVTG1	**0.87**	.316	.304	.127	**.766**	-.008	.082	.075
	ADVTG2		.271	.244	.126	**.838**	.049	.076	.005
	ADVTG3		.219	.195	.112	**.600**	.125	.104	.069
Perceived Ease of Use	EASE1	**0.88**	.148	.070	**.616**	.160	.278	.115	.084
	EASE2		.131	.099	**.756**	.099	.245	.153	.243
	EASE3		.058	.071	**.895**	.115	.327	.015	.130
Perceived Competitive Pressure	COMP1	**0.86**	.279	**.786**	.098	.216	.111	-.002	.030
	COMP2		.182	**.942**	.034	.168	.045	.029	.020
	COMP3		.100	**.604**	.060	.210	-.021	-.052	-.015
Perceived Behavioral Intention	INT1	**0.93**	**.825**	.200	.091	.278	.182	.180	.078
	INT2		**.797**	.239	.226	.334	.025	.143	.033
	INT3		**.775**	.261	.069	.271	.093	.126	.041

Table 9: Factor Loading. Extraction Method: Principal Axis Factoring.

Rotation Method: Varimax with Kaiser Normalization. Rotation converged in 7 iterations.

4. Results

4.1 Descriptive Statistics

Table 10 shows the results of descriptive statistics of the measures. All the measures use seven point Likert-type scale, where "1" indicates "strongly disagree" and "7" indicates "strongly agree," unless specified otherwise. The three behavioral intention scales all have a mean slightly over 4 and a standard deviation a little above 2.

	Measures (from Non-Adoption Group; Adoption Group Measures are worded slightly differently)	Mean	Std. Deviation
EXPT1	Managers: 1=Novice, 4=Competent, 7=Expert.	4.3	1.4
EXPT2	Other Employees: 1=Novice, 4=Competent, 7=Expert.	5.2	1.4
RESO1	Our firm already has a pretty good business website.	3.9	2.1
RESO2	We have the resources necessary to build an e-commerce website.	3.9	2.2
RESO3	We have the IT personnel necessary to maintain an e-commerce website.	3.6	2.2
RP1	Our firm is usually willing to take risks.	4.8	1.8
RP2	Our senior managers are willing to take risks.	4.8	1.7
ADVTG1	Selling online will increase our overall sales revenues.	4.2	2.0
ADVTG2	Selling online will bring us additional profits.	4.1	2.0
ADVTG3	Selling online will help improve our ordering process.	3.7	2.0
EASE1	Obtaining an e-commerce website to sell our products/services will be easy.	3.9	2.1
EASE2	Training competent personnel to support an e-commerce system will be easy.	3.9	1.9
EASE3	Maintaining an e-commerce website will be easy for our firm.	3.9	1.9
COMP1	Most of our competitors sell online.	3.6	2.1
COMP2	Our main competitors are already selling successfully online.	3.3	1.9
COMP3	Our main competitors are seizing our market share.	2.7	1.6
INT1	Our firm intends to sell products/services on the Internet within the next two years.	4.2	2.4
INT2	I predict my firm will start to sell products/services on the Internet within the next two years.	4.1	2.3
INT3	Our firm plans to sell products/services on the Internet within the next two years.	4.6	2.3

Table 10: Descriptive Statistics

4.2 Evaluation of Major SEM Assumptions

Some assumptions need to be met to assure that the findings of structural equation modeling are accurate and reliable. There are a series of assumptions for Structural Equation Modeling; I report in the following sections my evaluation of two most important assumptions—sample size assumption and normality assumption.

4.2.1 Sample Size

SEM requires the sample size to be sufficiently large. However, no universal rule exists defining a "sufficiently large" sample size. The medium sample size, based on a survey of 72 SEM studies, is 198 (Garson, 2007). Different researchers have made different sample size recommendations in SEM studies. For instance, Loehlin (1992) and Hoyle (1995) have recommended at least 100 cases, preferably 200. Kline (1998) has considered sample sizes under 100 to be "untenable" in SEM. ''10k rule of thumb'' is regarded as a benchmark in the building and diagnostics of a regression oriented model (e.g., an SEM model). The rule states that at least 10k observations are needed for a regression model with "k" independent variables (Troutt, 2006). This dissertation has seven independent variables and it uses a data set of 202 observations. While such sample size is not very large, it has exceeded the level commonly recommended. Therefore, the assumption of sample size is not a concern for this study.

4.2.2 Multivariate Normality

Univariate and Multivariate normality of the variables in the model is another important assumption in SEM. Simulation conducted by Kline (1998) indicates that SEM parameter estimates remain reasonably accurate when the assumption of normality is violated. However, the significance coefficients corresponding to such estimates are inflated. In particular, the Chi-Square is inflated, which causes researchers to believe that the hypothesized model needs further modification while it actually fits the data quite well. Another problem linked to the violation of multivariate normality assumption is that the lack of multivariate normality tends to cause the deflation of standard errors, which in turn, makes regression paths and factor/error covariances statistically significant more often than they should be (Byrne, 2001).

While testing univariate normality is relatively simple, directly examining multivariate normality is challenging due to the complexity of multidimensionality. In order to evaluate the multivariate normality in the present study, I have obtained Mardia's coefficient, which is a commonly used approach for assessing multivariate normality. The multivariate kurtosis value, or the Mardia's coefficient (Mardia, 1999), is 53.120, which is much larger than the recommended value of 1.96, indicating that there is a significant kurtosis, or significant multivariate non-normality.

4.2.3 Handling Nonnormality with Bootstrapping

One commonly used approach for handling multivariate nornormal data in SEM is to use a procedure known as "bootstrapping" (West, Finch, & Curran, 1995; Yung & Bentler, 1996; Zhu, 1997). The bootstrapping is essentially a procedure of re-sampling with replacements to generate multiple sub-samples from the original sample. Such a procedure enables the researcher

to examine the parameter (e.g., regression weights or standard errors) distributions of these samples, which, considered cumulatively, serve as a bootstrap sampling distribution, in the same manner as sampling distribution is associated with parametric inferential statistics (Byrne, 2001). However, while the sampling distribution of the inferential approach is restricted by the normality assumption, bootstrapping is free of such an assumption (Zhu, 1997). Essentially, bootstrapping provides an approach to addressing situations where assumption of multivariate normality fails to hold (Yung & Bentler, 1996).

Bootstrapping has usually been used to achieve two objectives: 1) to assess the overall goodness-of-fit of the model (Bollen & Stine, 1993), and 2) to assess the level of stability of parameter estimates (Byrne, 2001; Lunneborg, 1987; Schumacker & Lomax, 1996). In this dissertation, I have used Bollen-Stine bootstrap to assess the model fit. I have also used a bootstrap procedure to assess the stability of parameter estimates (refer to later sections of this dissertation).

4.3 Initial Research Model

4.3.1 Goodness of Fit

Goodness of Fit indicates the level of fit between the hypothesized model and the sample data. The objective of a goodness-of-fit test is to determine whether the hypothesized model should be accepted or rejected. Because such a test examines the global fit between the data and the model, only after such global fit is established can a researcher examine each individual path coefficient in the model and test the significance of relationships between latent variables.

A variety of goodness-of-fit tests exist, each of which calculates the goodness-of-fit index and deals differently with issues such as sample size. Which tests to conduct and which indices to

report are determined by the characteristics of the study. However, there is no single index that is sufficient to identify a correct model given a sample data (Shumacker & Lomax, 1996). Most researchers believe that multiple goodness-of-fit indices should be reported to justify a good fit. For instance, Jaccard and Wan (1996) recommended the use of at least three fit tests, and Kline (1998) recommended at least four different tests. The controversy remains regarding which fit indices to report.

Based on the characteristics of this study—moderate sample size and lack of multivariate normality—I have reported eight goodness-of-fit indices: Relative Chi-Square, Root Mean Square Error of Approximation (RMSEA), Normed Fit Index (NFI), Tucker-Lewis Index (TLI), Relative Fit Index (RFI), Incremental Fit Index (IFI), Comparative Fit Index (CFI), and Bollen-Stine Bootstrap Adjusted p-value.

Table 11 shows the results of a variety of goodness of fit indices and recommended values. All the index values indicate that the proposed research model has a good model fit.

Fit Index	**Recommended Value**	**Result**
Normed Chi Square	Chi-Square/df <=2 (Bollen, 1989a); 1.0 to 5.0 (Schumacker & Lomax, 1996).	1.335
RMSEA	<=0.08 (Browne & Cudeck, 1992); <0.05 (Schumacker & Lomax, 1996).	0.041
NFI	Value close to .9 reflects a good model fit (Schumacker & Lomax, 1996).	0.929
TLI	The typical range for TLI lies between zero and one, but it is not limited to that range. TLI values close to 1 indicate a very good fit. Value close to .9 reflects a good model fit (Schumacker & Lomax, 1996).	0.976
RFI	Ranges from 0 to 1. Value greater than .9 reflects a very good fit	0.912
IFI	Ranges from 0 to 1. Value greater than .9 reflects a very good fit.	0.981
CFI	Ranges from 0 to 1. Value greater than .9 reflects a very good fit	0.981
Bollen-Stine Bootstrap p-value	p >0.05 indicates good model fit	0.174

Table 11: Goodness of Fit (Initial Model)

4.3.1.1 Relative Chi-Square

The AMOS output generates a Chi-Square of 182.990, with degrees of freedom of 137. The associated p-value is 0.005, which is much smaller than 0.05, implying the null hypothesis (the hypothesized model is correct) should be rejected at the 0.05 level. However, researchers have found critical limitations of using Chi-Square as a model fit index. Analysis of covariance is based on large sample theory; large samples are critical for obtaining precise parameter estimates and for achieving asymptotic distributional approximations (MacCallum, Browne, & Sugawara, 1996). Therefore, findings of well-fitting hypothesized models in which the Chi-Square approximates the degrees of freedom have proven unrealistic (Byrne, 2001). Schumacker and Lomax (1996) have also pointed out that Chi-Square is very sensitive to sample size—as sample size increases, the χ^2 test would have an tendency to generate a significant probability level and indicate a poor fit of the model. The χ^2 test is also believed to be sensitive to departures from multivariate normality of the observed variables (Schumacker and Lomax, 1996).

The first statistic introduced to address the limitation of Chi-Square is relative Chi-Square or normed Chi-Square, which is the Chi-Square/degrees of freedom ratio (Wheaton, Muthén, Alwin, & Summers, 1977). Compared with Chi-Square, relative Chi-Square is less sensitive to sample size. Different researchers have recommended ratios ranging from 2 to 5 as reasonable fit (Marsh & Hocevar, 1985). Carmines and McIver (1981), for instance, have recommended 2:1 to 3:1 as an acceptable range. Ullman (2001) suggests that 2 or less reflects good fit. Kline (1998) argues that 3 or less is acceptable. Wheaton et al. (1977) regard a ratio of approximately five or less "as beginning to be reasonable." Byrne (1989, p. 55) states with confidence that a ratio greater than 2 represents an inadequate fit.

The relative Chi-Square for the present study is 1.335, which is within any range recommended by researchers cited above. That indicates a good fit of the hypothesized model to the data.

4.3.1.2 Root Mean Square Error of Approximation (RMSEA)

RMSEA is a model fit index based on the non-centrality parameter. While most goodness-of-fit measures overestimate goodness-of-fit for small samples (n<200), RSMEA is relatively less sensitive to sample size than others (Fan, Thompson, & Wang, 1999). Generally, an RMSEA value of.05 or less indicates a close fit of the model in relation to the degrees of freedom and an RMSEA value of 0.08 or less indicates a reasonable error of approximation (Browne & Cudeck, 1992). The lower value of the 90% confidence interval should be small, ideally, close to zero, and the higher value of the 90% confidence interval should be less than .08.

The RMSEA value of the hypothesized model in this study is .041, which is less than the cutoff value of .05. The lower value of the 90% confidence interval is .023, which is small and the higher value of the interval is .056, which is also less than the recommended cutoff value of .08. All these indicate that the hypothesized model fits well to the data.

4.3.1.3 Normed Fit Index (NFI)

Normed Fit Index transforms Chi-Square into 0 (no fit) to 1.0 (perfect fit) range (Bentler & Bonett, 1980). As a rule of thumb, models with NFI indexes of more than 0.9 indicate acceptable model fits. This study yielded a NFI index of 0.929, which demonstrates a good model fit.

4.3.1.4 Tucker-Lewis Index (TLI)

Tucker-Lewis Index (Tucker & Lewis, 1973) was initially developed for factor analysis but later extended to the context of analysis of moment structures by Bentler and Bonett (1980). Thus, it is also known as Bentler-Bonett Non-Normed Fit Index (NNFI). TLI is one of the few goodness-of-fit indices that are relatively independent of sample size (Marsh, Bella, & McDonald, 1988). TLI usually falls between 0 and 1 and a value greater than 0.9 and close to 1.0 indicates a good fit. The TLI index in the present study is 0.976, which is very close to 1, indicating a very good model fit.

4.3.1.5 RFI, IFI, and CFI

Relative Fit Index (Bollen, 1986) was built upon Bentler and Bonett's NFI (1980) and the RFI incorporated sample size in its calculation. RFI ranges from 0 (no fit) to 1.0 (perfect fit). As a thumb of rule, a value greater than 0.9 and close to 1.0 indicates a good model fit. The RFI of this study is 0.912, which is very close to 1, indicating a good model fit.

Bollen's Incremental Fit Index (IFI, 1989b) ranges from 0 (no fit) to 1 (perfect fit) with a value greater than 0.9 indicating a very good fit. The IFI of the hypothesized model in this study is 0.981, indicating a very good model fit.

The Comparative Fit Index **(**CFI; Bentler, 1990) is essentially identical to the Relative Noncentrality Index (RNI**;** McDonald & Marsh, 1990). CFI imposes a penalty of one for every parameter estimated. CFI ranges from 0 to 1 and a value close to 1 indicates a very good fit. The research model of this study yields a CFI of 0.981, which indicates a very good fit of the model.

4.3.1.6 Bollen-Stine Bootstrap Adjusted p-value

Considering the fact that the data for this study are not multivariate normal and that the departure from multivariate normality may have inflated the Chi-Square and deflated the p-value, I requested AMOS to perform a Bollen-Stine bootstrap, which is a procedure developed by Bollen and Stine (1993) to assess the overall goodness of fit of the hypothesized model when the data are not multivariate normal. The null hypothesis of Bollen-Stine bootstrap is that the hypothesized model fits the data properly. A p-value larger than 5% is needed in order for the null hypothesis not to be rejected. I requested AMOS to conduct a Bollen-Stine Bootstrap procedure with 200 bootstrap samples. The procedure yielded a p-value of 0 .174, indicating the null hypothesis fits the data well and should not be rejected.

4.3.1.7 Summary of Model Fit

In summary, the results of a variety of goodness-of-fit indices, including Relative Chi-Square, RMSEA, NFI, TLI, RFI, IFI, CFI, and Bollen-Stine Bootstrap adjusted p-value, have all demonstrated a good fit of the hypothesized research model (Refer to Table 11).

4.3.2 Parameter Estimates and Hypothesis Testing

Maximum Likelihood (ML) is used for the estimation of coefficients. ML chooses estimates with the greatest likelihood of reproducing the observed data. In particular, it chooses estimates that maximize the likelihood that the observed covariances are drawn from a population assumed to be the same as reflected in the coefficient estimates (Pampel, 2000).

Variable	Effect	Variable	Estimate	S.E.	C.R.	P
EASE	←	RP	.126	.061	2.056	.040
EASE	←	RESO	.489	.078	6.271	***
EASE	←	EXPT	.193	.115	1.687	.092
ADVTG	←	COMP	.508	.065	7.756	***
ADVTG	←	RP	.207	.080	2.600	.009
ADVTG	←	e17	1.444	.097	14.891	***
ADVTG	←	EASE	.258	.118	2.193	.028
ADVTG	←	EXPT	.036	.135	.266	.790
ADVTG	←	RESO	-.062	.104	-.594	.552
BI	←	COMP	.254	.073	3.481	***
BI	←	RESO	.109	.097	1.117	.264
BI	←	RP	.307	.078	3.940	***
BI	←	e16	1.338	.096	13.870	***
BI	←	ADVTG	.537	.084	6.372	***
BI	←	EXPT	.001	.126	.009	.993
BI	←	EASE	.034	.111	.306	.759
EXPT2	←	EXPT	1.000			
EXPT1	←	EXPT	.683	.166	4.108	***
EASE1	←	EASE	1.000			
EASE2	←	EASE	1.095	.091	12.006	***
EASE3	←	EASE	1.195	.096	12.512	***
ADVTG1	←	ADVTG	1.000			
COMP2	←	COMP	.955	.057	16.684	***
COMP3	←	COMP	.565	.054	10.538	***
INT3	←	BI	1.000			
INT2	←	BI	1.044	.056	18.670	***
INT1	←	BI	1.062	.058	18.417	***
RP2	←	RP	1.000			
RP1	←	RP	1.302	.180	7.247	***
ADVTG3	←	ADVTG	.754	.067	11.208	***
RESO3	←	RESO	1.000			
RESO2	←	RESO	1.088	.093	11.653	***
RESO1	←	RESO	.823	.085	9.645	***
ADVTG2	←	ADVTG	.989	.058	17.105	***
COMP1	←	COMP	1.000			

Table 12: Parameter Estimates (Initial Research Model)

***: 0.000

← : Indicates the direction of effect

I report in Table 12 the parameter estimates of regression coefficients, standard errors, critical values, and p-values. The results indicate that the following hypotheses are not supported at the 0.05 level:

- H2a--Effect of Expertise on Perceived Ease of Use
- H2b--Effect of Expertise on Perceived Advantage
- H2c--Effect of Expertise on Behavioral Intention
- H1a--Effect of Resource Slack on Perceived Advantage
- H1b--Effect of Resource Slack on Behavioral Intention
- H5b--Effect of Perceived Ease of Use on Behavioral Intention

4.4 The Revised Model

The testing on the initial research model reveals that none of the hypotheses related to Expertise, which include hypothesis 2a, 2b, and 2c, is supported at 0.05 level. Also, two hypotheses about the effects of Resource Slack, that is, H1a and 1b, have failed to receive support. Perceived Ease of Use is also proved to only have an indirect effect on Behavioral Intention; the direct effect (H5b) has not been supported.

Therefore, I modify the research model by dropping the relationships that have failed to receive support from the data (see Figure 6).

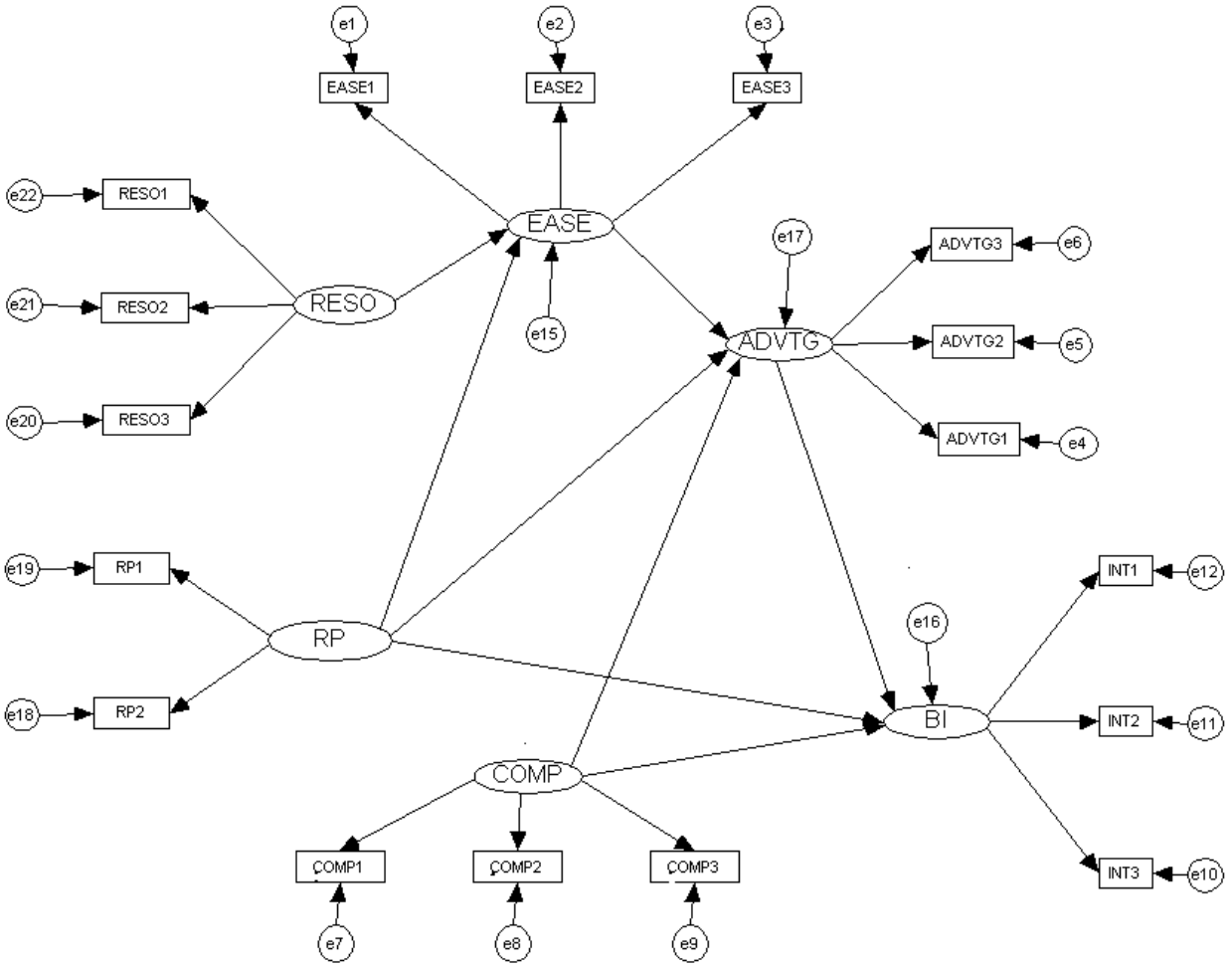

Figure 7: The Revised Model

4.4.1 Goodness of Fit

Table 13 presents a comparison of goodness of fit indices for the revised model and the initial model. The comparison demonstrates that the revised model maintains a very good model fit after dropping the Expertise variable and a few relationships related to resource slack and perceived ease of use, which were not supported in the initial model.

Fit Index	**Recommended Value**	**Result Initial Model**	**Result (Revised Model)**
Normed Chi Square	Chi-Square/df <=2 (Bollen, 1989a); 1.0 to 5.0 (Schumacker & Lomax, 1996).	1.335	1.42
Root Mean Square Error of Approximation (RMSEA)	<=0.08 (Browne & Cudeck, 1992); <0.05 (Schumacker & Lomax, 1996).	0.041	0.046
Normed Fit Index (NFI)	Value close to .9 reflects a good model fit (Schumacker & Lomax, 1996).	0.929	0.936
Tucker-Lewis Index (TLI)	The typical range for TLI lies between zero and one, but it is not limited to that range. TLI values close to 1 indicate a very good fit. Value close to .9 reflects a good model fit (Schumacker & Lomax, 1996).	0.976	0.975
Relative Fit Index (RFI)	Ranges from 0 to 1. Value greater than .9 reflects a very good fit	0.912	0.922
Incremental Fit Index (IFI)	Ranges from 0 to 1. Value greater than .9 reflects a very good fit.	0.981	0.98
Comparative Fit Index (CFI)	Ranges from 0 to 1. Value greater than .9 reflects a very good fit	0.981	0.98
Bollen-Stine Bootstrap p-value	p >0.05 indicates good model fit	0.174	0.124

Table 13: Comparison of Goodness-of-Fit Measures--Initial Model vs. Revised Model

4.4.2 Parameter Estimates and Hypotheses Testing

Table 14 is a summary of unstandardized ML estimates of regression coefficients, standard errors, critical values, and p-values. Those estimates indicate that, after dropping the relationships that are not significant in the hypothesized model, all of the remaining hypothesized relationships are supported at either 1% or 5% level (Table 14).

Hs	Variable	Effect	Variable	Estimate	S.E.	C.R.	P-value	Hypothesis Support
H3a	EASE	←	RP	.144	.062	2.308	.021	Supported
H1a	EASE	←	RESO	.541	.073	7.413	***	Supported
H5a	ADVTG	←	COMP	.504	.065	7.725	***	Supported
H3b	ADVTG	←	RP	.206	.079	2.611	.009	Supported
H6a	ADVTG	←	EASE	.226	.081	2.808	.005	Supported
H6b	BI	←	COMP	.261	.073	3.591	***	Supported
H3c	BI	←	RP	.337	.078	4.289	***	Supported
H4	BI	←	ADVTG	.563	.083	6.776	***	Supported
	EASE1	←	EASE	1.000				
	EASE2	←	EASE	1.088	.091	11.942	***	
	EASE3	←	EASE	1.207	.096	12.517	***	
	ADVTG1	←	ADVTG	1.000				
	COMP2	←	COMP	.953	.057	16.707	***	
	COMP3	←	COMP	.564	.054	10.533	***	
	INT3	←	BI	1.000				
	INT2	←	BI	1.044	.055	19.055	***	
	INT1	←	BI	1.059	.057	18.704	***	
	RP2	←	RP	1.000				
	RP1	←	RP	1.317	.173	7.627	***	
	ADVTG3	←	ADVTG	.758	.067	11.229	***	
	RESO3	←	RESO	1.000				
	RESO2	←	RESO	1.087	.095	11.445	***	
	RESO1	←	RESO	.829	.086	9.653	***	
	ADVTG2	←	ADVTG	.993	.058	17.084	***	
	COMP1	←	COMP	1.000				

Table 14: Unstandardized Regression Weights (Revised Model)

***: 0.000

← : Indicates the direction of effect

4.2.2.1 Effect of Decision Entity Factors

Resource Slack: Hypothesis 1a states that resource slack will positively affect an SME's perception of ease in implementing and using ODSC. The hypothesis is supported at the 0.001 level with a p-value of 0.000. Hypotheses 1b and 1c expect an SME's resources slack to exert a positive impact on perceived advantage and behavioral intention to adopt ODSC. Those two hypotheses failed in the testing on the initial research model and were excluded in the revised model.

Expertise in the Internet: I predict in Hypotheses 2a, 2b, and 2c that an SME's expertise in the Internet will have a direct as well as an indirect (with mediation of perceived ease of use and perceived relative advantage) effect on its behavioral intention to embrace the ODSC. The statistical test for any of the three hypotheses yields a p-value greater than 0.05, thus I have dropped them for further analysis in the revised model. A possible explanation that expertise has little direct or indirect effect on behavioral intention may be that an SME and its employees that have relatively more expertise in the Internet may have a better understanding of the complexity and problems associated with the Internet and e-commerce systems, and thus refrain from adopting such systems.

Risk Propensity: Hypotheses 3a, 3b, and 3c state that an SME's risk propensity will not only have a direct positive effect on its behavioral intention to adopt ODSC, but also have indirect positive effects on the SME's behavioral intention, with the mediation of its perception of relative advantage and ease of use of ODSC. All three hypotheses are strongly supported at the 0.05 or lower levels.

4.2.2.2 Effect of Decision Object Factors

Perceived Relative Advantages: In Hypothesis 4, I postulate that an SME's perception of the relative advantages of ODSC will positively influence its behavioral intention to adopt an ODSC. The p-value of 0.000 indicates that the hypothesis is strongly supported.

Perceived Ease of Use: Some earlier studies argue that perceived ease of use has both direct and indirect effects on behavioral intention to adopt a technology. However, this study has validated the claims by recent researchers (e.g., Gefen & Straub, 2000; Lee, 2004; Mollenkopf, et al., 2007; Yu, Ha, Choi, and Rho, 2005) that perceived ease of use tends to have only an indirect effect on behavioral intention, mediated through perceived relative advantage or perceived usefulness.

I hypothesized in the initial model for a direct (6b) as well as an indirect (6a) effect of perceived ease of use on behavioral intention. But the direct effect hypothesis was not supported in the initial model and thus dropped from the revised model. In the revised model, my prediction that perceived ease of use will have indirect impact on an SME's intention to adopt ODSC, with the mediation of perceived relative advantages, still holds. The hypothesis receives a p-value of 0.005 and thus is supported at the 0.01 level.

4.2.2.3 Effect of Decision Context Factor

Perceived Competitive Pressure: Influences from competitors have long been believed to be a factor underlying innovation adoption and diffusion. In this study, I posit through hypothesis 6a and 6b that an SME's perceived level of competitive pressure will not merely have a direct effect on its behavioral intention to adopt ODSC, but also have a indirect impact on its behavioral

intention, through the mediation of perceived relative advantages. Both hypotheses 6a and 6b are strongly supported with p-values of 0.000.

4.2.2.4 Standardized Estimates

It is controversial whether an unstandardized or standardized coefficient should be reported (Lomax, 1992). The standardized coefficients are believed to be sample-specific and are unstable across different samples because of changes in variance of variables. However, standardized coefficients are very useful in determining the relative importance of each variable to other variables (Schumacker & Lomax, 1996). Thus, I have reported the standardized estimates as well (refer to Figure 7).

The standardized estimates of the revised model as shown in Figure 7 include estimates of regression coefficients and squared multiple correlations. The squared multiple correlations for the dependent variable—Behavioral Intention to Embrace ODSC—is 0.54, which indicates that about 54% of its variance is accounted for by perceived relative advantages, resource slack, risk propensity, and perceived competitive pressure. The squared multiple correlations of BI in the initial model is also about 0.54. That indicates the variables and relationships that were not supported in the initial model and dropped from the revised model indeed contribute little to the explanation of the variance of the dependent variable.

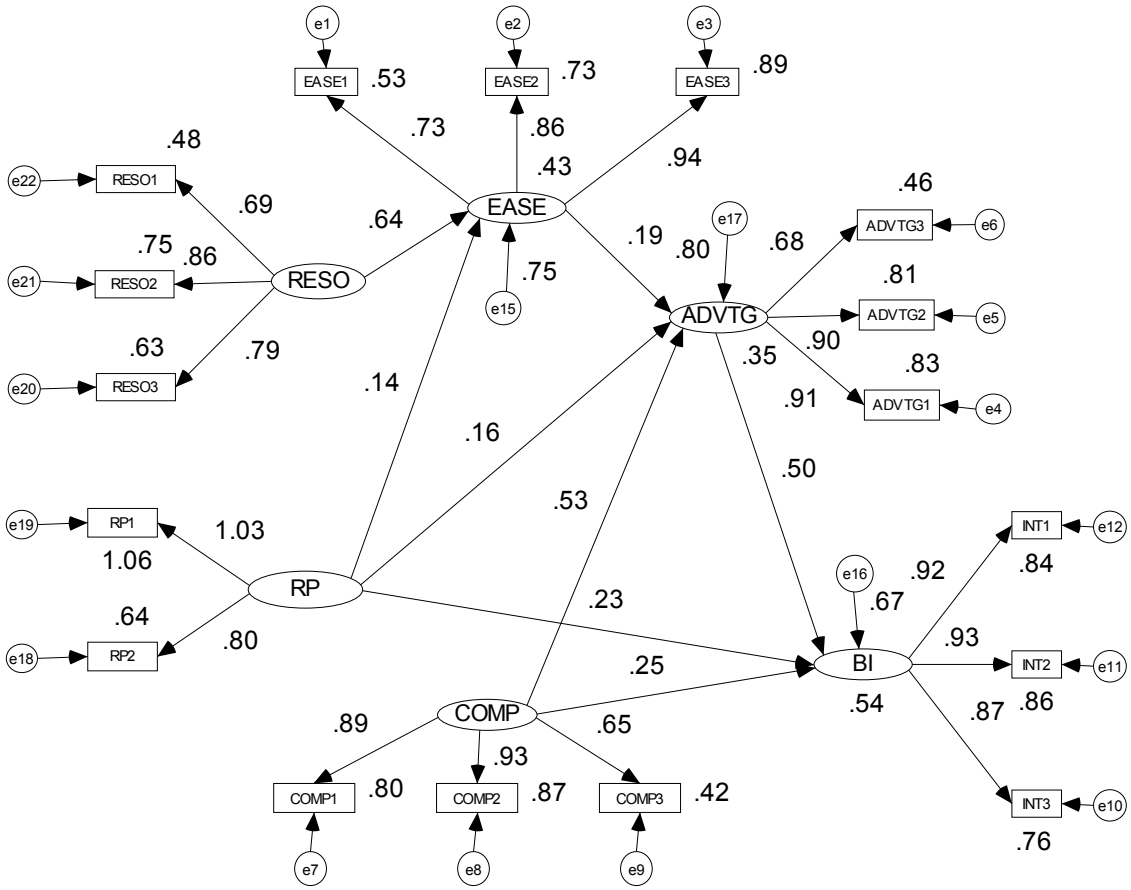

Figure 8: Standardized Parameter Estimates (Revised Model)

4.2.2.5 Bootstrapping Estimates

As discussed earlier, one commonly used approach for handling data that are not multivariate normal data in SEM is to use a procedure known as "bootstrapping" (West et al., 1995; Yung & Bentler, 1996; Zhu, 1997). The bootstrap procedure generates random sub-samples from the original sample and then calculates bootstrap estimates of regression weights and standard errors based on the sub-samples. The bootstrap estimators are then used to assess the reliability and stability of the ML estimates (Schumacker & Lomax, 1996). If the bootstrap estimates of regression coefficients and standard errors are similar to ML estimates of regression coefficients and standard errors, then the ML estimates can be interpreted without concerns that departures from multivariate normality have biased the calculation of parameters (Garson, 2007).

Refer to Table 15. The first column (SE) provides the bootstrap estimate of the standard error for the regression coefficient estimate. The Bootstrap standard error will be compared with ML standard error in the next section to determine the accuracy and stability of ML estimates of standard error.

The second column (SE-SE) lists the standard error of the bootstrap error. All the SE-SE values are very small, which indicates the stability of the Bootstrap estimate of the standard error.

The third column (Mean) provides the parameter estimate of means across the 200 bootstrap samples. This estimate may be different from the original ML estimate (Arbuckle & Wothke, 1999). But if there are only slight differences between the Bootstrap mean estimate and the ML estimate of regression coefficients, then we can conclude that the ML estimate has not been biased. The fourth column (Bias) is the difference between the bootstrap mean estimate and the original ML estimate, which, of course, is expected to be small so as to validate the ML estimate. The last column (SE-Bias) provides the standard error of the bias estimate.

Variable	Effect	Variable	SE	SE-SE	Mean	Bias	SE-Bias
EASE	←	RP	.073	.004	.144	.000	.005
EASE	←	RESO	.074	.004	.538	-.003	.005
EASE	←	e15	.110	.006	1.096	-.017	.008
ADVTG	←	COMP	.072	.004	.506	.002	.005
ADVTG	←	RP	.101	.005	.210	.004	.007
ADVTG	←	EASE	.098	.005	.227	.001	.007
ADVTG	←	e17	.088	.004	1.433	-.009	.006
BI	←	COMP	.096	.005	.260	-.001	.007
BI	←	RP	.103	.005	.340	.003	.007
BI	←	e16	.111	.006	1.332	-.022	.008
BI	←	ADVTG	.094	.005	.562	.000	.007
EASE1	←	EASE	.000	.000	1.000	.000	.000
EASE2	←	EASE	.103	.005	1.093	.005	.007
EASE3	←	EASE	.098	.005	1.218	.011	.007
ADVTG1	←	ADVTG	.000	.000	1.000	.000	.000
COMP2	←	COMP	.060	.003	.956	.003	.004
COMP3	←	COMP	.071	.004	.568	.005	.005
INT3	←	BI	.000	.000	1.000	.000	.000
INT2	←	BI	.058	.003	1.048	.004	.004
INT1	←	BI	.053	.003	1.060	.001	.004
RP2	←	RP	.000	.000	1.000	.000	.000
RP1	←	RP	.248	.012	1.347	.030	.018
ADVTG3	←	ADVTG	.066	.003	.757	-.001	.005
RESO3	←	RESO	.000	.000	1.000	.000	.000
RESO2	←	RESO	.109	.005	1.088	.000	.008
RESO1	←	RESO	.103	.005	.834	.005	.007
ADVTG2	←	ADVTG	.052	.003	.988	-.005	.004
COMP1	←	COMP	.000	.000	1.000	.000	.000

Table 15: Bootstrap Estimates (Revised Model)

← Indicates the direction of effect

The absolute values of bootstrap estimates as shown in Table 15 are less important. But the differences between the bootstrap and the ML estimates are crucial. They are useful in evaluating the stability and reliability of the ML estimates, particularly in case of departure from multivariate normality. Table 16 provides a comparison between the ML and Bootstrap estimates. The comparison reveals that the bias or the differences of regression weights between the ML and the Bootstrap estimates are all very small. In addition, the bootstrap S.E. estimates are also similar to the ML S.E. estimates. Therefore, we can conclude that there is no evidence that

departures from multivariate normality have biased the calculation of parameters. ML estimates are therefore trustable.

Hs	Variable	Effect	Variable	ML Estimate	Bootstrap Estimate	Bias	Bootstrap S.E.	ML S.E.
H3a	EASE	←	RP	.144	.144	.000	.073	.062
H1a	EASE	←	RESO	.541	.538	-.003	.074	.073
H5a	ADVTG	←	COMP	.504	.506	.002	.072	.065
H3b	ADVTG	←	RP	.206	.210	.004	.101	.079
H6a	ADVTG	←	EASE	.226	.227	.001	.098	.081
H6b	BI	←	COMP	.261	.260	-.001	.096	.073
H3c	BI	←	RP	.337	.340	.003	.103	.078
H4	BI	←	ADVTG	.563	.562	.000	.094	.083
	EASE1	←	EASE	1.000	1.000	.000		
	EASE2	←	EASE	1.088	1.093	.005	.103	.091
	EASE3	←	EASE	1.207	1.218	.011	.098	.096
	ADVTG1	←	ADVTG	1.000	1.000	.000		
	COMP2	←	COMP	.953	.956	.003	.060	.057
	COMP3	←	COMP	.564	.568	.005	.071	.054
	INT3	←	BI	1.000	1.000	.000		
	INT2	←	BI	1.044	1.048	.004	.058	.055
	INT1	←	BI	1.059	1.060	.001	.053	.057
	RP2	←	RP	1.000	1.000	.000		
	RP1	←	RP	1.317	1.347	.030	.248	.173
	ADVTG3	←	ADVTG	.758	.757	-.001	.066	.067
	RESO3	←	RESO	1.000	1.000	.000		
	RESO2	←	RESO	1.087	1.088	.000	.109	.095
	RESO1	←	RESO	.829	.834	.005	.103	.086
	ADVTG2	←	ADVTG	.993	.988	-.005	.052	.058
	COMP1	←	COMP	1.000	1.000	.000		

Table 16: Comparison of ML and Bootstrapping Results (Revised Model)

← Indicates the direction of effect

5. Discussion

SMEs have been a key contributor to national economies. Research focusing on the adoption and diffusion of information technologies among SMEs may not only enhance the awareness and use of those technologies among SMEs, but may point directly to the health and growth of a national economy.

The adoption and use of ODSC helps SMEs overcome their constraints in size and resources and compete with larger firms across the world. However, many SMEs still use their websites only as an advertising medium and few are ready for moving to e-commerce (Fisher et al., 2007). Based on a sample of 202 SMEs, this dissertation reveals that a total of 61 percent of SMEs is not using the Internet as a sales channel—among which 59 percent have never used the Internet as a sales channel and 2 percent of SMEs have once sold on the Internet but have stopped the practice.

The study demonstrates that risk propensity (a DE factor) significantly impacts an SME's behavioral intention to embrace ODSC. The finding is consistent with those of earlier studies (e.g., Keil & Wallace, 2000) on the relationship between risk propensity and organizational decisions on IT adoption and investment. In addition to a direct effect on behavioral intention, risk propensity is also found to influence an SME's decision to embrace the ODSC indirectly, through the mediation of DO factors--perceived relative advantage and perceived ease of use.

Resource slack is another DE factor found to impact an SME's behavioral intention to adopt ODSC. However, unlike earlier studies (e.g., Aiken & Hage, 1971; Cragg & King, 1993; Damanpour, 1991; Lee, 2004) that suggested direct relationship between resource slack and

adoption (or behavioral intention to adopt), this study reveals only an indirect effect of resource slack on behavioral intention, with the mediation of perceived ease of use.

I have found no evidence in this study that expertise in the Internet has any significant impact, direct or indirect, on an SME's behavioral intention to embrace the ODSC, despite the fact that some earlier studies (e.g., Dubelaar, Sohal, & Savic, 2005; Lucchetti & Sterlacchini , 2004) did reveal a positive effect of knowledge and expertise on the adoption and diffusion of computer-related systems.

Regarding the two DO factors--perceived relative advantage and perceived ease of use--this study has validated findings of some recent works (e.g., Lee, 2004; Mollenkopf, Rabinovich, Laseter, & Boyer, 2007; Yu, Ha, Choi, & Rho, 2005) that, while value-oriented variables such as perceived relative advantage directly impact behavioral intention, perceived ease of use only has an indirect effect on behavioral intention, with the mediation of perceived relative advantage.

Competitive pressure, a DC factor, has been found in numerous studies (Barnes, Hinton, & Mieczkowska, 2003; Dholakia and Kshetri; 2004; Dubelaar, Sohal, & Savic , 2005; Dos Santos and Peffers, 1998; Zhu, Kraemer, Xu, & Dedrick, 2004; Sandy & Graham, 2007) to have an significant impact on the adoption of E-commerce. This study has further validated such findings: it reveals that competitive pressure not merely directly influence an SME's behavioral intention to embrace the ODSC, but also indirectly affect behavioral intention with the mediation of perceived advantage.

5.1 Implications for Research and Practice

This dissertation has made several major contributions to academic research in innovation adoption and diffusion. First, the classification model provides a simple but robust framework for categorizing existing factors in the literature. It will also be useful for guiding the

identification of new factors in future IS adoption studies. Second, the research model on the adoption of ODSC by SMEs, which is proposed and empirically tested in this dissertation, will not only enhance our knowledge of the pattern of SMEs' adoption of ODSC, but also improve our understanding of SMEs' adoption and use of IS innovations in general. Third, the measures that I have developed and validated for this dissertation may be useful for future studies of adoption and diffusion of IS innovation, particularly the adoption of Internet related technologies. Finally, the study may trigger interests among researchers in Online Direct Sales Channel and topics related to Internet channel such as Internet channel strategies and Internet channel conflict management.

This dissertation has significant implications for practice as well. The examination of ODSC adoption among SMEs provides empirical evidence regarding what drive the adoption and use of ODSC among SMEs, which in turn, will help facilitate better decision-making by managers of electronic market service providers, e-Commerce system developers, and policy-makers of relevant governmental agencies to stimulate the use of ODSC among SMEs.

The findings of the study imply that, to accelerate the adoption and diffusion of the ODSC among the ODSC, e-Business systems developers and small business governing agencies should first focus on strategies that enhance and publicize the ODSC's values and advantages (in particular, economic values and process efficiency) to small businesses.

E-Business systems vendors may also analyze and profile potential SME clients based on their resource availability, risk propensity, and competitive situation, and accordingly, determine their marketing strategies.

In addition, the findings of this study provide SMEs with an overall picture of the use of the ODSC by other SMEs, which may eventually influence their own decisions in the future on the adoption and use of ODSC.

5.2 Limitations

Some limitations of this study must be pointed out. First, the study relies on a single informant of each participating SME for information. A possible problem that may result from that is single-informant bias: the responses provided by the informant may not fully represent the perspectives of the whole organization. Considering the fact that SMEs are less complex and that owners and high-profile managers who are used as informants of the study are generally knowledgeable about their organizations, the single-informant bias should not be a serious issue in this study, except for a few questions in the survey that are related to senior managers, such as the questions that explore senior managers' expertise in the Internet and their risk propensity. In those cases, the scores are likely to be inflated, but such inflation is systematic and should not result in biases that affect the construct relationships in the research model.

Second, the sample of SMEs used for this study is drawn from a single state of the United States. That may limit the generalizability of findings of the study. My concerns about generalizability is eased a little by the fact that Ohio's SMEs seem not to be significantly different from the overall US SMEs, at least in terms of industry and firm size distributions (Table 17). Anyhow, future studies that use a sample drawn from different regions or even different countries will be meaningful in assuring generalizability and facilitating comparison of SMEs in different regions or countries.

	<500 Employees			
	Percent of Employer Firms		Employment	
	Ohio	US	Ohio	US
Total	98.3%	99.7%	49.3%	50.7%
Agriculture	0.2%	0.4%		
Mining	0.3%	0.3%	0.1%	0.2%
Utilities	0.1%	0.1%		
Construction	12.4%	12.5%	4.0%	4.8%
Manufacturing	6.8%	5.1%	7.4%	5.4%
Whole sales trade	5.8%	5.9%	3.0%	3.2%
Retail sales trade	11.9%	12.7%	5.2%	5.6%
Transportation and warehousing	2.8%	2.8%	1.2%	1.4%
Information	0.9%	1.3%	0.5%	0.8%
Finance and insurance	4.4%	4.2%	1.6%	1.8%
Real estate, and rental and leasing	3.6%	4.7%	1.0%	5.6%
Professional, scientific, and technical services	10.8%	12.3%	3.3%	4.0%
Management of companies and enterprises	0.4%	0.4%	0.3%	0.3%
Admin, support, waste mgt	5.3%	5.1%	2.8%	3.1%
Educational services	1.1%	1.2%	1.1%	1.2%
Health care and social assistance	9.6%	9.9%	7.1%	6.6%
Arts, entertainment, and recreation	1.7%	1.8%	1.0%	1.1%
Accommodation and food services	7.8%	7.6%	5.3%	5.6%
Other services	12.9%	11.6%	4.2%	4.1%

	<100 Employees			
	Percent of Employer Firms		Employment	
	Ohio	US	Ohio	US
Total	95.9%	98.2%	34.4%	36.2%
Agriculture	0.2%	0.4%	0.0%	0.0%
Mining	0.3%	0.3%	0.1%	0.1%
Utilities	0.1%	0.1%		
Construction	12.3%	12.4%	3.4%	3.9%
Manufacturing	6.3%	4.8%	4.1%	3.2%
Whole sales trade	5.5%	5.7%	2.2%	2.3%
Retail sales trade	11.7%	12.5%	4.1%	4.5%
Transportation and warehousing	2.7%	2.7%	0.9%	1.0%
Information	0.8%	1.3%	0.4%	0.5%
Finance and insurance	4.3%	4.1%	1.2%	1.2%
Real estate, and rental and leasing	3.6%	4.6%	0.8%	1.0%
Professional, scientific, and technical services	10.6%	12.2%	2.6%	3.1%
Management of companies and enterprises	0.2%	0.2%	0.1%	0.1%
Admin, support, waste mgt	5.1%	5.0%	1.7%	1.8%
Educational services	1.1%	1.1%	0.7%	0.7%
Health care and social assistance	9.2%	9.7%	4.0%	4.1%
Arts, entertainment, and recreation	1.7%	1.8%	0.7%	0.7%
Accommodation and food services	7.6%	7.4%	3.9%	4.2%
Other services	12.8%	11.5%	3.7%	3.5%

Table 17: Comparison of Ohio and US SMEs
Source: SBA (2006b).

Third, the data for the study are collected through an online survey. A general limitation of an online survey is that potential participants that do not have Internet access are systematically excluded from the sample. The survey for the present study is conducted on the Internet and participants are invited through emails, therefore, the sample systematically excludes those SMEs whose owners or high-level managers (potential informants of the study) do not have email and Internet access. However, given the fact that email and Internet penetration rates are extremely high in the United States and the fact that the informants of the survey are business owners or high-rank managers, the likelihood that they do not have email and Internet access is slim. So this issue should not significantly bias the sample.

Fourth, the study cannot totally eliminate the possibility of non-response bias. But the wave analysis results demonstrate that severe non-response bias is unlikely.

Finally, the effects of firm size and industry were not incorporated in the structural equation model of this research. Since significant differences may exist between SMEs of different sizes and industries (Johnston & Wright, 2004), future research should incorporate those variables in the research model and examine the differences across different industry and size groups of SMEs.

5.3 Future Research

The present study can be extended in several aspects in future research: First, the Classification Model can be used as a guiding framework in future research to identify critical factors underlying adoption of specific types of information technologies.

The current study investigates the adoption and use of ODSC among all SMEs. A future study can focus on the adoption of ODSC by small manufacturing firms only. Such a study will be particularly interesting and meaningful if it is conducted from the DC perspective. Small

manufacturing firms tend to face a variety of external pressures and influences that may eventually shape their ODSC adoption decision. In addition to competitive pressure, for example, small manufacturing firms face influences from distributors and customers. Small manufacturing firms may choose not to adopt an ODSC just because they are concerned about possible retaliation from their traditional distributors, on which they may have relied for years to sell their products. They may also be compelled by larger customers to adopt some e-Commerce technologies that they have no needs for.

The present study has revealed that about 2% of SMEs used ODSC in the past but has stopped the practice. A future study is needed to explore the reasons and rationales behind those SMEs' abandoning of ODSC. Because only a small percentage of SMEs once abandoned ODSC, it will be challenging to obtain a large sample and conduct a quantitative study. A good alternative is to run a qualitative study, in which a few SMEs that have once abandoned ODSC are contacted and studied in great depth through interviews or other qualitative methodologies.

The level of sophistication of ODSC has not been considered in this dissertation. The only requirement for ODSC is that the sales transactions are done on the Internet. But using ODSC may involve different levels of sophistication. While some SMEs adopt only rudimentary e-commerce technologies that can carry out only sales transactions, other SMEs may have adopted a well-integrated e-business technology that can facilitate a variety of business functions such as order taking, order tracking, e-payment, and post-sales customer service. Therefore, a future study is needed to explore the determinants of sophistication of ODSC use among SMEs.

SMEs' past experiences in ODSC (e.g., some of them has never experienced ODSC; others experienced in the past but for some reasons have stopped the practice; still others are currently experiencing ODSC) may have an effect on their behavioral intention to embrace or

continue to embrace ODSC. An empirical study modeling such effects will be useful in understanding SMEs' organizational behavior in technology adoption and investment.

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Appendices

Appendix 1: Initial Invitation Email Message

We are assisting with a study on the use of E-Commerce technologies by small and medium-sized firms. Findings of the study will enable us to better understand the factors underlying the adoption of those technologies among small businesses.

To obtain data for this project, we invite you to complete an online survey. There is no right or wrong answer to any of the question in the survey. Whether you are intending to use the Internet as a sales channel or not, your responses will be of equal importance for the research.

The survey takes about 10 minutes to complete. All the data we collect in the survey are for academic research only; they will not be shared with any third party. User or firm identifiable information will not be disclosed in any manner. In appreciation of your participation in the survey, we will provide you with a summary of findings of the survey upon completion of the project.

Please help us by clicking the link below and completing the survey by_____.

http://websurveyor.net/wsb.dll/10978/E-commerce.htm

Sincerely,

John Doe

Director of XYZ SBDC

E-Mail: john.doe@xyz.org

Tel: 123-456-7890

Appendix 2: 1st Reminder Message

We would like to remind you to take the survey on the use of E-Commerce technologies among small and medium-sized enterprises (SMEs). This is a large-scale research initiative being conducted simultaneously in different regions of the State of Ohio. Findings of the study will enable us to better understand the critical factors that affect SMEs' adoption and use of E-Commerce technologies. It will also provide you with information about what Internet technologies other SMEs have been using and what technologies your organization may need to achieve competitiveness.

The survey takes only about 10 minutes to complete. In appreciation of your participation, we will provide you with a copy of the findings of the survey upon completion of the project.

Please help us by clicking the link below and completing the survey by _____.

http://websurveyor.net/wsb.dll/10978/E-commerce.htm

Sincerely,

John Doe

Director of XYZ SBDC

E-Mail: john.doe@xyz.org

Tel: 123-456-7890

Appendix 3: 2nd Reminder Message

This is the final reminder for you to take the survey on the use of E-Commerce technologies among small and medium sized enterprises (SMEs). This is a large-scale research initiative being conducted simultaneously in different regions of the State of Ohio. Findings of the study will enable you to better understand what Internet technologies other SMEs' have been using and what technologies your organization needs to achieve competitiveness.

The survey takes only about 10 minutes to complete. In appreciation of your participation, we will provide you with a copy of the findings of the research upon completion of the project. All data collected from this survey will be strictly kept confidential.

Please click the following link to activate the survey:

http://websurveyor.net/wsb.dll/10978/E-commerce.htm

Sincerely,

Sincerely,

John Doe

Director of XYZ SBDC

E-Mail: john.doe@xyz.org

Tel: 123-456-7890

Appendix 4: Survey Instruction

More and more small and medium-sized businesses are using the Internet to penetrate new markets in which to sell their products/services. We are interested in better understanding the role that E-commerce plays in these activities.

In order to do this, we are conducting a survey on the use of E-Commerce technologies by small and medium-sized enterprises (SMEs). We would like you to participate in this research by completing this Internet-based survey.

All survey responses are anonymous. Neither you nor your company will be identified in any way.

As a participant, you will receive a copy of summary of the study. Whether you are already using or are considering using the Internet to sell your products/services, the results of this survey should prove helpful.

Appendix 5: Scales and Measures (Non-Adoption Group)

Decision Object Factors

Perceived Relative Advantage

Rated from 1=Strongly Disagree to 7=Strongly Agree

ADVTG1--Selling online will increase our overall sales revenues.

ADVTG 2-- Selling online will bring us additional profits.

ADVTG 3--Selling online will help improve our ordering process.

Perceived Ease of Use

Rated from 1=Strongly Disagree to 7=Strongly Agree

PEU2-- Obtaining an e-commerce website to sell our products/services will be easy

PEU3-- Training competent personnel to support an e-commerce system will be easy.

PEU4--Maintaining an e-commerce website will be easy for our firm.

Decision Entity Factors

Expertise in Internet

Scale: 1=Novice, 4=Competent, 7=Expert.

Rate the level of expertise your managers and employees have in the Internet

Managers:	1	2	3	4	5	6	7
All Other Employees	1	2	3	4	5	6	7

Resource Slack

Rated from 1=Strongly Disagree to 7=Strongly Agree

RESO1--Our firm already has a pretty good business website.

RESO2--We have the resources necessary to build an e-commerce website.

RESO3--We have the IT personnel necessary to maintain an e-commerce website.

Risk Propensity

Rated from 1=Strongly Disagree to 7=Strongly Agree

RP1--Our firm is usually willing to take risks

RP2--Our senior managers are willing to take risks

Decision Context Factor

Perceived Competitive Pressure

Rated from 1=Strongly Disagree to 7=Strongly Agree

COMP1--Most of our competitors sell online.

COMP2--Our main competitors are already selling successfully online.

COMP3--Our main competitors are seizing our market share.

Behavioral Intention to Adopt ODSC

Rated from 1=Strongly Disagree to 7=Strongly Agree

BI1--Our firm intends to sell products/services on the Internet within the next two years.

BI2--I predict my firm will start to sell products/services on the Internet within the next two years.

BI3--Our firm plans to sell products/services on the Internet within the next two years

Appendix 6: Scales and Measures (Adopt-and-Abandon Group)

Decision Object Factors

Perceived Relative Advantage

Rated from 1=Strongly Disagree to 7=Strongly Agree

ADVTG1--Selling online again will increase our overall sales revenues.

ADVTG 2-- Selling online again will bring us additional profits.

ADVTG 3--Selling online again will help improve our ordering process.

Perceived Ease of Use

Rated from 1=Strongly Disagree to 7=Strongly Agree

PEU2-- Obtaining an e-commerce website to sell our products/services will be easy

PEU3-- Training competent personnel to support an e-commerce system will be easy.

PEU4--Maintaining an e-commerce website will be easy for our firm.

Decision Entity Factors

Expertise in Internet

Scale: 1=Novice, 4=Competent, 7=Expert.

Rate the level of expertise your managers and employees have in the Internet

Managers:	1	2	3	4	5	6	7
All Other Employees	1	2	3	4	5	6	7

Resource Slack

Rated from 1=Strongly Disagree to 7=Strongly Agree

RESO1--Our firm already has a pretty good business website.

RESO2--We have the resources necessary to build an e-commerce website.

RESO3--We have the IT personnel necessary to maintain an e-commerce website.

Risk Propensity

Rated from 1=Strongly Disagree to 7=Strongly Agree

RP1--Our firm is usually willing to take risks

RP2--Our senior managers are willing to take risks

Decision Context Factor

Perceived Competitive Pressure

Rated from 1=Strongly Disagree to 7=Strongly Agree

COMP1--Most of our competitors sell online.

COMP2--Our main competitors are already selling successfully online

COMP3--Our main competitors are seizing our market share.

Behavioral Intention to Adopt ODSC

Rated from 1=Strongly Disagree to 7=Strongly Agree

BI1--Our firm intends to sell products/services on the Internet again within the next two years.

BI2--I predict my firm will start to sell products/services on the Internet again within the next two years.

BI3--Our firm plans to sell products/services on the Internet again within the next two years.

Appendix 7: Scales and Measures (Adoption Group)

Decision Object Factors

Perceived Relative Advantage

Rated from 1=Strongly Disagree to 7=Strongly Agree

ADVTG1-- Selling online has helped increase our overall sales revenues.

ADVTG 2-- Selling online has brought us additional profits.

ADVTG 3-- Selling online has helped improve our ordering process.

Perceived Ease of Use

Rated from 1=Strongly Disagree to 7=Strongly Agree

PEU1-- Implementing an e-commerce website was easy for our firm.

PEU2-- Training personnel to manage our online sales has been easy for our firm.

PEU3-- Maintaining the e-commerce website has been easy for our firm.

Decision Entity Factors

Expertise in Internet

Scale: 1=Novice, 4=Competent, 7=Expert.

Rate the level of expertise your managers and employees have in the Internet

Managers:	1	2	3	4	5	6	7
All Other Employees	1	2	3	4	5	6	7

Resource Slack

Rated from 1=Strongly Disagree to 7=Strongly Agree

RESO1--Our firm already has a pretty good business website.

RESO2-- We have the resources necessary to run our e-commerce website.

RESO3-- We have the IT personnel necessary to maintain an e-commerce website.

Risk Propensity

Rated from 1=Strongly Disagree to 7=Strongly Agree

RP1--Our firm is usually willing to take risks

RP2--Our senior managers are willing to take risks

Decision Context Factor

Perceived Competitive Pressure

Rated from 1=Strongly Disagree to 7=Strongly Agree

COMP1--Most of our competitors sell online.

COMP2--Our main competitors are already selling successfully online

COMP3--Our main competitors are seizing our market share.

Behavioral Intention to Continue to Use ODSC

Rated from 1=strongly Disagree to 7=Strongly Agree, Reverse Scored

BI1-- Our firm will stop selling on the Internet in the next two years.

BI2-- Our firm intends to reduce our online selling efforts in the two years.

BI3-- Our firm will stop selling on our own website in the next two years.

Appendix 8: Additional Questions in the Pilot Study

We would appreciate any comments you may have about the questionnaire. Please briefly answer the following questions to provide your opinion about the questionnaire.

- About how much time did it take you to complete the survey?
- Is the length of the survey reasonable?
- Are the survey questions clear and easy to understand? If not, please explain.
- Are the questions relevant to your decision on selling online?
- Are there any other factors that affect your decision on selling on the Internet but the survey has failed to include?
- All other comments: