An empirical investigation of the adoption behavior of technological service innovation

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Abstract

This study examines the adoption propensity of 379 randomly selected American firms. Inquiry is made regarding organizational and managerial determinants of these firms. Two primary questions are addressed. Can the categorization of technology adopting firms be classified? Second and foremost, which behavioral determinants are the most effective in differentiating between the adopters and non-adopters of technology service innovations? An Artificial Neural Network is selected as the statistical method because of the different perspective it provides for a highly non-linear function having many variables. It also offers results that consistently prove to numerically approximate such functions more easily than conventional methods, together with the ability to dependably and accurately classify adoption membership while providing weighted analyses of input variables. Findings suggest that each group's propensity can be consistently and accurately identified and further suggest which determinants dominantly impact category membership as supported by differences in the feature extraction phase of the neural network approach.

Keywords: innovation, adoption, service technology, neural networks

INTRODUCTION

The adoption and diffusion of innovations is a theme that has been widely studied across a broad continuum of disciplines, including social science, marketing, engineering and management. While the literature on innovations and their adoption is extensive (Rogers, 1983), relatively few studies focus on the adoption of technology services. Since the early computerization of accounting transactions in the 1950s, high-technology innovations have become increasingly widespread in industrial organizations. And while substantial literature exists on organizational innovation in general, it has only recently been extended to technological innovations in particular (Tornatsky and Fleischer, 1990). Furthermore, not only has there been a void in the adoption patterns of technology services in the text, there has also been an obvious omission of any sophisticated statistical approaches to the analysis of adoption propensity patterns or adoption rates to revenue performance.

A similar situation has evolved with regard to inquiry on the marketing issues related to these innovations. As noted by Jackson et al. (1995), marketing to industry is essentially different from marketing to consumers. The organizational buying process is more complex, takes place over a longer period of time, and is influenced by a greater number of forces both inside and outside the buyer firm (Gupta and Rogers, 1991). In addition, the service nature of the marketing effort is also different than that of the tangible good.

Therefore, the intent of this study is to (1) examine various frequencies and descriptives of technology service adoption; (2) confirm that the innovation adoption of technology services can be classified; and (3) identify managerial determinants that influence the adoption of technological services.

THEORETICAL UNDERPINNINGS

There are numerous studies in the literature regarding typical product adoption patterns, however technological innovation literature is less replete. Foster (1982) suggests that different approaches are necessary when adopting discontinuous innovations. Smith (2009) for example, contends that the appropriate approach to high-tech marketing should be focused more on the solution the technology provides rather than the technology's feature and benefits. Furthermore, the service component of the technology product must highlight value added, visible to late adopters, if widespread adoption is to occur.

Simpson and Docherty (2004) offer specific rationale explaining the reasons for barriers to technology adoption in small and medium sized organizations. The internal barriers include: management resistance, technology concerns, resource issues, lack of awareness, lack of information, and market orientation. This final barrier, market orientation, has had notable research over the last 20 years, (Kohli and Jaworski 1990; Narver and Slater1990), while work by Chang and Chen, (1998) addressed technological innovation in the service sector.

Chong (2001) provides insight into the external environment factors likely to influence the adoption of technology oriented products. These include: government influences, environmental uncertainty, issues related to infrastructure, pressure from trading partners, industry-specific competitive pressures, critical mass, and accepted industry standards. In markets where competition is fierce, elasticities of demand are going to be higher due to the availability of close substitutes, therefore having the ability to control future innovative behaviors within the firm (Majumdar and Venkataraman, 1993).

The diffusion of technology does not occur at a similar rate to tangible products. There are several general models that address this phenomenon. The first model speaks to the amount of information that exists with the technology and how easily it can become available. The second model deals with the technology's differences, goals and capabilities. The final model examines density dependence that considers diffusion as the result of legitimization and competition (Rogers, 1995).

Perceptions of innovation features and socioeconomic distinctiveness have been asserted as determinants of technological innovation adoption (Gatignon and Robertson, 1985; Labby and Kinnear 1985). The decision to use a new technology is determined by the extent to which the user believes it is cost effective, either with goods or services. Perceived benefits are conceptually analogous to relative advantage, which is defined as "the degree to which an innovation is perceived better than the idea it supersedes" (Rogers 1985; p. 212). Past studies have found that relative advantage has a significant impact on the adoption rates of many technological innovations (Tornatzky and Klein, 1982).

Recent Studies of Firm-Based Innovation Adoption

Wu, Mhajan and Balasubramanian (2003) found top management emphasis, learning ability, customer power, and normative pressures to be significant determinants for predictive value for e-business adoption in communication. They also established that in internal administration, customer orientation and normative pressures are two significant antecedents to e-business. For online order taking, the significant antecedents were top management emphasis and normative pressures. An organization's learning ability and normative pressures were found to be significant antecedents of e-procurement.

A study of electronic commerce adoption in New Zealand businesses found evidence of an incipient exploitation of EC technology on a local level. The study surmised that both adopting firms and those that do not adopt EC technologies are separated by a number of noteworthy differences. Among these differences are that the adopters trend to be more proactive, more aware of the various opportunities afforded by new technology, more centered on the customer and more receptive to changes taking place in customer/competitive environments. Non-adopters were found to have negative attitudes towards EC, the prevailing belief being that numerous barriers exist preventing them from selling their goods and services online. These companies are also slower in detecting changes in technologies that might have an effect on the firms' business (McCole and Ramsey, 2005).

Slow adoption of a product has been linked to high introductory prices and uncompetitive products of low quality. A company may also be slow in adopting a product due to failure to develop niche markets. Consumer resistance to an innovation is another reason, and this can happen because of a conflict between innovation, on the one hand, and consumers' ingrained belief structures, that requires acceptance of unfamiliar routines or the abandonment of deep-rooted traditions. When consumer barriers to an innovation permeate an entire industry, a coopetition marketing strategy may be the best choice for overcoming this resistance. The coopetive marketing strategy sends consumers a signal of serious, permanent changes in products or services, which then serve to reduce consumers' psychological switching costs (Garcia, Bardhi and Friedrich, 2007).

Quaddus and Hofmeyer (2007) discovered significant statistical evidence that points to a positive relationship between awareness of innovation and the influence of the vendors of B2B trading exchanges in the context of small businesses in Western Australia. The study found that small business organizational characteristics are likely to exert an influence on the business' attitude towards adopting a B2B trading exchange. The study asserted that awareness is a considerable perception or belief factor. Specifically, it found that vendors of an innovation influenced the awareness of an innovation.

Two types of institutional forces, coercive and normative, have significant influence on attitude and intention to use Internet banking. The results indicate that this technology service can benefit from social influences that could result in potential customers jumping on the bandwagon. In order to create normative expectations, banks may need to construct an IB user base and develop referral champions. With respect to coercive forces, banks can make certain services available only on the Internet and provide enticements and rewards for IB users (Shi, Shambare, and Wang, 2008).

In a study of IT adoption by Chinese companies, evidence suggested that government can have a significant influence on firms' IT infrastructure construction and management, but it cannot directly influence firms' IT usage. The value creation process of firms' informatization may be thought of in several phases. The first phase is that of IT infrastructure construction. Companies use IT application systems to support their business and management, thus realizing the value of IT. Not unexpectedly, management has an important role in a company's IT usage. (Cui, L., Zhang, C., Zhang, C., Huang, 2008).

Brand and Huizingh (2008) studied the factors impacting e-commerce adoption in small and medium-sized enterprise. The authors pointed out that explicit knowledge plays a much more important role when the innovation is new to the company than when the company has accumulated hands-on experience with the innovation. One conclusion is that knowledge is more weakly linked to adoption intention for firms at the advanced level. The same should be true of satisfaction.

When analyzing e-commerce adoption among SME's in the UK, the following findings were made: Internal pressures, such as those from family and friends, seemed to be more significant determinants of adoption than competitive pressures. E-commerce adoption was credited with the ability of rescuing struggling businesses. The study found that SMEs need support and advice for e-commerce. Typically government, while having an opportunity to exploit the demand, may be reluctant to do so, or is otherwise burdened by the bureaucracy inspired by the old Business Link formula (Simpson and Docherty, 2004).

Behavioral Determinants of Decision Making

The behavioral theory of the firm was developed by Cyert and March (1963), furthering earlier work by Simon (1955, 1959). This theory is an interpretation and explanation of how businesses make economic decisions. Cyert and March believe that a firm's behavior reflects the managers who control the firm. Individual decision-makers pursue different goals for different purposes. Decision constraints lead to alternative choices and expected outcomes. Decisions made by managers vary depending on the particular situation (Anderson, 1982). Four components from the behavioral theory of the firm are used for the basis of this study. These components are commonly cited characteristics of internal activities and motivations driving innovation adoption.

First suggested in the behavioral theory of the firm is the awareness of firm competencies and advantages. Specifically, managerial awareness about the organization's differential advantages acts as a catalyst for decision behavior. Particular advantages studied include the firm's product, managerial knowledge, sales volume, and firm size (employees, assets, or sales). The second component of the theory states that aspiration levels of management are a primary element of organizational behavior. Studies (Siegel, 1957; Atkinson, 1957; Cyert & March, 1963) empirically associate varying levels of risk-taking and aggressiveness by decision makers of the firm with managerial aspirations. The third general determinant category derived from the behavioral theory of the firm is management's expectation of business activity. Cyert and March (1963) further assert that expectations directly influence behavior. Early empirical work regarding expectations focused on profitability, growth, and their relationship in determining innovation adoption outcomes.

The final component derived from the behavioral theory of the firm is resource allocation, more commonly referred to as managerial commitment. Managerial commitment often determines organizational behavior in several areas, such as budgetary focus, search behavior, uncertainty avoidance and organizational learning. The independent variables used in this study reflect the behavioral drivers primarily established from the theory of the firm (see Table 1). Studies continue to follow the foundational works cited here.

As a precursor for decision making and risk taking, Cyert and March's work, along with others, has continued to be examined in the context of organization expansion and best practice behavior. The characteristics displayed by organizational leaders suggest a common underpinning of behavior that all successful and influential leaders display, with respect to organizational development and expansion. Although the innovation adoption literature is substantive, few studies have examined the managerial motivations of behavior in a contemporary context with the Theory of the Firm.

TABLE 1
INDEPENDENT VARIABLES

DIFFERENTIAL FIRM ADVANTAGES	
Unique Product	DA_UP
Management Strength	DA_MS
Capital Investment	DA_CI
Sales Volume	DA_SV
Employee Size	DA_ES
MANAGERIAL ASPIRATIONS	
Aspirations for Growth	A_G
Aspirations for Profit	A_P
Aspirations for Efficiency	A_E
Aspirations for Security of Markets	A_SM
MANAGERIAL EXPECTATIONS	
Expectations for Growth from Innovation	E_GI
Expectations for Profit from Innovation	E_PI
Expectations for Efficiency from Innovation	E_EI

Expectations for Security of Markets from Innovation	E_SMI
MANAGERIAL COMMITMENT	
Commitment to New Business Processes	C_NBP
Commitment to Expanding Market Share	C_EMS
Commitment to Development of New Markets	C_DNM
Commitment to a Formal Innovation Adoption Policy	C_FIP
Commitment to being an Early Adopter	C_EA

METHODOLOGY

The specific population examined in this study is organizations doing business in Atlanta, Georgia, regardless of revenue size, asset size, employee size, or industry sector. Firms whose headquarters were known to be outside the survey area were not approached. Included with the questionnaire was a letter of introduction explaining the purpose of the survey, information regarding informed consent, and details of a response incentive. During a four-week response period, 1168 surveys were delivered with 386 surveys returned (33%). Of the responses, seven were considered unusable, generating a net usable result of 379. The usable respondent surveys are considered adequate for this type of research.

The survey employs a systematic random sample approach and is delivered through the U.S. Postal Service. Each survey is addressed to the owner/general manager of the business. The questionnaire uses multiple response formats, gathering nominal, ordinal and interval data. In keeping with accepted statistical practice, an examination of the questionnaire's reliability and numerous validity measures were performed. Specifically, a questionnaire pre-test was conducted for face validity, and after 3 iterations, acceptable limits were obtained. The inter-item reliability alpha (Cronbach Alpha = .77) was also calculated and found to be in line with acceptable consistency and accuracy thresholds for research of this type. The gathering of results concluded in October 2006.

The four proposed technology services under investigation in this study are:

Email Recovery Service - will offer redundancy for an organization's Internet or external e-mail services. This service is provided by receiving the organizations e-mail in the data centre and then forwarding a copy to the customer organization. This buffering connectively permits: storage of copy/archiving; spam filtering; virus detection and removal; web access in the event of a fault in the customer's e-mail server for e-mail retrieval. Add-on/additionally priced services are: spam filtering; virus detection and removal; consulting services for loaner and/or replacement servers and configuration.

Online Backup - facilitates the continuous on-line backup of designated servers, designated data drives, or specific directories/sources of data. The service functions by the installation of a utility that transmits the designated data to a remote server at predetermined intervals. A key attribute is the ability to provide quick, high capacity data restoration capability.

Managed Servers - involves the hosting and complete management of a server in a data centre environment. It is intended to provide a server in a virtual configuration that emulates a service that resides in a customer facility. Normally, the provision of licenses and OS maintenance are part of the base service so that the customer does not have to worry about the conventional IT operational responsibilities. Server reboots and performance/capacity monitoring are also included with 24x7 tech support.

Co-Location Servers - involves the installation of a customer owned server in the telecommunication's host data centre environment. The server will be installed in a physically segregated environment (either caged or within a cabinet). Telecommunication host can provide maintenance and upgrades on the server if requested by the customer or they may be provided by the customers. Customer access will be via escort only. Product is sold in terms of space allocation, access to server (Bandwidth) part of cost.

Statistical Approach

Artificial Neural Networks (ANN's) are increasingly receiving considerable attention in solving complex practical problems in non-engineering areas for which conventional approaches have proven ineffective. ANN's have many advantages including data compression, parallel computation, and ability to learn and generalize. Neural networks are selected as the statistical method because the research questions involve a highly nonlinear function with several variables and they have been proven to numerically approximate such functions much easier than conventional methods.

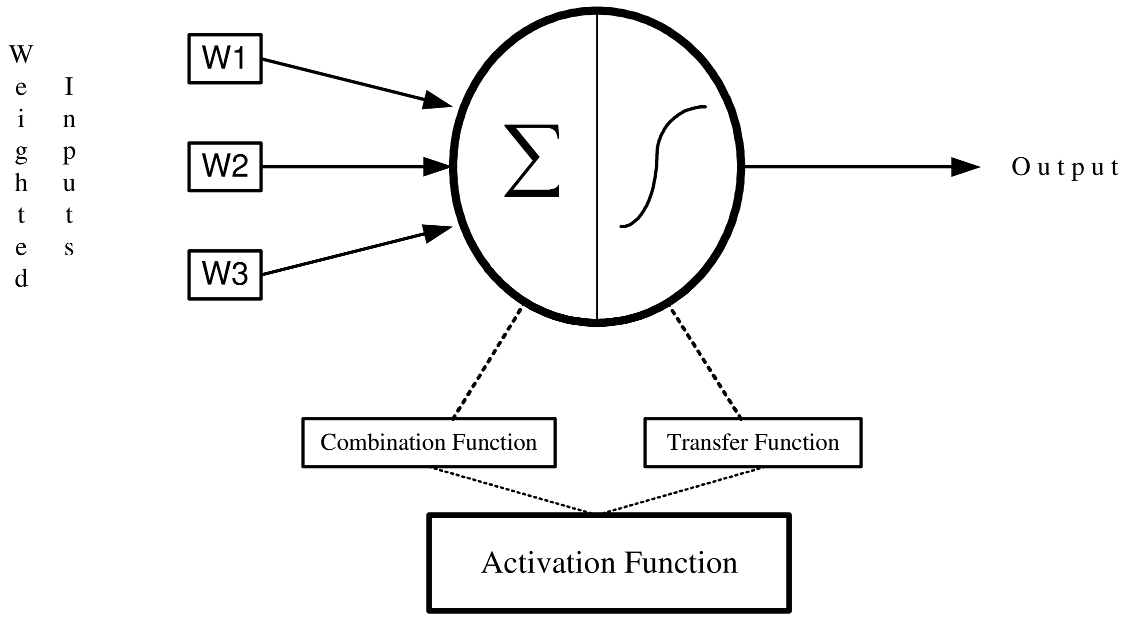
The process consists of three phases, learning, validation, and feature extraction. The ANN approach to data analysis is chosen because of its ability to consistently and accurately predict membership classification and for providing weighted analyses of independent (input) variables. This growing trend can be attributed to several reasons: Neural networks are very sophisticated modeling techniques capable of modeling extremely complex functions. Specifically, neural networks are nonlinear. For many years linear modeling has been the commonly used technique in most modeling domains since linear models have well-known optimization strategies. Where the linear approximation was not valid, (which was frequently the case) the models suffered accordingly.

Neural networks also control dimensionality, a problem that negatively affects the attempts to model nonlinear functions with large numbers of variables. Neural networks learn by example. The neural network user gathers representative data and then invokes training algorithms to automatically learn the structure of the data. Neural networks are applicable in virtually every situation in which a relationship between the predictor variables (independents, inputs) and predicted variables (dependents, outputs) exists, even when that relationship is very complex and not easy to articulate in the usual terms of "correlations" or "differences between groups."

The Basic Artificial Model

A model of the basic artificial neuron (see Figure 1) receives a number of inputs (either from original data (can be scaled), or from the output of other neurons in the neural network). Each input comes via a connection that has strength (or weight); these weights correspond to synaptic efficacy in a biological neuron. Every neuron also has a single threshold value. The weighted sum of the inputs is formed (combination function), and the threshold subtracted, to compose the activation of the neuron (transfer function). These two actions together constitute the activation function, thereby producing the output of the neuron. The neuron acts comparable to the biological neuron, subtracting the threshold from the weighted sum and comparing with zero, and is equivalent to comparing the weighted sum to the threshold.

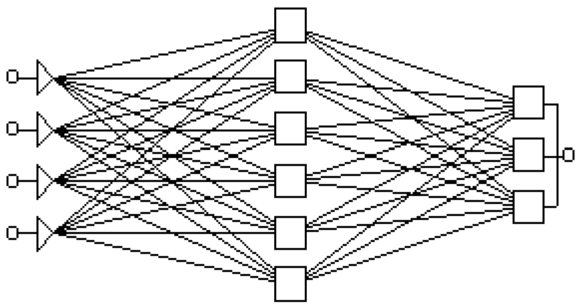
FIGURE 1
BASIC UNIT OF AN ARTIFICIAL NEURAL NETWORK



A typical feedforward network, as used in this study (see Figure 2), has neurons arranged in a distinct layered topology. The input layer is not really neural at all: these units simply serve to introduce the values of the input variables. The hidden and output layer neurons are each connected to all of the units in the preceding layer. Again, it is possible to define networks that are partially connected to only some units in the preceding layer; however, for most applications, fully connected networks are better. When the network is executed (used), the input variable values are placed in the input units, and then the hidden and output layer units are progressively executed. Each of them calculates its activation value by taking the weighted sum of the outputs of the units in the preceding layer, and subtracting the threshold. The activation value is passed through the activation function to produce the output of the neuron. When the entire network has been executed, the outputs of the output layer act as the output of the entire network. The feedforward networks inherently have no time dependence, which makes them good candidates for static nonlinear mapping, pattern classification, and function approximation, making them appropriate here. The functionality of an ANN is determined by modifying the weights of the connections during the learning phase.

FIGURE 2
FEEDFORWARD ARTIFICIAL NEURAL NETWORK STRUCTURE

Inputs *Neurons* *Outputs*



(Hidden Layers)

This study also uses a back propagation algorithm, whereby the gradient vector of the error surface is calculated. The generalization ability of the trained neural network was established with no indications of over and underfitting. The criteria for successful use of neural networks are found through convergence and consistency of the results. The architecture of the neural networks (number of neurons and layers) has been established through trial and error guided by the authors' experience in similar studies.

RESULTS

Respondent Profile

This section provides some general demographic and technological profile results from the survey. Percentage results provided are from those individuals responding to the specific questions, also referred to as the valid percentage. Every respondent did not answer every question, in every case. Respondent profile characteristics appear to reflect the business population in Ontario and are consistent with characteristics exhibited in previous similar studies (See Appendix 1).

In further examination of market viability, various business characteristics and their association with priority choices and expected adoption estimates are presented. Although these associations are quite useful, they are only a brief offering of some of the more complex analyses that can be employed, on these or additional variables not included. The examination of characteristics with first priority choice compares each of the characteristics (business type, revenue, education level) with their percentage of selecting one of these services as their first choice (see Appendix 2).

Neural Network Findings

Learning Phase The ANN consists of 18 input neurons (corresponding to the number of independent determinants), 2 hidden layers with 20 and 10 neurons, and 2 outputs (corresponding to performance membership and scaled to .25 for *Adopting*, and .75 for *Non-Adopting*). An adopting firm is considered one that expected to adopt any of the four products over the next year. The learning rate was set at 0.7; the momentum rate was 0.9. The training set included 369 arbitrarily entered samples. The number of iterations to complete the learning phase was 4977. The normalized system error upon completion of the training was 0.00001.

Using two arbitrarily selected respondents (samples 71 and 126 – one representative from each propensity category), the results of the learning phase indicate that the neural network learned the sequencing of proper membership classification (see Table 2). The expected score (TRUE-0.250000, 0.750000) and the calculated ANN (0.234412, 0.778001, respectively) score is extremely close indicating that the patterns have been learned. The TRUE outputs of respondents are known (based on the scaled survey results) and expectations are that the learned ANN scores would be close to the TRUE scores, which is confirmed here.

The leaning phase results suggest confidence when adding additional new samples in the validation phase. Although the number of cases in the training set (369) is somewhat low, results are encouraging nonetheless. The results may have been better if the training set was larger. However, the minimum of 180 samples in the training set is met. Ten samples per input is a common rule to follow. The classification estimate in the learning phase is 92.6 percent.

TABLE 2
SELECTED RESULTS, LEARNING PHASE

Respondent	*Output*	*Adopting Score*	*Non-Adopting Score*
# 71 Adopting	ANN	**0.234412**	0.001203
	TRUE	**0.250000**	0.000000
# 126 Non-Adopting	ANN	0.000315	**0.778001**
	TRUE	0.000000	**0.750000**

Validation Phase Table 3 provides the results of the validation phase. This section is used to determine validity of the algorithm established in the previous learning phase and is done using a holdout approach. Using ten withheld samples (five from each membership category), response data were entered and calculated using the same algorithm from the learning phase. The anticipation is that membership category classification will again be correctly classified. The resulting ANN scores should hover around the TRUE scores (.250000 and .750000).

Results show that the ANN places the firms into their prospective membership categories with precision to those established in the learning phase. The ANN scores of the five *Adopting* firms are very close, to the anticipated TRUE score for that category, with the largest deviation from holdout respondent five (0.217624). The *Non-Adopting* firm scores are also extremely close to the TRUE score, with the largest deviation coming from holdout respondent six (0.720061). Therefore, propensity category membership of *Adopting/Non-Adopting* firms can be estimated, given these internal determinants and this learned algorithm.

TABLE 3
VALIDATION RESULTS FROM HOLDOUT SAMPLES

Respondents	*Outputs*	*Adopting Score*	*Non-Adopting Score*
Adopting			
Holdout #1	ANN	0.228932	
Holdout #2	ANN	0.242655	
Holdout #3	ANN	0.281383	
Holdout #4	ANN	0.224498	
Holdout #5	ANN	0.217624	
	TRUE	0.250000	
Non-Adopting			
Holdout #6	ANN		0.720061
Holdout #7	ANN		0.758981
Holdout #8	ANN		0.728521
Holdout #9	ANN		0.749835
Holdout #10	ANN		0.788274
	TRUE		0.750000

Feature Extraction Phase Using the feature extraction option of the NeuroShell Classifier software program, the results suggest that the independent variables can be clustered into three impact groups (dominant, moderate, passive), based on weights associated with percentage change in ANN scores. The ability to cluster the determinants allows for the generalization of similarities and differences among the two propensity categories. These generalizations are used in addressing which determinants are the most effective in differentiating between the adopting and non-adopting firms.

Performance Profile When examining the determinant impact strengths, many practical conclusions may be formed, and generally concur with those found in earlier studies. These conclusions are based on the differences of impact strength as identified in the feature extraction phase. The five determinants with the most significant impact (dominant) on new technology adoption propensity are: aspirations for efficiency; expectations for profit from innovation; expectations for efficiency from innovation; commitment to new business processes; and commitment to a formal innovation adoption policy. Two obvious themes are evident. First, adopting firms appear to be motivated by efficiency. Second, adopting firms appear to be committed to staying on the forefront of new business processes and innovations (see Table 4).

Conversely, six determinants appear to have little impact on the adoption of new technology services. These are the capital investment size of the firm, the employee size of the firm, the managers' aspirations for growth, the managers' aspirations for profits, the managers' expectations for growth from innovations, and any commitment by the managers' to be an early adopter of innovations.

TABLE 4
DETERMINANT IMPACT OF ADOPTERS FOUND THROUGH FEATURE EXTRACTION

DOMINANT		
	Aspirations for Efficiency	A_E
	Expectations for Profit from Innovation	E_PI
	Expectations for Efficiency from Innovation	E_EI
	Commitment to New Business Processes	C_NBP
	Commitment to a Formal Innovation Adoption Policy	C_FIP
MODERATE		
	Unique Product	DA_UP
	Management Strength	DA_MS
	Sales Volume	DA_SV
	Aspirations for Security of Markets	A_SM
	Expectations for Security of Markets from Innovation	E_SMI
	Commitment to Expanding Market Share	C_EMS
	Commitment to Development of New Markets	C_DNM
PASSIVE		
	Capital Investment	DA_CI
	Employee Size	DA_ES
	Aspirations for Growth	A_G
	Aspirations for Profit	A_P
	Expectations for Growth from Innovation	E_GI
	Commitment to being an Early Adopter	C_EA

Associated determinants with labels are found in Table 1.
Dominant – greatly influence the dependent variable classification
Moderate – somewhat influence the dependent variable classification
Passive – minimally influence the dependent variable classification

CONCLUSION

This study’s intent is to: (1) examine various frequencies and descriptives of technology service adoption; (2) confirm that the innovation adoption of technology services can be classified; and (3) identify managerial determinants that influence the adoption of technological services. A further intent is to employ a proven non-linear approach for classifying a firms propensity to adopt or not to adopt a new technological service innovation.

Managerial implications are for firms seeking to potentially adopt new technology innovations. Findings identify particular determinants within the control of management that play a vital role in the adoption propensity of firms. Most notably, managements’ focus on efficiencies of the organization along with a commitment for making the organization better are the key determinants of adopting firms. Furthermore, it is also apparent that differential firm advantages, such as size or investment patterns, along with managers’ aspirations for growth or profit play an insignificant role in technological service adoption rates.

The study is useful because it: (1) provides a framework for analyzing the adoption patterns of firms, (2) presents insight into the behavior of American firms and their propensity to adopt innovations; (3) identifies variables associated with service technology adoption determinants, (4) provides managers with a benchmark to assess their adoption posture. Further research in this area should include the use of longitudinal studies, cross-cultural studies and the development of more complex operational variables.

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APPENDIX 1
Demographic

Gender	*percentage*
Male	65.2
Female	34.8

Age	*years*
Minimum	23
Maximum	73
Average	48

Highest Level of Completed Education	*percentage*
high school diploma	33.3
vocational or college diploma	23.6
university degree	34.8
additional university degree	5.6
none of the above	2.7

Years in Business	*years*
Minimum	1
Maximum	100
Average	21

Primary Business Type	*percentage*
Retail	34.5
Wholesale	2.7
Manufacturing	9.7
Professional Services	25.1
Personal Services	13.3
Other	14.7

Number of Employees	*count*
Minimum	1
Maximum	841
Average	23

Revenues for FY2005	*percentage*
less than $25,000	2.7
$25,000 - $49,999	7.4
$50,000 - $99,999	12.1
$100,000 - $249,999	19.8
$250,000 - $499,999	14.2
$500,000 - $999,999	16.5
$1,000,000 - $5,000,000	20.9
greater than $5,000,000	6.5

Technological Orientation

Importance of Computer to the Firm	*percentage*
not important	15.6
somewhat important	13.3
important	45.4
extremely important	25.7

Do you expect to upgrade current company computers/servers within the next 12 months?	*percentage*
No	33.9
Yes	66.1

Is there a person in your organization whose sole responsibility is to manage and protect company data?	*percentage*
No	64.2
Yes	35.8.

Is there a person in your organization whose sole responsibility is to maintain and update company computers/servers?	*percentage*
No	54.3
Yes	45.7

If you were going to adopt one of these services, what type of provider would you look for first?	*percentage*
IT Solutions firm (i.e.,IBM)	29.2
National Solution Contractor (i.e.,Accenture)	6.5
Regional Telecommunications firm (i.e., Atlanta T1)	20.1
National Telecommunications firm (i.e., ATT)	26.8
Internet Facilitator firm (i.e., Microsoft)	14.5
Science Institution (i.e., Univ of Georgia)	2.9

APPENDIX 2

TABLE 5
BUSINESS TYPE WITH FIRST PRIORITY CHOICE

	Email Recovery	Online Backup	Managed Servers	Co-Location Servers
Retail	27%	44%	26%	1%
Wholesale	45%	12%	45%	1%
Manufacturing	30%	18%	39%	11%
Professional Services	33%	55%	13%	2%
Personal Services	38%	46%	16%	0%

TABLE 6
REVENUE SIZE WITH FIRST PRIORITY CHOICE

	Email Recovery	Online Backup	Managed Servers	Co-Location Servers
less than $25,000	67%	33%	0%	0%
$25,000 - $49,999	20%	48%	32%	0%
$50,000 - $99,999	29%	39%	32%	0%
$100,000 - $249,999	38%	51%	9%	3%
$250,000 - $499,999	27%	44%	27%	2%
$500,000 - $999,999	30%	38%	32%	0%
$1,000,000 - $5,000,000	32%	30%	23%	3%
greater than $5,000,000	9%	27%	50%	14%

TABLE 7
BUSINESS TYPE WITH EXPECTED ADOPTION

	Email Recovery	Online Backup	Managed Servers	Co-Location Servers
Retail	34%	33%	20%	0%
Wholesale	22%	44%	11%	0%
Manufacturing	24%	15%	24%	15%
Professional Services	33%	28%	16%	1%
Personal Services	29%	29%	16%	0%

TABLE 8
REVENUE SIZE WITH EXPECTED ADOPTION

	Email Recovery	Online Backup	Managed Servers	Co-Location Servers
less than $25,000	44%	44%	11%	0%
$25,000 - $49,999	40%	32%	32%	0%
$50,000 - $99,999	29%	29%	20%	0%
$100,000 - $249,999	27%	28%	12%	3%
$250,000 - $499,999	33%	38%	19%	4%
$500,000 - $999,999	29%	23%	20%	0%
$1,000,000 - $5,000,000	28%	28%	15%	0%
greater than $5,000,000	27%	18%	23%	18%