Global Expansion Strategies for Variations in Innovative Service Technology Adoption

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The aim of this work is explore the relationship between market and technological uncertainties with a firm's international expansion strategy. To be effective in recognizing potential innovations and exploiting them worldwide, firms should focus manpower where uncertainties are, that is where information collection and processing needs are the greatest. Whether these uncertainties are market based such as understanding local consumer tastes and preferences or technology based, such as R & D, rate of technological change, or environmental impacts on innovation diffusion, firms should strive to employ an international expansion strategy that will leverage its associated capabilities and potential. Using a proven multinational expansion framework, this paper seeks to examine the aforementioned uncertainties associated with global innovation expansion and overlay them with a strategic objective for maximizing the firm's potential. Whether maximizing is associated with adoption rates, investment returns, profitability or some other metric is inconsequential at this point as reasons may vary from firm to firm. Using an artificial neural network, with the data from 162 samples, the study specifically examines fourteen independent variables of market and technological uncertainty with Bartlett and Ghoshal's "Categorization for Multinational Organizations". The findings suggest the level of relationship between the uncertainty determinants and the international strategic choice a firm undertakes.

INTRODUCTION

The proliferation of innovation research over the last 20 years has been impressive. Starting with Rogers' Diffusion of Innovation theories, researchers have continued to develop this stream in various contexts, primarily dealing with product adoption rates. However, there has been little research addressing the specific nature or difference of services (intangible product) adoption behavior with goods (tangible product) adoption behavior. Moreover, even less research has been concluded looking at the cultural composites of adoption rates, specifically within the service context. International firms have been using a hit or miss approach when it comes to truly understanding the complexities and uncertainties of a potential service's innovation adoption rate. This paper seeks to lay some groundwork for establishing a theoretical approach to the various strategic options a firm may use when introducing a technological service innovation.

LITERATURE REVIEW

Studies addressing the technology adoption life-cycle suggest that a different approach is necessary when marketing truly discontinuous innovations (Foster, 1982). In Inside the Tornado, Moore (1995) examines the difficult, indeed sometimes chaotic, process of successfully marketing these innovations to segments beyond the early adopters. Moore's primary tenet is that the appropriate approach in high-tech marketing must be on the "whole product" solution. That is, the product offering must provide applications with exemplary added value if the high-tech product is ever going to gain acceptance in the mainstream market, achieving this sales level is of paramount importance to marketers.

Simpson and Docherty (2004) provide a detailed discussion of the reasons for and barriers to technology adoption in SMEs. Internal to the firm include: management resistance; technology concerns; resource issues; lack of awareness; and lack of information. Another internal factor that is likely to influence technology adoption is market orientation. Market orientation (or market-oriented behavior) can be viewed as the implementation of a particular corporate philosophy, the marketing concept (Gray et al., 1998). Market orientation goes beyond simply responding to customer needs: it also includes countering competitor actions. Since the initial empirical research by Kohli and Jaworski (1990) and Narver and Slater (1990), a growing number of studies have supported the links between market-oriented behavior and company performance, including recent studies in the services sector (Chang and Chen, 1998).

A market orientation essentially involves doing something new or different in response to market conditions, and may be viewed as a form of innovative behavior (Gray et al., 1998). The opportunities for growth as well as the need to keep up with competition are often regarded as the driving forces behind technology adoption (Drew, 2003, p. 84). More market-oriented firms therefore will show greater responsiveness to technology innovation.

Chong (2001) provides an excellent discussion of some of the external environment factors likely to influence the successful adoption of electronic commerce. These include: environmental uncertainty; pressure from other trading partners as well as other industry-specific competitive pressures; government influences; critical mass; issues related to infrastructure; and technological standards.

Experience tells us that technology adoption is primarily market-driven, either by competition or by the availability of new technologies and the search for new industrial applications (Rogers, 1995). In those markets where competition is intense, demand elasticities are expected to be higher because of the existence of close substitutes and this has the potential to drive innovative behaviors within the firm (Majumdar and Venkataraman, 1993).

Technologies do not easily diffuse in industries. In general, the use of new technologies is expected to increase by time due to different reasons (Rogers, 1995). One model of technology diffusion is the epidemic model, indicating that the lack of information available about the new technology can limit the diffusion of technology. Another model suggests that different firms adopt new technology at different times due to their differences in goals and abilities. An alternative model is related to density dependence that considers diffusion as the result of legitimization and competition.

Past research on consumers' adoption of innovations has identified isolating communication factors that can predict individuals' adoption (Lee Lee and Schumann, 2002). Researchers have found that adopters of technology-based financial service innovations have distinct demographic characteristics, such as youth, affluence, and higher education levels. Furthermore, the diffusion literature and previous studies of consumers' use of self-service technology suggest that consumer' perceptions of innovation characteristics, such as complexity, trialability, and observability (Rogers 1995); perceived benefits of technology (Davis, 1989); reliability (Parasuraman, Zeithaml and Berry, 1988); and security (Swaminathan Lepkowska-White and Rao, 1999) are potential determinants of consumers' willingness to adopt technology-based service innovations. Selected individual characteristics, such as age, education, land income (Rogers, 1995), also affect consumer adoption of new technologies. Having a personal computer (PC) at home may also encourage consumer adoption of service technology.

Perceptions of innovation characteristics and socioeconomic characteristics have been proposed as determinants of consumers' adoption of technological innovations (Gatignon and Robertson, 1985).

Labby and Kinnear (1985) suggest that perceived innovation characteristics can be significant predictors of consumer adoption and that the predictive power of these variables is stronger than socioeconomic characteristics.

Davis (1989) asserts that the decision to use a new technology is determined by the extent to which the consumer believes it is cost effective in providing goods or services compared to the current method. Perceived benefits of electronic banking are conceptually similar to Rogers' (1995) relative advantage, defined as "the degree to which an innovation is perceived better than the idea it supersedes" (p. 212). Past studies have found that relative advantage has a significant effect on consumers' adoption of many technological innovations (Tornatzky and Klein, 1982).

Five key area concentrations of innovation research: (Hauser, Tellis, Griffin, 2006)

1. Consumer response to innovation
2. Organizations and innovation
3. Market entry strategies
4. Techniques for product development
5. Defending against market entry

Bartlett and Ghoshal's Categorization for Multinational Organizations (1989)

International Strategy – is based on the diffusion and adaptation of the parent company's knowledge and expertise to foreign markets. Country units are allowed to make some minor modifications to product offerings and decisions coming from head office. The primary goal is the worldwide exploitation of the parent firm's knowledge and capabilities.

Global Strategy – emphasizes economies of scale due to standardization of product offerings, and the centralization of operations in a few locations. One advantage here is that innovations that come about through efforts of either the business unit of the head office, can be transferred more easily to other locations. Firms here focus on cost control and may forgo revenue opportunities since it does not invest extensive resources in adapting product offerings from one market to another.

MultiDomestic Strategy – is focused on differentiating its product offerings to adapt to local markets. Decisions tend to be decentralized to permit the firm to tailor its products to respond rapidly to changes in demand. This enables a firm to expand its market and offer different prices in different markets. Firms using this strategy must be focused on language, culture, customer income, preferences and taste. Product innovations move primarily from the local unit back to the central headquarters.

Transnational Strategy – considers optimization and efficiencies associated with local adaptation and learning. Efficiency is sought as a means to achieve global competitiveness. This strategy approach recognizes the importance of local responsiveness but only as a tool for flexible international operations. Innovations are regarded as an outcome of larger process of learning. The firm's assets and capabilities are dispersed according to the most beneficial location for each activity, appearing as a hybrid between a global strategy and a multidomestic strategy.

FIGURE 1
BARTLETT AND GHOSHAL'S CATEGORIZATION FOR MULTINATIONAL ORGANIZATIONS

Technological Uncertainty	**Unfamiliar**	**10**	**MultiDomestic** – Market information bound. ***Unilever - cereal***	**Transnational** – Market and information bound. ***Caterpillar – heavy equip.***
	Familiar	**0**	**International** – Neither market nor technology bound. ***McDonald's – fast food***	**Global** – Technology information bound. ***Merck - pharmaceuticals***
			0	**10**
			Familiar	**Unfamiliar**
			Market Uncertainty	

Using the above two by two matrix, we call a product *market information bound* if the market uncertainty needed to offer new products worldwide is high whereas the technological uncertainty is low. Branded packaged goods such as cereals would be in this category. Just what customers in different parts of the world would prefer in these goods can differ significantly, changes often or is difficult to discern.

Next, there are *technology information bound* products where offering new products involves a high level of technological uncertainty but a low level of market uncertainty. Many pharmaceutical drugs would fall in this category. It takes a great deal of resources to discover, develop, manufacture, and deliver new drugs, but their applications do not change much.

Then there are products that are associated with both high technological and high market uncertainty. We say that they are *technology and market information bound*. Earth moving equipment such as tractors fall in this category since terrain varies from region to region and the technologies that go into such equipment can be complex.

Finally, McDonald's food services would be in the opposite category, *neither market nor technology bound*, where neither the technological nor the market information needed to offer them has relatively less uncertainty.

The specific variables included in the study (see Figure 2) focus on the market and technological uncertainties firms are challenged with when deciding which approach may be the most beneficial when entering a new market with a new product. Furthermore, the dependent variables are directly adopted from Bartlett and Ghoshal's Categorization of Multinational Organizations.

FIGURE 2
VARIABLES OF STUDY

(Independent)
Market Uncertainty

CCR-TASTE	Rate of change for customer tastes
CCR-PREFERENCE	Rate of change for customer preferences
CCR-EXPECTATIONS	Rate of change for customer expectations
FUM-KNOWLEDGE	Current knowledge and tacit level of the potential market
FUM-TRANSFUSION	Firm's transmission capacities toward the potential market
FUM-ABSORPTION	Firm's absorption capability of the product (understanding customer wants)
CR-REGIONAL GOVERNMENT	Rate of change in regional government policies
FAM-HOMOGENIETY	Product's similarity in use to the firm's current markets

CCR - CUSTOMER CHANGE RATE
FUM - FIRM UNDERSTANDING OF MARKET
CR - CHANGE RATE
FAM - FIRM ASSESSMENT OF MARKET

Technological Uncertainty

PCR-TECHNOLOGY	Rate of change in the product's technology
CUP-KNOWLEDGE	Customer's current knowledge and tacit level of the potential product
CUP-TRANSFUSION	Customer's reception capacity toward the potential product
CUP-ABSORPTION	Customer's absorption capability of the product (understanding use of product)
T-COMPLEXITY	Technological complexity of the potential product
E-SOCIOPOLITICAL	Level of sociopolitical impacts that are possible with new product introduction

PCR	PRODUCT CHANGE RATE
CUP	CUSTOMER UNDERSTANDING OF PRODUCT
T	TECHNOLOGICAL
E	ENVIRONMENT

(Dependent)
International Approach
Multi-Domestic Approach
Transnational Approach
Global Approach

DATA ANALYSIS

Sampling

The respondent group for this study are firms with their primary core product identified as a service based offering (telecommunications, education, medicine, engineering, computer science, etc.) that are actively engaged in offering billable services outside their domestic borders and are not subsidiaries or related to any other firms within the study, and have information available for accessing senior company officials. The data were gathered using in-person interviews. Data was then coded into a usable metric form for further analysis. The questionnaire demonstrated validity confidence and an acceptable inter-item reliability with a .71 Cronbach alpha. Collected data was processed using the NeuroShell Classifier software package and SPSS.

Artificial Neural Networks

Artificial neural networks (ANNs) are receiving considerable attention in solving complex practical problems in non-engineering areas for which conventional approaches have proven ineffective. ANNs have many advantages including data compression, parallel computation, and ability to learn and generalize. Neural networks are selected as the statistical method of choice because the research questions involve a highly non-linear function with several variables and they have been proven to numerically approximate such functions much easier than conventional methods (Smith, 2007).

The process consists of three phases, learning, validation, and feature extraction (Bigus, 1996). The ANN approach to data analysis is chosen because of its ability to consistently and accurately identify and predict membership classification and for providing weighted analyses of independent (input) variables. 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, models suffered accordingly.

Neural networks also control dimensionality, a problem that negatively affects the attempts to model nonlinear functions with larger 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. These 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.”

A model of the basic artificial neuron (see Figure 3) 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 (Berry & Linoff 1997, p.298).

The primary network design in this study utilizes a feedforward, back propagation algorithm. Feedforward networks inherently have no time dependence, which makes them good candidates for static nonlinear mapping, pattern classification, and function approximation, rendering them appropriate here. A back propagation approach calculates the gradient vector of the error surface. This vector points along the line of steepest descent from the current point, to determine if movement along it a “short” distance will decrease the error. A sequence of such moves (slowing towards the bottom) will eventually find a minimum of some sort. In practice, the step size is proportional to the slope (so that the algorithms settle down to a minimum) and to a special constant known as the learning rate. The correct setting for the learning rate is application-dependent, and is typically chosen by experiment.

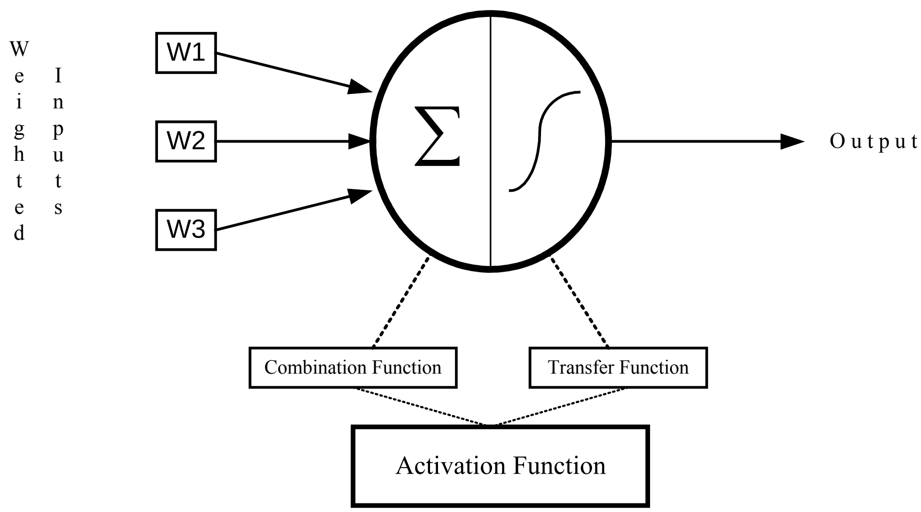
The algorithm progresses iteratively, through a number of epochs. On each epoch, the training cases are submitted in turn to the network, with target and actual outputs compared and the error calculated. This error, together with the error surface gradient, is used to adjust the weights, and then the process repeats. The initial network configuration is random, and training stops when a given number of epochs elapses, or when the error reaches an acceptable level, or when the error stops improving.

The optimization of an ANN is determined by modifying the weights of the connections during the learning phase (McClelland & Rumelhart 1986) with the intent of establishing the specific architecture of the neural network (number of neurons and layers). Networks with too few hidden processing elements will generalize poorly and result in underfitting (insufficient specification of the mapping between the inputs and the outputs). Meanwhile networks with too many hidden processing elements will also generalize poorly and result in overfitting (which produces a model of statistical noise as well as the desired signal). Since there is no theoretical basis for defining the number of hidden processing elements, this aspect of the architecture is obtained through trial and error.

RESULTS

As noted above, there are three phases to assessing the results of an ANN. First is the learning phase, which trains the network with the intent of measuring the needed weights to accurately reflect the model and relationships between the independent and dependent variables. The learning phase uses 70 percent of the sampled respondents. Second is the validation phase. This is where a holdout (remaining 30 percent of the sampled respondents) are entered into the learned network to determine if results are similar. Finally, the feature extraction is performed to determine which variable affects the network, in what way. For example, how does the "rate of change in a product's technology" relate to the choice of international strategic entry into a foreign market?

FIGURE 3
BASIC UNIT OF AN ARTIFICIAL NEURAL NETWORK



Learning Phase

The ANN consists of 14 input neurons (corresponding to the number of independent determinants), 2 hidden layers with 10 and 5 neurons, and 4 outputs (corresponding to performance membership and scaled to .25 for International, ,50 for Multi-Domestic, .75 for Transnational, and 1.0 for Global). Scaling is a common practice when using ANNs, because of the activation function's sigmoidal nature, producing a range of data output between zero and one. By scaling between .25 and 1.0, the entire range of network output is possible providing good quality results. The learning rate was set at 0.7; the momentum rate was 0.9. The training set included 114 (70 percent) arbitrarily entered samples, regardless of international approach. The number of epochs to complete the learning phase was 5,025. The normalized system error upon completion of the training was 0.00001.

Results of the learning phase reveal that the neural network learned the sequencing of proper membership classification (see Table 1). The expected scores (.25, .50, .75, and 1.0) and the calculated ANN scores are extremely close, indicating that the patterns have been learned. The TRUE outputs of respondents are known, from the data (based on the scaled survey results, as mentioned earlier) and expectations are that the learned ANN scores will be close to the TRUE scores, and is confirmed here. The learning phase results provide confidence when adding additional samples in the validation phase. Moreover, the ability of the network algorithm to correctly classify the service exporting firms is 92.3 percent, substantiating confidence in the technique.

TABLE 1
LEARNING PHASE RESULTS

Respondent Category	*Output*	*Mean Score*
International	ANN	**0.24662**
	TRUE	**0.250000**
Multi-Domestic	ANN	**0.483198**
	TRUE	**0.500000**
Transnational	ANN	**0.75882**
	TRUE	**0.750000**
Global	ANN	**0.987222**
	TRUE	**1.000000**
Cases Correctly Classified = 92.3%		

Validation Phase

The validation phase, one determining the validity of the algorithm established in the previous learning phase, employs a holdout approach. Using the 48 (30 percent) randomly withheld samples from learning phase, response data were entered and calculated using the same algorithm from the learning phase (see Table 2). The expectation is that membership category classification will be comparable. The resulting ANN scores should hover around the TRUE scores. As with the case above, the percentage of correctly classified cases is robust, at 91.7 percent, within one percent of the learning phase. Results demonstrate that the ANN places the holdout firms into their prospective membership categories with precision, confirming findings established in the learning phase.

TABLE 2
VALIDATION PHASE-HOLDOUT SAMPLE CLASSIFICATION RESULTS

Respondent Category	*Output*	*Mean Score*
International	ANN	**0.243985**
	TRUE	**0.250000**
Multi-Domestic	ANN	**0.490092**
	TRUE	**0.500000**
Transnational	ANN	**0.756635**
	TRUE	**0.750000**
Global	ANN	**0.987821**
	TRUE	**1.000000**
Cases Correctly Classified = 91.7%		

Feature Extraction Phase

The feature extraction phase is the stage at which most constructive information about the characteristics of the service providers can be found. Here, features are identified through their importance to model development. The rank order weighting of each variable and its impact on the model's performance are scored. Variables having higher importance (rank) imply that the constructed model is more sensitive to smaller changes with those input variables, similar to coefficient strengths in regression.

Findings suggest that the independent variables can be clustered into three impact groups (dominant, moderate, passive), based on ranked weights associated with percentage change in ANN scores (i.e. dominant=high-ranking). The capability of clustering the determinants allows for the generalization of similarities and differences among the performance membership categories. These generalizations are captured when addressing which determinants are the most effective in differentiating between the international strategic approaches.

Examining the determinant impact strengths provides practical conclusions that largely concur with those found in earlier studies. These conclusions are based on the differences of impact strength as identified (see Table 3). The ANN model weights are the coefficient scores of strength for each determinant, based on importance to model construction, totaling 1.0 for all input variables combined.

CONCLUSION

The early data analysis suggests that specific market and technological uncertainties are directly related to the approach that international firms use when introducing technological service innovation. The purpose of this study was not to determine whether one approach was working better than another, but rather to determine if the selection of a particular international strategy is related to the nature of the market being entered and the product being offered. Clearly, the findings suggest that specific uncertainty variables play a part in the firm's strategic selection. The next iteration in this research stream will be measure some level of performance metric rather than just the strategic option. In addition, further research directions may include:

1. How do market and technological uncertainty impact innovation adoption patterns?
2. Which strategic approach for multinational expansion is the most effective at recognizing the potential for an innovation? (using B&G's approach)
3. Can a model be developed that would be universal across industry type?
4. How will market uncertainty and technological uncertainty be measured?
5. What is the desired outcome for the multinational innovation, …adoption, ROI, profitability…?
6. Does this research lend itself to any particular statistical methodology, ie data collection, statistical approach

TABLE 3
DETERMINANTS FOR INTERNATIONAL STRATEGIC CHOICE

Determinant Impact with ANN Model Weights	
DOMINANT	
FUM-ABSORPTION	0.0858
CCR-EXPECTATIONS	0.0842
FAM-HOMOGENIETY	0.0810
CUP-KNOWLEDGE	0.0810
CUP-TRANSFUSION	0.0800
T-COMPLEXITY	0.0785
MODERATE	
CCR-PREFERENCE	0.0702
FUM-KNOWLEDGE	0.0700
FUM-TRANSFUSION	0.0632
CUP-ABSORPTION	0.0629
PASSIVE	
CCR-TASTE	0.0555
CR-REGIONAL GOVERNMENT	0.0551
PCR-TECHNOLOGY	0.0498
E-SOCIOPOLITICAL	0.0496

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