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SHIFTING THE INTERPRETIVE FRAMEWORK OF BINARY CODED DUMMY VARIABLES

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ABSTRACT

The traditional binary coding scheme is the starting point, and often the ending point, for the coding and interpretation of dummy variable coefficients for qualitative variables in regression analysis. The binary coding scheme produces an interpretive framework for the coefficients that measure the net effect of being in a given category as compared to an omitted category. This may result in coefficients that are as arbitrary as the selection of the omitted categories. Two methods for shifting the binary coded coefficients are presented to assist in establishing a more meaningful interpretive framework. The shifted frameworks allow for interpretation of the coefficients about an "average" of the dependent variable. One method allows for each coefficient to be interpreted as a comparison to the unweighted average of the dependent variable when averaged over all subcategory means. The second method allows for an interpretation of the coefficients to the overall mean of the dependent variable. Since the shifted framework coefficients are compared to an "average," the coefficients are insensitive to the omitted categories. The effort to shift the interpretative framework is minimal and can be effected without the use of a computer program. The shifted frameworks can be determined by incorporating alternative coding schemes using a computer program.

INTRODUCTION

The use of dummy variables to represent qualitative variables in regression analysis has become quite prevalent in introductory business and economic statistics courses (Daniel & Terrell, 1992; Anderson, Sweeney & Williams, 2002). The specific information on coding the dummy variables is typically presented using a binary coding scheme (0,1). The binary scheme assigns members of a particular category for the qualitative variable a code of 1 and members not in that particular category receive a code of 0. Usually, the zero coded category is selected to serve as the reference or comparison point for the interpretation of the regression coefficients. These coefficients will express the difference between a selected category and the reference category for the qualitative variable. The choice of a reference category is arbitrary and may present problems of interpretation. When a number of binary coded qualitative variables are used for a regression model, a reference category for each qualitative variable is selected as the comparison points. The resulting regression coefficients may yield unclear and sometimes awkward interpretations as to which categories have been designated for comparisons.

The purpose of this paper is to illustrate processes for shifting the interpretive framework of binary coded regression coefficients. A major reason for the shifting processes is to provide coefficients that lend themselves to more meaningful interpretations. Starting with binary-coded coefficients, usually generated with the assistance of a statistical computer package, the shifting process can be accomplished with or without the assistance of a computer program. The shift in the interpretative framework is such that the contrast of a regression coefficient for a designated category is made to an "average" value for the dependent variable and not to a specified zero coded category. While the shifting processes will yield numerically different coefficients, the overall fit and significance of the regression model remain unchanged. A main advantage of shifting the interpretative framework of binary coded dummy variables to an "average" is that the coefficients are no longer sensitive to which class is treated as the omitted class.

FRAMEWORK SHIFTING WITHOUT A COMPUTER PACKAGE

The process of shifting the interpretive framework of binary coded coefficients can be made without the use of a computer program by adding a constant, k, to the coefficients within each set of coefficients for a qualitative variable and subtracting k from the regression equation constant or intercept. The general relationship for determining k is

$$\Sigma\, b_i^* = \Sigma\, w\,(b_i + k) = 0. \tag{1}$$

Where b_i represent the binary-coded regression coefficients, b_i^* represent the shifted regression coefficients, and w represents a weight for the importance of each coefficient within a set of regression coefficients for a qualitative variable. The resulting value of k yields the condition that the new set of coefficients, b_i^*, will average zero.

Suits (1983) suggested a shifting process, Shifting Process I, which expresses the category regression coefficients as deviations from an "average," where the "average" is the unweighted mean of the dependent variable across all categories for a categorical variable. In calculating the unweighted mean of means, each category receives an equal weight of 1, regardless of the number of cases in that category. Thus, when binary coded coefficients are shifted using Shifting Process 1, the value of *w* in Equation (1) is set at 1. The unweighted mean of all group means is reported as the regression equation constant, b_0, and is the reference point from which all category differences can be calculated.

The unweighted mean has the consequence that category means may be based on a few cases and are treated the same as category means based on much large category size. Obviously, when the category cases are unequal, the unweighted mean of means and the overall mean are difference measures. Thus, the overall mean of the dependent variable may be the more desirable "average" as the comparison measure for the regression coefficients.

Sweeny and Ulveling (1972) suggested a process, referred to as Shifting Process II, for shifting the interpretative framework of the coefficients to an "average," where the "average" is indeed the overall mean of the dependent variable. The shifting process can be accomplished by computing the constant k, for Equation (1), using the sample proportion, p, of cases for the categories within each qualitative variable. For Shifting Process II, the value of *w* in Equation (1) is set at *p*. Each coefficient is compared to the regression equation constant, b_o, which is the overall mean of the dependent variable.

Framework Shifting Illustration

The interpretive framework shifting processes will be illustrated by data collected for a maintenance service company. A request was made for an analysis of the maintenance service repair time, in hours, based on the type of repair and the person performing the repair. For a sample of 40 repair times, a summary of the qualitative variables, repair type and repair person, is presented in Table 1.

TABLE 1
Summary of the Cases for the Maintenance Service Qualitative Variables and Categories

Cases	Repair Type		Repair Person		
	Electrical	Mechanical	Jake	Dave	Bob
Frequency	24	16	12	18	10
Proportion	0.6	0.4	0.300	0.450	0.250

As mentioned previously, a binary coded dummy variable regression equation is usually the framework selected for the interpretation of the coefficients for introductory statistics courses. The binary coded dummy variable regression equation is necessary for interpretative framework shifting. The two qualitative variables, repair type and repair person, can be completely represented by a set of binary coded dummy variables that have a specific value when an observation is found in a given category. The binary-coded dummy variables for repair type, D1 and D2, and for repair person, D3, D4 and D5, are defined in Table 2.

TABLE 2
Binary Coding Scheme for the Maintenance Service Company Qualitative Variables

Repair Type	Dummy Variable		Repair Person	Dummy Variable		
	D1	D2		D3	D4	D5
Electrical	1	0	Jake	1	0	0
Mechanical	0	1	Dave	0	1	0
			Bob	0	0	1

When an observation is in the repair type electrical category, the dummy set is defined as D1 = 1 and D2 = 0. For repair person, Jake, the dummy set is defined as D3 = 1, D4 = 0 and D5 = 0. Other categories are defined in a similar manner. Using the binary coded dummy variable, the following general regression equation may be formed:

$$\hat{Y} = b_o + b_1\, D1 + b_2\, D2 + b_3\, D3 + b_4\, D4 + b_5\, D5 \tag{3}$$

With the equation in this form, there are two more coefficients to be estimated than there are independent normal equations. One of the extra coefficients is associated with the repair type dummy variables, and one with the repair person dummy variables. In general, each qualitative variable represented by dummy variables gives rise to one superfluous coefficient. The remedy typically utilized in the introductory course in statistics is to constrain a coefficient from each dummy set to a value of 0. For example, when $b_2 = 0$ and $b_5 = 0$, Equation (3) reduces to

$$\hat{Y} = b_0 + b_1\,D1 + b_3\,D3 + b_4\,D4 \tag{4}$$

When D2 = 1 and D5 = 1, then D1 = D3 = D4 = 0. Since D2 and D4 are not in Equation (4), the equation reduces to the following when an observation is a member of both excluded categories:

$$\hat{Y} = b_o \tag{5}$$

Equation (5) represents the regression estimated for a mechanical repair type and for Bob as the repair person. From Equation (4), the regression coefficient, b_1, is the net amount by which the intercept, b_o, must be adjusted to account for repair type mechanical instead of electrical. A similar statement can be made of the remaining dummy coefficients for repair person with respect to the omitted class, repair person Bob. In general, this procedure produces coefficients for each dummy variable that measure the net effect on the intercept of the equation that membership in that class has as to the omitted class.

For the maintenance service problem, the binary coded dummy variable regression equation to estimate the repair time is often determined by means of a computer program. The equation is

$$\hat{Y} = 4.2645 + 0.5925\,D1 - 0.5762\,D4 - 1.4159\,D5 \tag{6a}$$

Including the two excluded dummy variables, D2 and D5, the equation can be restated as

$$\hat{Y} = 4.2645 + 0.5925\,D1 + 0\,D2 - 0.5762\,D4 - 1.4159\,D5 + 0\,D6 \tag{6b}$$

Interpretation of the coefficients is somewhat more difficult when two or more qualitative variables are included. The coefficient for D1, b_1, is interpreted as the difference between the electrical repair type as compared to the mechanical repair type. The coefficient for D3, b_3, is interpreted as the difference between repair person Jake as compared to repair person Bob. A similar statement can be made for the other coefficient, b_4. To enhance the understanding and use of the dummy variable coefficients in Equation (6b), the interpretive framework for comparison of the coefficients can be shifted to an "average" for the dependent variable.

Based on Suits' suggestion, referred to as Shifting Process I, each coefficient, b_i, receives a weight of 1, i.e., w = 1 for Equation (1). Since two sets of dummy variables are included in the maintenance service problem, a constant must be computed for each set and added to the coefficients of the respective sets, k_1 and k_2. The sum of the constants, k, is subtracted from b_o. Referring to Equation (6b), for repair type, the constant k_1 is computed as $-(0.5925 + 0)/2$ and for repair person, the constant k_2 is computed as $-(-0.5762 - 1.4159 + 0)/3$. The required constants are $k_1 = -0.2963$ and $k_2 = 0.66400$. The sum of the constants, k, is 0.3677. The transformed or shifted equation is obtained by adding each constant, k_1 and k_2, to the respective set of coefficients and subtracting the sum of the constants, k, from the regression equation intercept or constant. The Suits' shifted equation for Equation (6b) is

$$\hat{Y} = 3.8968 + 0.2963\ D1 - 0.2963\ D2 + 0.0878\ D3 - 0.7519\ D4 + 0.6640\ D5 \quad (7)$$

The interpretation of the coefficients now indicates the extent to which behavior in the respective repair type and in the respective repair person categories vary from the unweighted average of repair type, when averaged over all subcategory means for repair time. For the repair type electrical coefficient, $b_1 = 0.2963$, an electrical repair type adds 0.2963 hours to the unweighted average, 3.8968 hours of repair time. Also, repair person Bob subtracts 0.7519 hours from the unweighted average.

To shift the interpretation framework of the coefficients to an "average" that is the overall mean of the dependent variable, referred to as Shifting Process II, Sweeny and Ulveling suggested using the sample proportions for categories of each qualitative variable as weights in Equation (1). Using Table 1, for repair type, k_1 is computed as (0.6*-0.2963 + 0.4*0.2963) and k_2 is computed as - (0.300 * 0.0878 + 0.450 * -0.7519 + 0.2500 * 0.6640). The required constants are k_1 = + 0.0593 and k_2 = +0 .1460. The sum of the constants, k, is +0.0867. As for Process I, k is subtracted from the constant and each constant, k_1 and k_2, is added to the coefficients of their respective dummy regression coefficients in Equation (7). The Sweeny and Ulveling's shifted equation is

$$\hat{Y} = 3.8100 + 0.2370\ D1 - 0.3556\ D2 + 0.2339\ D3 - 0.6059\ D4 + 0.8100\ D5 \quad (8)$$

The interpretive framework for comparison of the dummy coefficients now represents the net effect of being in the category associated with the dummy variable as compared to the overall mean or grand mean of the dependent variable, $Y = b_o$. For example, a mechanical repair type subtracts 0.3556 hours from the average repair time, 3.810 hours, and repair person Bob adds 0.8100 hours to the repair time average hours.

One further note is that a shift in the binary coded dummy regression coefficients, Equation (6) can be made directly to the "average" that is the overall mean of the dependent variable, Equation (8), by using Shifting Process II.

FRAMEWORK SHIFTING WITH A COMPUTER PACKAGE

The interpretive framework of dummy variable coefficients resulting for Shifting Processes I and II may also be obtained by using coding schemes that are alternatives to the binary coding scheme (Parker & Wrighton, 1975). The alternative coding schemes require that one category for each qualitative variable be excluded when calculating the regression equation. Referring to the maintenance service problem, repair type mechanical and repair person Bob are selected as the excluded categories.

When using the binary coding scheme the reference category is always coded zero. An alternative scheme, referred to as Alternative Scheme I, is to uniformly code the reference category with the value of -1. A value of 1 is assigned to categories in the same manner as the binary coding scheme. When an observation is in the repair type electrical category, D1 = 1, and when the repair type is mechanical, D1 = -1. For repair person, the selected dummy variables are D3 and D4. These dummy variables are defined in Table 3.

TABLE 3
Alternative Coding Scheme I for the Maintenance Service Company Qualitative Variables

Repair Type	Dummy D1	Dummy D2	Repair Person	Dummy D3	Dummy D4	Dummy D5
Electrical Mechanical	1 -1	omitted class	Jake Dave Bob	1 0 -1	0 1 -1	omitted class

For Alternative Coding Scheme I, the following computer regression equation is generated

$$\hat{Y} = 3.8968 + 0.2963\ D1 \quad + 0.0878\ D3 - 0.7519\ D4 \tag{9}$$

Equation (9) does not contain the coefficients, b_2 for D2, and b_5 for D5. These coefficients are easily determined as follow:

$$b_2 = -b_1 = -0.2963 \text{ and } b_5 = -(b_3 + b_4) = -(0.0879 - 0.7519) = 0.6640.$$

When these coefficients are included in Equation (9) the resulting equation is the same as Equation (7). The coefficients are equivalent to Shifting Process I, as suggested by Suits.

Another coding scheme, Alternative Scheme II, for a qualitative variable is to code a selected category, j, as 1, and the excluded category, e, as the ratio, p_j, of the number of cases in the selected category, n_j, to the number of cases in the excluded category, n_e, where $p_j = n_j / n_e$. For the maintenance service problem, when a case is in the repair type electrical category, D1 = 1 and for a mechanical repair type, D1 = -1.5. Dummy variables D3 and D4 can be used to represent repair person. Alternative Scheme II dummy variables are defined in Table 4.

TABLE 4
Alternative Coding Scheme II for the Maintenance Service Company Qualitative Variables

Repair Type	Dummy D1	Dummy D2	Repair Person	Dummy D3	Dummy D4	Dummy D5
Electrical Mechanical	1 -1.5	omitted class	Jake Dave Bob	1 0 -1.2	0 1 -1.8	omitted class

The computer regression equation resulting for Alternative Scheme II is

$$\hat{Y} = 3.8100 + 0.2370\ D1 \quad + 0.2339\ D3 - 0.6059\ D4 \tag{10}$$

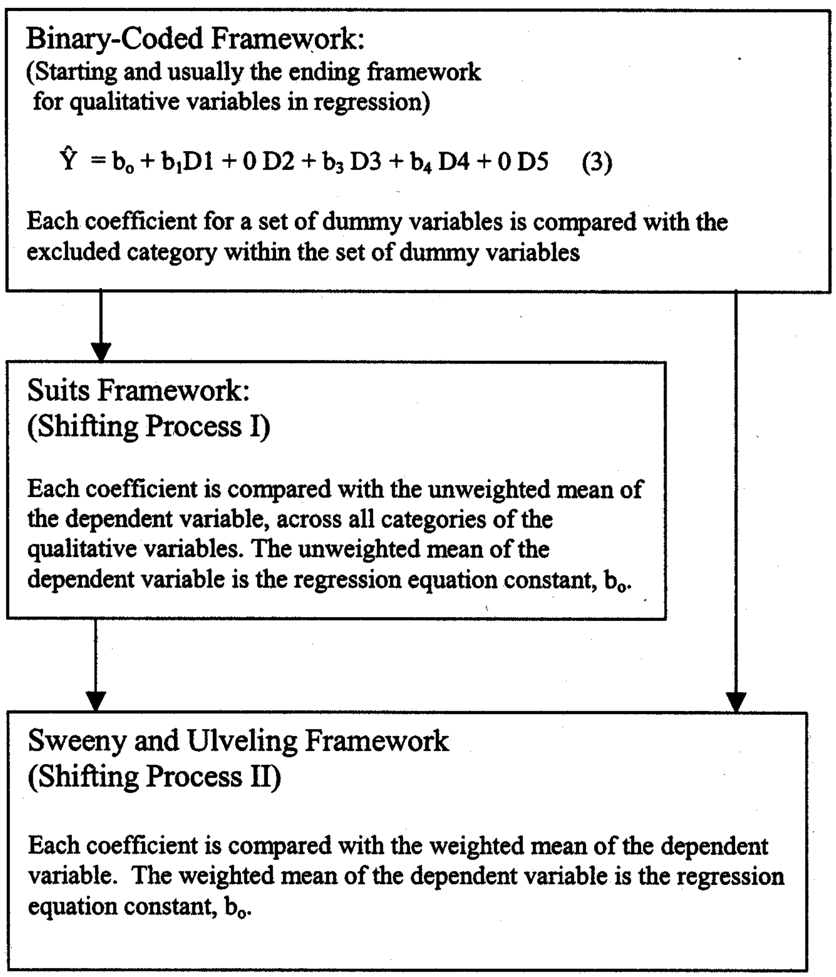
As before, Equation (10) does not contain the coefficients for D2 and D5. These coefficients can be calculated as follows:

$$b_2 = p_{mechanical} * b_1 = -1.5 * .2963 = - 0.3556 \text{ and}$$

$$b_5 = p_{Jake} * b_3 + p_{Dave} * b_4 = -1.2 * 0.2338 \quad -1.8 * (-0.6059) = 0.8100$$

When these coefficients are included in Equation (10), the resulting equation is the same as Equation (8). The coefficients are equivalent to Shifting Process II as suggested by Sweeny and Ulveling. The relationship of the interpetative frameworks are summarized in Figure I.

Figure I: Interpretive Frameworks for Dummy Variable Regression Coefficients



SUMMARY

Two processes for shifting the interpretive framework of binary-coded dummy variable regression coefficients are summarized in this paper. The frameworks assist in a more meaningful interpretation of the coefficients and allow for interpretation of the coefficients about an "average" of the dependent variable. One method suggested by Suits allows for each coefficient to be interpreted as a comparison of the coefficient to the unweighted average of the dependent variable over all subcategory means. The method suggested by Sweeney and Ulveling allows for an interpretation of the coefficients to the overall mean of the dependent variable. The effort to shift the interpretative framework is minimal and should be worth the effort. Comparing the coefficients to an "average" makes the coefficients insensitive to the selection of the category to be omitted. The processes of shifting can be accomplished with or without the assistance of a computer package. The shifted interpretive frameworks may be employed by practitioners who will use the shifted coefficients to disseminate to individuals are who heterogeneous in regard to the use and interpretation of the regression model. As an additional note, if quantitative independent variables are to be included in the regression model, each quantitative variable should be coded as deviations from its mean.

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IMPROVING SOFTWARE QUALITY WITH A RELIABILITY IMPROVEMENT WARRANTY

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ABSTRACT

A Reliability Improvement Warranty (RIW) contract establishes a fixed price for a given level of performance based upon the anticipated number of failures and the cost of each repair action. The anticipated number of failures over the warranty period is determined by assuming that the reliability of the warranted item will improve from an initial level to some specified level. The philosophy behind RIW is that once the fixed price warranty contract is established the profit realized is dependent upon the equipment's reliability.

In our current software industry, the need for a commitment to software quality is evident. Although the subject of software warranty has been addressed in literature, the subject of RIW for software has not been given much attention. In this research, we explore RIW as a vehicle for improving the reliability of software. We focus on the development of a model to determine the cost of a software-related RIW contract and employ the Pearl-Reed economic growth model to emulate the effect of equipment modifications on the reliability of an item under contract.

INTRODUCTION

The software industry has been in existence for about five decades. During this time, it has survived its backwards progression of maturity, and has taken some strides forward in the development of quality software. However, the question of software quality still remains an evasive issue. In an internal e-mail on January 15, 2002 to employees, Bill Gates coined the term "trustworthy computing" to describe his ambitious goal of software improvement. "As an industry leader, we can and must do better," he wrote.

At this point in time, no one would disagree with Bill Gates. Gates' e-mail was sent the very day the company recovered from a five-day stretch of system glitches causing Microsoft's Windows update feature to fail intermittently. Users were unable to download software or security-related updates. A month earlier, Microsoft had to fix a potentially serious security hole in Windows XP, which it touts as its most secure operating system yet. Also in 2001, a spate of Internet worms infected Windows computers at thousands of companies (Hulme, 2002).

Many information technology (IT) professionals consider the commitment long overdue. Poor software quality and security remain major problems for many businesses as they struggle with a continual flow of upgrades and fixes for software applications. It's an issue that keeps IT departments busy and one that can put their business data at risk.

Microsoft is by no means alone in dealing with reliability shortcomings. Carnegie Mellon University's CERT Coordination Center, a security watchdog group, says the number of software vulnerabilities reported last year more than doubled to nearly 2,500 (Hulme, 2002).

So what's wrong? A fundamental problem with software quality is that programmers make mistakes. Research has shown that even experienced programmers inject about one defect into every 10 lines of code, according to the Software Engineering Institute. If 99% of those are caught, that's still 1,000 bugs in a 1 million-line software application.

In our research, the concept of a Reliability Improvement Warranty (RIW) contract is offered as a vehicle for improving the reliability of software. In linking the theme of using a RIW as a means of improving software reliability, we develop a model to determine the RIW's cost.

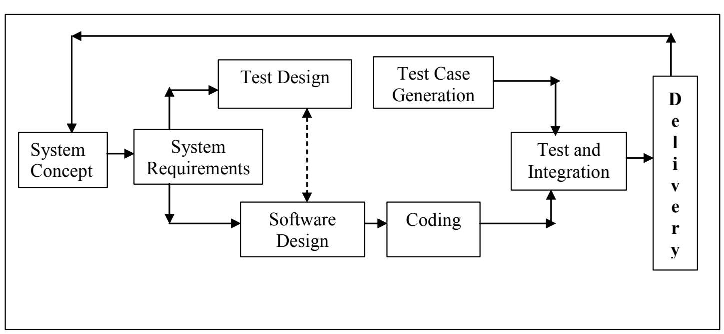
Although warranty cost has been a well-explored research topic, the subject of the cost of a RIW has not been given as much attention. Mamer (1987) researched the discounted and per unit cost of three common varieties of warranty without discussing RIW. Murthy and Blischke (1992) concentrated more on the effect of RIW on market behavior and the resulting social welfare implications. To extend the research, our work employs the Pearl-Reed economic growth model to emulate the effect of equipment modifications on the reliability of an item under contract.

SOFTWARE QUALITY

Quality is obviously a subjective term. The definition of quality software will depend on who the "customer" is and their overall situation. Each type of "customer" will have their own slant on quality. For example, the accounting department might define quality in terms of profits while an end-user might define quality as user-friendly and bug-free. In general, one might define quality software as software that is reasonably bug-free, delivered on time and within budget, meets requirements and/or expectations, and is maintainable.

The software life cycle for a system begins when an application is first conceived and ends when it is no longer in use. It includes aspects such as initial concept, requirements analysis, design, test planning, coding, integration, testing, and delivery. Figure 1 that follows depicts the software life cycle. Once delivered, the system requires maintenance, updates, and re-testing. Eventually the system will no longer be relevant and be phased out.

Figure 1
Life Cycle of Software System



According to Cho (1980), there are five common problems in the software life cycle that inhibit developers from achieving the goal of quality software. They include poor system requirements, unrealistic schedules, inadequate testing, scope creep of the requirements, and miscommunication. These five common problems can be marginally resolved if:

- ♦ Systems analysts develop clear, complete, detailed, cohesive, attainable, testable requirements that are agreed to by all stakeholders.
- ♦ Management provides realistic schedules that allow adequate time for planning, design, testing, bug repair, re-testing, changes, and documentation.
- ♦ An adequate test plan is executed that starts testing early with adequate time for testing and bug repair.
- ♦ Initial requirements should change as little as possible. If changes are necessary, they should be adequately reflected in related schedule changes.
- ♦ Walkthroughs and inspections when appropriate should be required to minimize miscommunications. Prototypes should be used throughout the project to clarify the customers' expectations relative to the system.

Unfortunately most software developers do not have the discipline to invoke the solutions to these common problems. In a recent survey by Information Week Magazine, 97% of 800 business-technology managers reported problems with software flaws in the past year, with 9 out of 10 reporting higher costs, lost revenues, or both (Hayes, 2002). Thus, a new approach is required to motivate developers to improve the quality of software.

SOFTWARE RELIABILITY

The reliability of a software system is a dynamic characteristic that is a function of the number of failures. Reliability is related to the probability of an error occurring. A program may contain known errors but may still seem reliable to its users. These users may apply the system in such a way that the system is always reliable. For example, a certain version of Microsoft Word may have an error in its Insert Object Math Equation Editor tool. But if a user never selects this tool, then the system will seem completely reliable (Sommerville, 1995).

To represent the failure rate of software systems, the Poisson distribution is generally used. This distribution leads to a simple negative exponential distribution to define the probability as a function of time. The reciprocal of the failure rate is the mean time between failures (MTBF). Thus, if is the constant failure rate, then the MTBF is 1/ . (Note: Throughout this paper, MTBF will be used rather than the failure rate since it is more convenient in expressing the reliability of a system.)

SOFTWARE WARRANTIES

If there is some doubt that there are persistent problems with the quality of software, look at the warranty on software systems. The warranted system is not guaranteed to meet specific quality standards. A software warranty is a manufacturer's guarantee to replace software that proves to be defective with a working copy of the same product and version. Software warranties do not cover interoperability problems that may arise from one software program interacting with another.

A software warranty is assurance that the supplier of the system will back the quality of the item in terms of correcting any legitimate problems with the item at no cost for a particular period of time or use. Warranties ensure that suppliers accept liability for the level of performance and quality they are offering, making software quality control a necessary element in order to offer software warranties (Brennan, 1994).

In order to establish a quality control program for software, the use of statistical quality control is a reality that cannot be escaped. The use of statistical quality control has come to be a powerful and widely used tool in the manufacturing industry. In manufacturing, a product's warranty is determined through the methods of statistical quality control (Schulmeyer, 1990). The manufacturer passes the cost of the warranty on to the customer in the form of a higher priced good. The manufacturer relies on the quality control principles in order to guarantee that the number of defective items produced does not cause the manufacturer's costs to exceed the additional cost carried by the customer.

The proposition for software warranties is that statistical quality control is just as applicable to software development. However, this is considered to be a myth by many software professionals, particularly those having no background in statistical quality control. It is not surprising, then, that a total commitment to product quality is lacking in the software industry. It is a widely accepted belief in the industry that current technology limits developers from offering a meaningful warranty. In fact, most off-the-shelf software packages offer no warranty at all except disclaimers. However, Cho (1987) has been an advocate of solving the many problems of the software industry in order to make software warranties an attainable dream to software users and developers. His methodology stresses the use of statistical quality control throughout every stage of the software life cycle.

In Cho's work, the software product population defective rate, obtained by statistical sampling, measures the goodness (or defectiveness) of the software. It can also provide a vehicle for which the software warranties can be delivered. According to Cho (1987), a software warranty can be written in terms of the following requirements:

Software Input Domain.	Conventionally, software input domain comprises four components: types of input, characteristics of each type of input, rules for using the input, and constraints on using the input.
Software Product Unit Definition.	The product unit definition identifies the desired output of the software.
Software Product Unit Defectiveness Definition.	Based on the product unit definition, a product unit will be considered defective if the desired output is not usable.
Sampling Plans.	The user should specify the most appropriate statistical methods consistent with the product unit definitions developed as part of the modeling activity.
Sampling.	The most appropriate statistical sampling methods consistent with the module product unit definitions during the modeling activity should be identified.

Acceptance Sampling.	A statistical sampling plan that most economically meets the specified producer's risk and user's risk levels can be selected.
The Defective Rate Less than α.	The user should establish the product unit population defective rate for each module.

RELIABILITY IMPROVEMENT WARRANTY

It is clear that one of the problems with the quality of software development is that there are no incentives for software developers to develop trustworthy software. The Department of Defense had the same problem of reliability with various subsystems in airplanes and weapons. They have been able to offset this problem with the application of the RIW concept, which was first developed in 1966 between Lear Seigler, Inc. and the Navy.

It is important to note initially that a RIW is not a warranty in the classic sense with respect to materials and workmanship. A typical item placed under RIW would be an airplane engine. It calls for the contractor to replace or repair, at his option, any warranted item within a specified time unit (in operating hours, calendar time or both), except on cases of obvious misuse. The contract establishes a fixed price for a given level of performance. This price is based upon the anticipated number of failures and the cost of each repair action. The anticipated number of failures over the warranty period is determined by assuming that the reliability of the warranted item will improve from the initial level to some specified level as a result of the contractor's planned reliability improvement program. The incentive comes in the form of an increased fee paid to the contractor if it can be demonstrated that the reliability of the item has been increased (Blischke and Murthy, 1996). In addition, a study by the Logistic Management Institute demonstrated investment in an RIW contract produced a net savings in total cost to the Defense Department, which helped to offset the effects of inflation and dwindling defense budgets (Logistic Management Institute, 1974).

The contractor, who is responsible for all failures, initiates an on-going reliability improvement program to improve the warranted item's initial reliability, θ_i, to a specified reliability, θ^*. The contract requires the manufacturer to replace or repair, at his option, any warranted item over the life of the contract.

Reliability information generated and recorded over time can be used to observe trends in the reliability of the product. The term "growth" can be used because it is assumed that the reliability of the product will increase over time as design changes and repairs are implemented. In other words, reliability growth is a projection of the reliability of a system, component, or product at some future development time. This projection is based upon information currently available from predictions or prior experience on identical or similar systems. Monitoring reliability, the MTBFs, and the failure rate of a system, equipment, or product, can establish an increasing trend in reliability, the MTBFs, or a decrease in the failure rate.

Such reliability growth occurs from corrective and/or preventive actions based on experience gained from early failures and corrective actions to the system, design, production, and operation processes. These actions represent an obvious reason for improved reliability. The philosophy behind RIW is that once the fixed price warranty contract is established, the profit realized by the contractor is dependent upon the equipment's reliability. Thus, contractors are motivated to focus their attention on the reliability of the items under contract through the use of "no cost" (to the buyer) engineering change proposals (USAF, 1974).

The advantages of the RIW for the buyer are reduced maintenance cost and increased reliability. The seller has the incentive to develop an on-going reliability (quality control) program because of the profit potential.

COST OF THE RIW CONTRACT

The contractor faces risk and uncertainty when he engages into a RIW contract. The risk and uncertainty increases as the length of the warranty increases. One risk function utilized by contractors to compensate for this is

$$R(T_w) = (1 + r)\ T^{w/12} \tag{1}$$

where r is the annual rate of risk (Balaban and Retterer,1973).

In equation 2, the total cost of employing a RIW contract for a given number of items for a warranty period is estimated by

$$C_{RWI} = (C_{MOD} + C_{DMC})^{*}\ R(T_w)(1 + X/100) \tag{2}$$

where

C_{RWI} = total cost of the RIW contract,

C_{MOD} = total expected modification cost of the contractor,

C_{DMC} = direct maintenance support cost to the contractor,

T_w = the length of the warranty period chosen for the RIW contract,

$R(T_w)$ = risk factor, and

X = percent profit of the contractor.

Next, methods of determining the expected modification cost of the contractor, C_{MOD}, and direct maintenance support cost to the contractor, $C_{DMC,}$ are explored. Before these costs can be defined, models for distributing modification factors for determining the expected times of the modifications during the warranty period, and for computing the expected MTBF over the warranty period must be developed.

THE EFFECT OF SYSTEM MODIFICATIONS ON THE MTBF

Modifications of a software system under a RIW are made through the use of software engineering change proposals. Each change proposal is designed to improve the current MTBF by a factor of M. Namely, if θ_{new} is the current MTBF, then the new MTBF $\theta_{new} = M^* \theta_{old}$. Within the lifetime of a RIW contract, a finite number of modifications may be implemented to cause the initial MTBF, θ_i, to approach a specified MTBF, θ^*, which was agreed upon during contract negotiations. Thus, a technique must be found to determine the improvement factor, M, defined by each modification.

The value of each M is bound such that $M \geq 1$ but $M < M'$, where M' is an upper bound for all such modifications pertaining to the particular item. Furthermore, the value of each M is dependent upon θ^*, the specified MTBF the contractor must try to reach with each modification, and upon θ, the current MTBF of the population of items procured.

One such function that is consistent with these assumptions is

$$M(\theta) = M' + (1 - M')\left(\frac{M' - M^*}{M' - 1}\right)^{\frac{\theta^*}{\theta}} \qquad (3)$$

where

M^* = the improvement factor expected if $\theta = \theta^*$.

Equation 3 is a form of the Pearl-Reed curve often used in economic growth models. Balaban and Retterer (1973) used a similar form of this equation in their study.

A numerical example is now considered to demonstrate the nature of the function M. Let the initial MTBF be 50 hours, the specified MTBF be $\theta^* = 111$ hours, M' = 4 and $M^* = 1.3$. For these values the modification function is

$$M(\theta) = 4 + (1 - 4)[(4 - 1.3)/(4 - 1)]^{(111/\theta)} = 4 - 3(0.90)^{(111/\theta)}.$$

Table 1 that follows indicates the values of M and the new MTBF, θ_{new}, after each modification is employed. Two modifications are required for θ_{new} to become greater than or equal to the specified MTBF of 111 hours.

Table 1: Modification Functional Values

Modification	θ	M(θ)	$\theta_{new} = M^*\theta$
1	50.0000	1.6257	81.2839
2	81.2839	1.4020	113.9818

TIME OF A MODIFICATION

The time at which a modification can be introduced is a random variable T_m. It is reasonable to assume that modifications will not occur before some minimum time T_α has occurred after procurement of the items or after a previous modification has been employed. One distribution that can be used to define T_m is the negative exponential distribution defined in equation 4,

$$f(T_m) = de^{-d(T_m - T_\alpha)} \tag{4}$$

for $T_m > T_\alpha$ and where the constant, d, represents the rate of modification. The cumulative distribution function F is defined in equation 5,

$$F(T) = P(T_m \leq T) = 1 - e^{-d(T_m - T_\alpha)} \tag{5}$$

for $T_\alpha < T_m \leq T$. Further, assume that a certain procurement results in k-modifications with values $M_1, M_2, M_3, \ldots, M_k$, and each modification occurs at some time T_m. The time between modifications is restricted so that each modification occurs only after some time T_α has occurred. Thus if k-modifications are involved, then the times of each are ordered as

$$0 < T_{\alpha_1} < T_{m_1} < T_{\alpha_2} < T_{m_2} < \ldots < T_{\alpha_k} < T_{m_k} < T_W.$$

Given that a modification occurs on some time interval (T_α , T_β), then the expected time of each such modification can be obtained by employing basic principles of probability theory. It can be shown that the expected time of each modification can be found by employing equation 6,

$$E(T_m \mid T_\alpha < T_m < T_\beta) = T_\alpha + \frac{1}{d} - \frac{(T_\beta - T_\alpha)e^{-d(T_\beta - T_\alpha)}}{1 - e^{-d(T_\beta - T_\alpha)}}. \tag{6}$$

AVERAGE MTBF OVER T_W

The average MTBF of the software system over the warranty period represents another important measure. If we assume that k-modifications occur respectively, at times T_{m1}, T_{m2}, T_{m3}, … T_{mn}, then the MTBF varies from θ_0 over [0, T_{m1}], to θ_1 over [T_{m1}, T_{m2}], to θ_2 over [T_{m2}, T_{m3}], …, to θ_k over [T_{mk}, T_w]. The values of the modification times T_{m1}, T_{m2}, T_{m3}, … T_{mk} can be estimated by employing equation 6 which defines the expected modification time.

Thus an estimate for the average MTBF is defined in equation 7,

$$\overline{\Theta} = \frac{\Theta_0(\overline{T}_{m1})}{T_w} + \frac{\Theta_1(\overline{T}_{m2} - \overline{T}_{m1})}{T_w} + \cdots + \frac{\Theta_k(\overline{T}_w - \overline{T}_{mk})}{T_w}. \qquad (7)$$

COST OF MODIFICATION

The cost of modification is a difficult cost to predict. Studies have shown that in general the greater the reliability improvement, the higher the cost. Certainly there are instances where high reliability improvement has resulted from low cost modification while low reliability improvement has resulted from high cost modification. In general the cost of modification is an increasing function of M and this assumption will be used.

A study by Mercurio and Skaggs (1973) utilized multiple regression analysis to obtain the cost of reliability improvement in terms of the resultant MTBF and the quantity of parts in the item modified. Balaban and Retterer (1973) in their study utilized a cost function in terms of the item modified. The cost function adopted in this study is essentially the same as Balaban and Retterer's except the cost is defined in terms of the amount of modification to increase the MTBF of the item. The function is denoted and defined in equation 8,

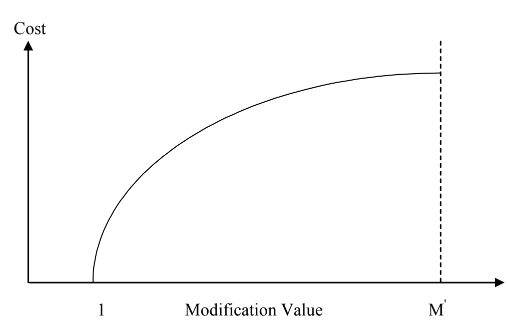
$$C(M) = 1.06(e^{[(M-1)/10M]} - 1)P \qquad (8)$$

where P = the purchase price of the item and $1 \leq M < M'$.

Presented below in Table 2 are the costs associated with the modifications defined previously in Table 1, assuming P = $10,000. The general shape of function C is illustrated in Figure 2.

Table 2: Cost of Modification		
Modification	M	C(M)
1	1.6257	$415.93
2	1.4020	$208.34

Figure 2
Graph of the Cost of Modification



If it is found that k-modifications are profitable, then the total cost of these modifications can be found using equation 9,

$$C_{MOD} = U\sum_{i=1}^{k} C(M_i). \qquad (9)$$

Additionally, the contractor will typically incur modification costs at time T_{mi}. If we assume the estimated modification costs are included by the contractor in the price of the RIW contract and the contractor pays the contract price at time 0, then these costs are discounted. Equation 10 that follows determines the total cost of all the modifications by discounting and amortizing each $C(M_i)$ with I = yearly interest rate. The modification times, T_{mi}, are again estimated by equation 6.

$$C_{MOD} = U\sum_{i=1}^{k} C(M_i)\frac{1}{(1+I/12)^{T_{mi}}}\frac{(T_w - T_{mi})}{(T_L - T_{mi})} \qquad (10)$$

DIRECT MAINTENANCE SUPPORT COST CDMC

The contractor incurs a total direct maintenance support cost, C_{DMC}, because the terms of the RIW contract make him responsible for failures. The value of the total direct maintenance support cost is determined by multiplying the expected number of failures by the cost per failure. This cost is determined by applying equation 11,

$$C_{DMC} = (U_o H_o T_w C_F)/\overline{\Theta} \qquad (11)$$

where

U_o = the number of operational units,

H_o = the average number of hours a unit operates in a month,

T_W = the length of the warranty in months,

C_F = the contractor cost per failed unit, and

$\overline{\Theta}$ = the average MTBF over the contract defined by equation 7.

EXAMPLE - HYPOTHETICAL PURCHASE

Table 3 below defines the parameters to be used for a hypothetical software purchase of an enterprise's information system.

Table 3: Parameters for the Example

Parameter	Symbol	Value
Expected Lifetime of Software	T_L	120 months
Minimum period before Modification	T_{win}	3 months
Length of RIW Contract	T_W	75 months
Discount Interest Rate	I	10%
Risk Factor	R	4%
Contractor Profit Factor	X	10%
Rate of modification	d	0.1096

The value of the rate of modification was derived assuming the probability that a software contractor would inaugurate a software modification over a 3 to 24 month period was 0.90. By employing equation 5 and the given information, a value for the rate of modification, d, can be found.

The key values M^* and M' which are required in the modification improvement function are defined as M' = 4 and $M^* = 1 + 0.20(\theta^* - \theta_i)/ \theta_i$ where θ^* is the specified MTBF and θ_i is the initial MTBF.

Table 4 lists the data elements for the hypothetical procurement. The results of applying the model for the cost of a RIW contract are summarized in Table 5. Notice that the unit cost of the RIW contract is $1,870.70 and the MTBF increases 61.7% from 312.4 hours to 505.0 hours over the warranty period for the given example.

Table 4: Data for the Example

Variable	Symbol	Value
Unit Price	P	$15,461.80
Operating Hours per Month	H_o	52
Number of Operational Units	U_o	27
Initial MTBF Specified	θ_i	312.4
MTBF	θ^*	472.3
Contractor Cost per Failed Unit	C_F	$500.00

Table 5: Results for the Example

Variable	Symbol	Value
Average MTBF over Contract	$\overline{\Theta}$	416.5
Final MTBF	FMTBF	505.0
Number of Modifications	k	5
Contractor Direct Maintenance Support Cost	C_{DMC}	$36,904.21
Contractor Modification Cost	C_{MOD}	$9,678.18
Cost of the RIW Contract	C_{RIW}	$65,474.58
Unit Cost of RIW Contract		$1,870.70

CONCLUSION

The concepts of using a RIW contract to increase the quality of software along with a model to determine the cost of a RIW contract have been presented. In our current software industry, the need for reliability improvement can be easily justified. With the pressure on software corporations to hurriedly put software on the market, it is no wonder that the vast majority of consumers fall victim to some type of error. It is vital to the leaders in the software industry to acquire and maintain trust and loyalty among customers. The main focus of this research lies in the ability to assign a tangible cost to a RIW for software. An integral part of this research is the use of the Pearl-Reed economic growth function, which determines the effects of modifications on the reliability of warranted items.

In this study, it has been shown that a plausible interpretation can be obtained by employing the methodology presented. Thus, a basis for an extension has been formed. Future studies can explore the use of other economic growth models relative to software modifications involved in the use of the concept of the RIW contract in the area of software warranties.

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UNDERSTANDING STRATEGIC USE OF IT IN SMALL & MEDIUM-SIZED BUSINESSES: EXAMINING PUSH FACTORS AND USER CHARACTERISTICS

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ABSTRACT

Globalization and competitive pressures have heightened the impetus for strategic use of IT. There is a common belief that if IT is strategically used, it will enable organizations (large or small) to meet their objectives, be competitive, and achieve a favorable business performance for long-term survival. This has led to a growing research interest in the use of IT as a strategic weapon by organizations in recent years. The current research examines the different concept of strategic use of IT, provides a synthesis of various ideas, and empirically investigates the characteristics of Malaysia small and medium-sized businesses that are strategizing with IT. Important theoretical and practical implications of the study are discussed.

INTRODUCTION

The term strategic use of IT has been inconsistently used by academicians and practitioners, thereby rendering understanding imprecise (King et al., 1989) and often misleading (Sutherland, 1991). Prahalad and Hamel (1990) and Williams (1992) have suggested that a truly strategic application must be assessed from the time-based sustainability, which is linked to core competence of the organization. Pederson (1990) stresses that strategic use of IT must result in observable competitive advantage, while Emery (1990) suggests that strategic information system can be deliberately planned and implemented to meet strategic objectives. As the number of criteria used grows, the concept of strategic use of IT becomes more complicated. In view of this, the current research reviews the various definitions of the term in an attempt to answer the question of what is strategic use of IT? The study also unveils the characteristics of SMBs that are strategizing with IT as well as discusses the strategies and action plans that will further enhance and promote greater strategic use of IT in SMBs

LITERATURE

To understand the term strategic use of IT, a review of the concepts of strategy will be helpful.

Strategy

Strategy has been defined by Chandler (1962) as the determination of the basic long-term goals and objectives of an enterprise, and the adoption of courses of action and the allocation of resources necessary for carrying out these goals. Andrews (1971) sees strategy as the pattern of objectives, purposes and goals, and major policies and plans for achieving these goals. Mintzberg (1979) defined the term as a plan, a set of intended action made in advance and consciously developed, aimed at achieving a purpose; a ploy which seeks to maneuver or deceive an opponent; a pattern of streams of important actions taken consistently by an organization over time regardless of whether that action has been intended or not; a position - a match between organization and environment; and a perspective which is embedded in the minds of decision makers and reflected in their intentions or actions. Strategy is a fundamental means an organization uses to achieve its objective (Hofer & Schendel, 1978). Strategy is also seen as a coherent pattern of decisions a firm makes to select the firm's present and future businesses (Hax, 1990).

Moreover, Porter's (1980 & 1985) definitions focus on a firm's ability to influence the collective effect of five competitive forces; the rivalry among industry competitors, the bargaining power of buyers, and suppliers, the threat of new entrants, and the pressure from companies offering substitute products or services. In his view, the concept of strategy lies in the way a company finds the best defensive position against these forces, or influences them in its favour.

Strategic Use of IT

The term strategic use of IT has evolved over the last decade and has been often associated with organizational competitiveness. Strategic use of IT is a system that is used to support or shape an organisation's competitive strategy, its plan for gaining and maintaining competitive advantage (Wiseman, 1988; Rackoff et al., 1985). It is a use that directly supports the creation, modification and implementation of an organisation's implicitly and explicitly stated plans (Huff & Beattie, 1985).

An application is strategic if it fundamentally changes the way the firm competes in its industry and ultimately improves the business performance (McNurlin, 1986). According to McNurlin, strategic IT application is outward looking, has close interface with the outside world, and aims at providing new services to customers and suppliers. Clemons (1986) examines strategic use of IT from sustainability of advantage viewpoint. To be strategic, application must be able to withstand its duplication by competitors. Clemons further observed that an application might be 'interesting' but unlikely to be strategic if it is not supported by firm's core competencies.

In turn, Ashmore (1988) sees an application as strategic if it adds significantly to company's bottom line, while Wiseman (1988) reasons that strategic use of IT must consider three key targets for IT applications: customers, suppliers, and competitors. If strategies designed to address these targets are supported by IT applications, then these applications are strategic in nature. Besides, the idea of strategic use of IT according to King et al. (1989) is that an application plays a direct role in the implementation of the business strategy and the achievement of comparative advantage.

Another definition of strategic use of IT is from Sabherwal and King (1991). They defined the term as 'the outcome or effect an application has on a company's success and destiny, either by influencing or shaping the company's strategy, or by playing a direct role in the implementation of the strategy. According to them, an application is strategic if it either provides the company with a competitive advantage or reduces the competitive advantage of a competitor.

Besides, Bergeron et al., (1991) sees strategic use of IT as a means used to secure gains over competitors, while Fripp, (1991) says it is a system, which companies developed that has either given it competitive advantage or has significantly affected the overall conduct and success of their organizations. Alter (1991) insists that only if an organisation's production, sales, and services functions are dependent on the systems can the applications be considered strategic.

Another view of strategic use of IT emanates from Schutzer's (1991), which describes strategic use of IT as an application that helps to maintain competitive parity over the long term. He explains that strategic system may not be necessarily competitive but suffices if it can create an environment conducive to the continued generation of innovative solutions and if it can create an environment that supports the production of continuous, small improvements.

Some writers have also considered what is not strategic IT application. It is clear that an IT application is not strategic by virtue of its sophistication and complexity. In fact there is even the tendency for very highly sophisticated systems to be resented. An application cannot be strategic if it only provides organizational support for greater internal efficiency and fails to produce results that support the company strategy and long term profitability (Zain, 1998), or if an IT investment serves merely to keep up to actions of competitors (King et al., 1989).

In this paper, the working definitions of strategic use of IT were taken from Zain (1998) and Ndubisi and Jantan (2001). Zain asserts that a common view of strategic use of IT often reflects the use of IT to support planning and management control and operations i.e. tactical and transactional considerations (Zain, 1998). Ndubisi and Jantan (2001) view the concept of strategic use of IT as the application of IT in critical areas of the business functions of the organization, in order to enhance job effectiveness, improve job performance, and increase productivity above competition. The implication of this definition is that employment of IT resources in critical areas of the business function must result in achievement of goals and objectives (operational effectiveness) competently (operational efficiency).

The views are similar to leveraging IT in the value chain (see Laudon & Laudon, 1997, p48). Laudon and Laudon identified the various examples of strategic information systems and the activities of the value chain where they can be applied.

METHOD

Participants & Procedure

The Northern Malaysia-based Malay, Chinese and Indian Chambers of Commerce and Industry as well as the national association of women entrepreneurs in Malaysia were contacted for the list of the members. The lists serve as the study's sampling frame. A set of questionnaire was sent to all the members of these associations, out of which 177 usable responses were received. The CEO represented the firms, as they are in a position to furnish reliable information about their firms since they are in charge of the day-to-day management of the business. Primary business activities of the firms range from manufacturing, to sales, education, interior decoration, fashion designing, etc.

Data were collected using structured questionnaire made up of three parts. Part 1 measures the actual system usage with two indicators of the number of job tasks where systems are applied such as for planning and control purposes. These indicators were taken from Rahmah and Arfah (1999). Part 2 measures strategically targeted benefits of the application such as: enhancement of job effectiveness (B1), improvement in job performance (B2), and increase in productivity (B3) taken from Ndubisi et al., (2001); Davis et al., (1989). Part 3 of the questionnaire measures demographic factors. Reliability analysis of the items measuring IT usage and strategically targeted benefits were performed to evaluate the Cronbach's Alpha value, which shows a value of .87 for usage and .91 for target benefits. The reliability test results in this study show alpha values exceeding .60 to .70 recommended by Hairs (1998) as the lower limit of acceptability. This ensures that the items grouping are reliable under the conditions of the local survey. Test of mean differences and the regression analysis were mainly used in the study.

RESULTS

Key Respondents' Profile

Table 2 shows key organization and CEO characteristics.

Table 2: Profiles of the Firms			
1. Industry Type	**Percent (%)**	**5. Computing Experience**	**Percent (%)**
Manufacturing	24.9	11 years or more	11.3
Service	75.1	1-5 years	44.1
2. Years of Establishment	**Percent (%)**	6-10 years	44.6
5 years or less	31.6	**6. Age**	**Percent (%)**
More than 5 years	68.4	41 years or more	44.0
3. Number of Employees	**Percent (%)**	40 years or less	56.0
101 or more	14.6	**7. Sex**	**Percent (%)**
Below 5	25.5	Male	58.2
5-100	59.9	Female	41.8
4. Respondent's Education	**Percent (%)**		
University graduate	45.2		
Non-University graduate	54.8		

The majority (68.4%) of the firms have been established for more than five years. Approximately 15% are considered medium size having between 100-200 employees, 60% are small sized (5-100 employees), and 25% are very small in size (below 5 employees). Many of the firms (75%) operate in the service sector, while the rest (25%) are manufacturing outfits. Close to 55% of the respondents are universities graduates, 56% have over five years of computing general experience, and 58% are male.

Target Benefits

Respondents have the following perception of systems' strategic benefits: 84.8% of respondents either agree or strongly agree that the system improves their job performance (B1), 84.2% agree or strongly agree that systems help increase their productivity (B2), and 85.3% at least agree that system enhances their job effectiveness (B3). The means for B1, B2, and B3 are respectively 4.21, 4.10, and 4.17 (min. = 1, max. = 5), showing that on the whole, respondents find the systems to improve their job performance, increase their productivity, and enhance their job effectiveness

IT Usage

Table 3 shows the IT usage characteristics of respondents.

Table 3: IT Usage

System Variety	Usage (%)	Specific Job Tasks	Usage (%)
Word processing	91.5	Letters and memos	85.9
Electronic mail	78.0	Producing report	75.1
Spreadsheets	55.9	Communication with others	73.4
Application packages	53.6	Data storage/retrieval	59.9
Graphics	44.6	Planning/Forecasting	46.3
Database	37.3	Budgeting	44.1
Programming languages	26.0	Controlling & guiding activities	38.4
Statistical analysis	25.4	Analyzing trends	34.5
		Making decisions	34.5
		Analyzing problems/alternatives	23.2

The results show that approximately ninety-two and seventy-eight percents of the respondents are respectively using word processing and electronic mail. Only approximately, twenty-six and twenty-five percents of the entrepreneurs are using programming languages and statistical analysis tools respectively. Among the job tasks where systems are used, letters and memos top the list, followed by producing reports, and communication with others, with approximately eighty-six percent, seventy-five percent, and seventy-three percent respectively, of the respondents using an application for these job tasks. It was further observed that 59.88% are using 4 (one-half) out of the 8 varieties of systems presented, and that 53.11% use a system to do 5 (one-half) out of the 10 job tasks listed.

IT Usage Pattern

Specific job tasks were grouped into those for administrative purposes (e.g. producing reports, letters and memos, data storage/retrieval, & communication with others), planning purposes (e.g. analyzing trends, planning/forecasting, analyzing problems/alternatives, & making decisions), and control purposes (e.g. budgeting, controlling & guiding activities). All respondents use a computer system for at least one administrative task, 59.9% of respondents are using a system for a minimum of one planning task, and 54.8% of respondents are using a system for at least one control task. Tabulated results are shown in Table 4.

Table 4: Usage Pattern and Percentage of Respondents

Job Tasks where systems are used	Percentage of respondents using
Administration	100
Planning	59.9
Control	54.8

Usage Pattern and Strategic Benefits

Each of the strategic benefits was recoded into two levels - low and high and the planning and control purposes reported in Tables 5. Low signifies that firms have a low perception of the system's benefits in terms of improvement in job performance, increase in productivity, or enhancement of job effectiveness. High means the reverse.

Table 5: Job Tasks

Strategic Benefits	Benefits Level	Planning		Control	
		Mean	SD	Mean	SD
Improvement in job performance	Low	0.00	0.00	0.00	0.00
	High	1.46	1.44	0.87	0.07
Increase in productivity	Low	0.33	0.89	0.08	0.29
	High	1.46	1.44	0.88	0.84
Enhancement of job effectiveness	Low	0.00	0.00	0.00	0.00
	High	1.46	1.43	0.87	0.84

Tables 5 shows that systems' usage for planning and control purposes is very low among respondents with low perceptions of the systems' benefits, and much greater for those with high perceptions, suggesting the salience of perceived benefits in inspiring greater strategic IT usage.

Tests of Differences

Using multivariate analysis of variance (MANOVA) the study examined differences in strategic use of IT based on demography. MANOVA is an extension of ANOVA to accommodate more than one dependent variable. Multivariate differences across groups were assessed using the Wilks' Lambda criterion (also known as the U statistics). This is because Wilks' Lambda examines whether groups are somehow different without being concerned with whether they differ on at least one linear combination of the dependent variable, and also because it is highly immune to violations of the MANOVA assumptions (Hair et al. 1998, p. 362). Table 6 shows the MANOVA results.

Table 6: MANOVA Results of Test of Differences

Demography	F-ratio	Sig. Level	Group Mean			
			Job tasks	Performance	Productivity	Effectiveness
Primary activity:	.87	.500				
Manufacturing			5.71	4.07	4.11	4.14
Service			4.97	4.11	4.19	4.23
Years of Establishment:	2.64	**.025**				
5 years or less			4.71	3.98	3.88	4.05
More than 5 yrs			5.36	4.15	4.31	4.28
Computer experience:	5.98	**.000**				
5 years or below			3.60	3.83	3.92	3.95
6 - 10 years			6.22	4.33	4.39	4.44
11 years or more			7.00	4.20	4.25	4.30
No. of employees:	5.4	**.000**				
Below 5			4.13	4.27	4.44	4.33
5 - 100			4.93	3.98	4.01	4.09
101 or more			7.81	4.27	4.35	4.46
Education qualification:	10.26	**.000**				
Non graduate			3.68	3.80	3.99	3.93
Graduate			6.14	4.29	4.29	4.40
Age:	1.67	.144				
40 years or below			5.66	4.13	4.21	4.24
41 years or more			4.51	4.05	4.12	4.17
Sex:	5.28	**.000**				
Male			4.95	3.97	3.93	4.04
Female			5.43	4.27	4.50	4.45

As reported in table 7, the multivariate F-ratio of MANOVA is significant at five percent level for years of company establishment, computing experience, number of employees, educational qualification, and sex, suggesting that strategic use of IT differ with respect to the business experience of the firms, firm size, user computing experience, education level, and sex.

Prior research on gender differences in the salience of instrumentality in decision- making processes about a new system provides a basis to expect that male CEOs will differ significantly from the female in strategizing with IT. Hennig and Jardim state that men adopt strategies focused on bottom-line results, while women tend to focus on the methods used to accomplish a task - suggesting a greater process orientation (Hennig & Jardim, 1977; Rotter & Portugal, 1969). Other plausible explanations for the greater strategic use of IT by male CEOs as compared to the female are computer anxiety and computer aptitude. Bozionelos (1996) and Morrow et al. (1986) suggest that women display somewhat higher levels of computer anxiety; and lower computer aptitude (Felter, 1985) compared to men (Chen, 1985).

Both general and computer-based learning are positively associated with strategic use of IT among SMB CEOs. A number of studies (e.g. Igbaria et al., 1997; Ndubisi et al., 2001) have shown that the more training users received, the greater usage of systems they make. In fact, Ndubisi et al., show that graduate users of technologies often make greater usage of applications than non-graduates. Moreover, that users with more computer-based education make greater use of advanced or sophisticated technologies than those with less computer-based training. This research observes a similar trend in the strategic use of IT.

In the context of technology adoption and usage in the workplace, there is evidence to suggest that the availability of support staff is an organizational response to help users overcome barriers and hurdles to technology use, especially during the early stages of learning and use (e.g. Bergeron, Rivard, & De Serre, 1990). Ndubisi and Ndubisi (2003) have shown that usage of technology in the workplace is positively associated with firm's size. Since larger organizations are more likely to engage more IT support staff, it is therefore logical that such organizations make greater strategic use of IT than smaller organizations do.

An innumerable body of IS research has related computing experience with adoption and sustained usage of technologies. Taylor and Todd (1995) found a stronger link between behavioral intention and technology acceptance behavior for more experienced users. Others, (e.g. Bagozzi 1981; Ndubisi et al; 2001) have found prior experience to be an important determinant of behavior. Experience may make low probability events more salient, thereby ensuring that they are accounted for in the formation of attitude (Ajzen & Fishbein, 1980), thus, possibly explaining why CEOs with more computing experienced make greater strategic use of IT than less experienced users.

Mean Differences in Usage Pattern Based on Strategic Benefits

Mean differences in usage pattern were examined in the light of perceived system benefits (i.e. improvement in job performance, increase in productivity, and enhancement of job effectiveness) using t-tests. The results are as follows:

i. Usage of systems for planning and control tasks is respectively higher (t-value = -13.176; p-value = .000) and (t-value = -13.451; p-value = .000) for firms with high perception of the system's ability to improve job performance than for those with low perception. There is no significant difference in usage of systems for mundane administrative tasks between the two groups.

ii. Usage of systems for planning and control tasks is respectively higher (t-value = -4.032; p-value = .001) and (t-value = -7.511; p-value = .000) for executives with high perception of the system's ability to increase their job productivity than for those with low perception. There is no significant difference in usage of systems for mundane administrative tasks between the two groups.

iii. Again usage of systems for planning and control tasks is respectively higher (t-value = -13.176; p-value = .000) and (t-value = -13.451; p-value = .000) for firms with high perception of the system's ability to enhance job effectiveness than for those with low perception. There is no significant difference in usage of systems for mundane administrative tasks between the two groups.

With respect to systems usage for planning and control purposes, usage is higher when the applications improved job performance, increased productivity, or enhanced job effectiveness (see Ndubisi & Richardson 2002 for more on these benefits). In line with the study's working definitions, this finding supports the opinion of Zain (1998) that strategic use of IT often reflects the use of IT to support planning and management control, and that of Ndubisi and Jantan (2001) which argues that for IT to be strategically used, it should lead to improvement in job performance, increase in productivity, and enhancement in job effectiveness.

Multivariate Analysis

Some authors (Zain 1998) have argued that strategic use of IT reflects system's deployment for planning and control tasks. Using multiple regression analysis, the study examined the impact of CEO characteristics on the strategic use of IT based on the above definition. The results are shown in Table 6.

Table 6: User Characteristics and Usage for Planning

User Characteristics	Planning		Control	
	Beta Coefficient		Beta Coefficient	
Innovativeness	.457***		.551***	
Risk-taking propensity	.018		-.072	
Perseverance	.107		.085	
Flexibility	.017		-.112	
	R^2 = .322	AR^2 = .306	R^2 = .245	AR^2 = .227
	F = 20.429	Sig. = .000	F = 13.958	Sig = .000
*** p < .001				

The results of the regression analysis show that user's characteristics such as innovativeness, risk-taking propensity, perseverance, and flexibility contribute significantly (F = 20.42; p < .001);

(F = 13.96; p < .001) and predict approximately 32% and 25% variations in usage for planning and control purposes respectively. The results also show that innovativeness has a significant relationship with usage for planning (t = 4.10; p = .000) and control (t = 4.69; p = .000). There is no significant relationship between risk-taking propensity, perseverance, and flexibility in one hand and usage for planning (p = .828; .351; .872) and control purposes (p = .418; .482; .324). Therefore, innovativeness is the only users' characteristic that is robust in determining strategic use of IT.

Other factors that push for strategic use of IT investigated in this study include outcome and process orientations, training, staff support, vendors' technical support, and computing experience. Table 7 shows the results of the analysis.

Table 7

User Characteristics	Planning		Control	
	Beta Coefficient		Beta Coefficient	
Usefulness	.227*		.357**	
Use Ease	-.064		.022	
Computing Experience	.342		.168**	
Vendor's Technical Support	.210*		-.017	
Training	.102		-.015	
Staff Support	-.059		.014	
	R^2 = .329	AR^2 = .305	R^2 = .245	AR^2 = .227
	F = 13.90	Sig. = .000	F = 13.958	Sig = .000
* p < .05	** p < .01	*** p < .001		

The results of the second regression analysis show that usefulness, ease of use, training, computing experience, staff, and vendor's support contribute significantly (F = 13.90; p < .001); (F = 6.97; p < .001) and predict approximately 33% and 17% variations in usage for planning and control purposes respectively. The results also show that usefulness, vendor's support, and computing experience are important determinants of usage for planning purposes, while usefulness and computing experience determines usage for control purposes. In other words, system's usefulness and user's computing experience are strong determinants of both job tasks. Vendor's support determines usage for planning purposes but not for control tasks. Ease of use, staff support, and training neither determines usage for planning nor for control task.

DISCUSSION AND IMPLICATIONS

This research has assessed the extent and pattern of IT usage by Malaysian SMBs, in response to the need for more empirical research on this sector. It was found that more than half of respondents (approximately sixty percent) are using four out of the eight varieties of systems presented. Five out of the ten job tasks listed were done using a computer technology by slightly over fifty-three percent of the firms.

Additionally, all of the firms are using a computer system for a minimum of one administrative task. Only approximately sixty and fifty-five percent of the firms are respectively using computer systems for planning and control tasks. System usage for planning and control purposes is lagging behind; as high as forty percent and forty-five percent of the firms respectively are not yet using any system for their planning or control tasks.

Looking back at the common view of strategic use of IT, which often reflects the use of IT to support planning and management control (see Zain, 1998), one can safely argue that only about half of the firms included in the study are strategically using IT. Except for the basic systems employed for mundane administrative purposes such as communication with others, data storage and retrieval, letters and memos, etc, by all the respondents, IT usage for other purposes is yet to reach full level. The non-usage of systems for planning and control purposes by nearly half of the respondents informs the conclusion of this research that not too many of the firms are strategizing with IT.

Based on the study's second working definition of strategic use of IT, which argues that applications must be directed at the critical business functions and should result in enhanced job effectiveness, improved performance in the job, and increased productivity, it is observed that strategic use of IT differ in terms of the years of company establishment, firm size, computer experience, educational qualification, and sex of users. It is also noted that in instances where the applications improved job performance, enhanced job effectiveness, or increased job productivity, usage of advanced systems, and usage in critical business functions (e.g. planning and control tasks) increased.

Strategic use of IT is important to SMBs. Information technology has become increasingly vital for creating and delivering products and services in most nations (Lohr 1997), since IT has a strategic significance in an information rich economy to reduce cost, upgrade quality, improve customer service, and enhance integration with vendors to increase the economic power of the firm (Jantan & Kannan, 1997). This not withstanding, SMBs still suffer the problem of under utilization despite increasing investment in information technologies and their benefits (Moore, 1991; Weiner, 1993; Johansen & Swigart, 1996), especially when strategically deployed (Ndubisi et al., 2001). Landauer, (1995) and Sichel, (1997), have suggested that such low usage of installed systems has been a possible key explanation for the 'productivity paradox'. This could also explain the Malaysian SMBs' inability to make its full impact yet on the economic development of the nation. It is needful to use systems strategically, and to enjoy strategic benefits of these systems. According to Sabherwal and King (1991), these systems can fundamentally change the firm's goals, products, services, or internal and external relationships to help the organization gain a competitive advantage. They are able to alter the way the firm conducts its business or the very business of the firm itself.

Besides its significance to the Malaysian SMBs, this research has obvious implications for systems designers and vendors. They should commit to creating awareness on the gains of using technologies strategically and also provide expert guide on 'how'. Repositioning of systems targeted at SMBs to expound their strategic benefits is very vital as this will lead to greater usage of systems for planning and control purposes as shown earlier. Rather than promoting the administrative uses of future designs, emphasis should be on their planning and control capabilities. Above this, system designers and vendors may wish to address the latent demand for strategic information systems in SMBs by targeting this sector with such systems. With the growing number of enterprises today, selling strategic information systems, and training on the systems to small and medium-sized businesses may create a viable niche market for systems designers and vendors. In addition, if backed by technical support (see Ndubisi et al., 2001), strategic information systems providers can count on the acceptance and patronage of SMBs.

FUTURE RESEARCH

As noted in the literature that there are a number of criteria suggested by other scholars for measuring strategic use of IT, these differences must be taken into account by future research assessing strategic use of IT. Future research could replicate this study in SMBs in other nations for comparative purposes, as well as in larger firms before any generalization could be made.

CONCLUSION

Various viewpoints on the definition of strategic use of IT were reviewed. IT usage pattern of the firms were examined, and the results (based on the working definitions) show that in slightly over half of the firms, IT is being used strategically but not in the rest. The characteristics of firms and CEOs using IT strategically were noted. Length of business experience, firm's size, user computing experience, level of education, and gender are important consideration in strategizing with IT. Push factors for strategic use of IT are usefulness (e.g. improvement in job performance, enhancement of job effectiveness, and increase in productivity), computing experience, vendor's technical support. Important user characteristic is innovativeness.

Strategic IT is that which brings about improved performance, enhanced effectiveness, and increased productivity at the critical business functions where they are applied such as in planning and control situations.

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TOWARD AN UNDERSTANDING OF MIS SURVEY RESEARCH METHODOLOGY: CURRENT PRACTICES, TRENDS, AND IMPLICATIONS FOR FUTURE RESEARCH

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ABSTRACT

This study is a comparison of survey research methodology applied by research papers published during 1996 to 1999 on three major MIS journals. Through a content analysis of articles from MIS Quarterly (MISQ), Journal of Management Information Systems (JMIS) and International Journal of Information Management (IJIM). There are 75 papers that adopted questionnaire survey as the major research methodology to study for MIS research issues. With the consideration of PK list, SMA and other textbooks about business research methods, the authors have developed a checking list containing essential procedures to perform a questionnaire survey research. It consists of six parts: demographics, research design, questionnaire development, sampling procedure, data collection, and data analysis methods. Results indicate some potentially important trends in reports of research methodologies and the methodology usage is generally improved after analyzing our recording data and comparing with early assessment studies.

INTRODUCTION

A multisite, multisource research methodology is suggested for students of information management in order to attain generalizability and statistical significance in reporting findings. Such data may inform us of whether methods are becoming more standardized or more diversified over time. Examination of such patterns may provide some insights into the possible future development of research methodology. This paper describes methodologies that are appropriate for investigating the above and other contingency approaches in MIS field. It captures the dynamic aspects of environmental evolution and competitive changes and act on by changing patterns of resource allocation.

The purpose of this article was to identify possible trends in the use of various research methodologies in MIS studies. The rigor of survey research methodology had been discussed by several researchers. Pinsonneault and Kraemer (1993) considered that those investigations were done from three perspectives: constructing and illustrating research methodologies, examining the usage of methodology and identifying appropriate situation for applying survey research. This study is to investigate the survey research methodology applied to research papers published during 1996 to 1999 on three major MIS journals, including MIS Quarterly (MISQ), Journal of Management Information Systems (JMIS) and International Journal of Information Management (IJIM). There are 75 papers that adopted questionnaire survey as the major research methodology to study MIS related issues.

Pinsonneault and Kraemer (1993, will be abbreviated as PK later) had implemented an assessment of survey research methodology. They collected 122 MIS research papers published on sixteen journals during 1980 to 1990 and designed a list (will be called PK list later in this paper) to record how the research methodology were processed and described. The PK list examined survey methodologies mainly on research design, sampling procedures, and data collection. They concluded five general misapplications suffered for the survey research: (1) single-method designs where multiple methods were needed. (2) Unsystematic and often inadequate sampling procedures. (3) Low response rate. (4) Weak linkages between units of analysis and respondents. (5) Overreliance on cross-sectional surveys where longitudinal surveys were really needed.

Grover, Lee and Durand (1993, will be abbreviated as GLD) developed a list called SMA (Survey Methodological Attributes), that consists of nine Boolean statements about the technical processes of the survey methodology, such as sampling, data collection, validity and reliability of the instrument (The SMA list is included in the end of Appendix). They used SMA to evaluate 227 MIS research papers published during 1980 to 1989. The results showed that most papers have scores between two and four, and the mean score is 3.133. However, SMA didn't include the statistic analysis methods.

With the consideration of PK list, SMA and other textbooks about business research methods, we developed a checking list containing essential procedures to perform a questionnaire survey research, called LYCHEE (Lin, Yu, and CHen's Empirical Examination for the survey methodology) (Lin,2001). It consists of seven parts: demographics, research design, questionnaire development, sampling procedure, data collection, data analysis methods, and SMA list. The records of SMA list would be used to compare with GLD's result.

Our analyses show some possible patterns in the methodologies employed in MIS studies. Also, examination of the methods reported in MIS field might provide insights for those who aspire to have their research published in top-tier publication outlets. It is thus necessary to begin an examination of management journal content with respect to research methods. This awareness is important, since researchers should be mindful of what methodological procedures are being rewarded by the top journals (Scandura & Williams, 2000).

The next section is about the contents of LYCHEE (Lin,2001) containing essential procedures to perform a questionnaire survey research. The third section describes the research method and the profile of sample papers. The fourth section presents the results with some discussions. The last section summarizes the results and recommendations that were made throughout this article.

THE ASSESSMENT INSTRUMENT: LYCHEE

Research design

Kerlinger (1986) defined the research design as a plan and structure of investigation in order to answer questions. The plan is an outline of research procedures from setting the hypotheses to the final analysis of data. The structure, on the other hand, is a paradigm or model of the relations among the variables of a study. Because this study focused on the survey research, the "plan" is referred to the methodology to perform a survey. Therefore, we set five questions about research design: purpose, survey type, hypotheses, analysis unit and respondent positions.

Questionnaire development

The questionnaire is a communication instrument to obtain opinions from respondents. How to correctly measure attitudes of respondents is the essential issue for the questionnaire development. In the mean time, the questionnaire should fully represent the research structure or models. The wording of questions and the scales for answers are all matters to the measurement. There are four questions for this part in LYCHEE: close questions or open questions, pilot study, pretest and whether the questionnaire was appended with the sample paper.

Sampling procedure

Sampling is taking a portion of elements in a population as the representative of that population (Kerlinger, 1986). The conclusions are inferred for the population from sample results. Whether a sample is representative or not will affect the consequence of research. LYCHEE listed five questions related to sampling procedure: sample frame, sampling method, sample size, sample bias testing and external validity explanation.

Data collection

Data collection usually is the most cost consuming part of a survey research. Three items would be recorded: data collection methods, discussion of validity and reliability.

Data analysis methods

For the past decade, the statistic software is getting more powerful, such as SPSS, SAS, LISREL, and EQS. Multivariate statistic analyses are easier to perform so that researchers are able to explore more possibilities to interpret their empirical data. There are totally thirteen statistic modules listed in LYCHEE.

RESEARCH METHODOLOGY

Three major MIS journals (MIS quarterly, Journal of MIS, and International Journal of Information Management) with volumes from 1997 and 1999 were reviewed. The three journals have been included in the Social Science Citation Index (SSCI). Papers published on them had been through the review process. We adopted LYCHEE to record research methodology for each survey research paper. There are seventy-five papers using survey as main research methodology, in which thirty-two were from IJIM, twenty-seven were from JMIS and sixteen were from MISQ.

RESULTS AND DISCUSSION

This study is to investigate the survey research methodology applied by those research papers published during 1996 to 1999 on three major MIS journals, including MIS Quarterly (MISQ), Journal of Management Information Systems (JMIS) and International Journal of Information Management (IJIM). There are 75 papers that adopted questionnaire survey as the major research methodology to study for MIS related issues. Table1 shows the papers are published on three journals. There are 32 of 75 papers are published on IJIM, 27 papers are published on JMI, and 16 papers published on MIS. In the Table2, shows papers are published during 1996 to 1999. There are 23 papers are published at 1996, 16 papers are published at 1997, 20 papers are published at 1998 and 16 papers are published at 1999.

Table 1

Journal	P	%
IJIM	32	42.67%
JMIS	27	36.00%
MISQ	16	21.33%

Table 2

Year	P	%
1996	23	30.67%
1997	16	21.33%
1998	20	26.67%
1999	16	21.33%

In the table3, the most surveys focus on I &I(Introduction and Impact) topic (21 papers), E&S(Economics and strategy) topic(16 papers), and User topic(13 papers).

Table 3

	P	%
Introduction and impact(I&I)	21	28.00%
Users	16	21.33%
Economics and strategy (E&S)	13	17.33%
Evaluation control(EvCtr)	6	8.00%
System project(SP)	5	6.67%
Electronic commerce(EC)	4	5.33%
IS ethics(ISE)	4	5.33%
IS research(ISR)	4	5.33%
Computer-supported cooperative work(CSCW)	3	4.00%
Decision support and knowledge-based systems(DSS)	1	1.33%

Research Design

The second part of LYCHEE is research design that contains research purpose, hypotheses, analysis unit of the research and respondent positions.

Research Purpose

For the research types, the results show that the exploratory researches are about a half (53%), almost twice amount of descriptive studies (23%) or explanatory studies (20%). In our database (table5), there were very few longitudinal studies (3 out of 75 studies or 4%).

Table 4

Research Purpose	P	%
Descriptive	17	22.67%
Explanatory	15	20.00%
Exploratory	40	53.33%
Instrument/measure development	3	4.00%

Table 5

Survey Type	P	%
Cross-sectional	72	96.00%
Longitudinal	3	4.00%

The result is quite different from Pinsonneault and Kraemer's (1993). They had 29%, 25% and 46% of sample papers as exploratory, descriptive and explanatory studies, respectively. Pinsonneault and Kraemer thought that the volumes of explanatory studies should be increasing in years because the knowledge of MIS has been cumulated. However, we have the results that exploratory and descriptive studies are the majority of the research type. In addition, only three longitudinal studies out of 75 papers are quite similar to the result of Pinsonneault and Kraemer's. It indicates that the survey research is mainly performed through the cross-sectional approach.

There may be two possible reasons. The first one is that the quick evolution of information technology generates new problems and issues. Researchers need to explore new topics from time to time. The "new" research topics mean there maybe less people have heard about or experienced about it. Therefore, to collect people's opinions by survey would face the limitation of available respondents. The prospect can be supported by another finding that over a half of sample papers adopted nonprobabilistic sampling methods.

Our database indicates that hypothesis is adopted frequently in describing the research questions (In the table6, 31 out of 75 papers or 41%). The average number of hypothesizes are about three or four in each study, that means the research variables are around two or three. There are fifteen percent of surveys manipulated over six variables in their research. However, there are 4 papers abuse propositions to present their research question in the survey research.

Furthermore, there are more than half of all studies (52 percent or 64 studies) either do not provide research hypotheses/questions or do not describe them clearly enough to get an understanding of the study's aim. This is problematic because research hypotheses or questions determine the research design and shape the sampling procedures, data collection, and data analysis. If there are no questions or hypotheses, or if they are poorly formulated, it is unlikely that the survey effort will yield useful results except by accident.

Table 6

	P	%
Hypothesis	31	41.33%
Proposition	4	5.33%
Question	6	8.00%
Not Mentioned or Vague	37	49.33%

Table 7

Number of Hypothesis	P	%
1	1	1.33%
3~5	23	30.67%
6~7	7	9.33%
8~12	5	6.67%
Not Mentioned	39	52.00%

Analysis Unit

Table8 presents studies group by unit of analysis and journals. It indicates that most surveys used organizations (41%) and individuals (33%). The department, project (6.6%), and application (8 %)are seldom used.

Table 8

Analysis Unit	P	%
Application	6	8.00%
Department	4	5.33%
Individual	25	33.33%
Organization	31	41.33%
Project	5	6.67%
Not Mentioned	4	5.33%

Respondent Position

Our data also show that students are seldom used as respondent positions. CEO(22%), CIO(21%), manager (28%), and IS professionals(21%) are respondents frequently in these surveys (Table9). This fact is even more striking when the most surveys adopt organization analysis-unit.

Table 9

Respondent Position	P	%
CEO	17	22.67%
CIO	16	21.33%
Managers	21	28.00%
IS Professionals	16	21.33%
Staff Professionals	8	10.67%
Project Leaders	8	10.67%
Students	3	4.00%
Not Restricted	12	16.00%
Not Mentioned	11	14.67%

Questionnaire Development- Question Scale

Table10 present the distribution of question scale. The most frequently used form is Likert scale (7-point is 34.6%, 5-point is 37.3%). With this scale the respondent is asked to respond to each statement by choosing one of five or seven agreement choice. The item analysis procedure evaluates an item based on how well it discriminates between those persons whose total score is high and those whose total score is low.

Table 10

Question Scale	P	%
7 points	26	34.67%
Likert-5	28	37.33%
Other	12	16.00%
Not Mentioned (Close-ended)	17	22.67%
Open-ended	3	4.00%

Pilot Study

Table11 presents the distribution of pilot study. There are few papers report the pilot study (around 30%). There are a number of variations on pilot study which some are intention ally restricted to data collection activities. In the table12, experience survey/ interview (21%) and Expertise (14%) are the most be adopted method of pilot study. In the data collection, many studies draw subjects from the target population (17%) and the average number of sample is ten.?

Table 11		
Papers Report the Pilot Study	P	%
Experience survey/interview	16	21.33%
Focus group	1	1.33%
Expertise	11	14.67%
Panel discussion	2	2.67%
Others	1	1.33%
Without pilot study	53	70.67%

Table 12		
Pilot Study	P	%
A sample of the population	13	17.33%
Experts	5	6.67%
Student	1	1.33%
Not mentioned(with pilot study)	3	4.00%

For the assessment of questionnaire development, over a half of those papers did not perform pilot study, pretest, neither appended the survey instrument. Usually these terms "pretest," "pilot study" and "pilot test" may cause confusion and can be exchangeable in the writing.

In this study, the authors have made operation definitions for the terms and then performed the paper evaluation according to those definitions. Pinsonneault and Kraemer (1993) stated that only 24% of 122 papers reported the pretest in their papers. Although they didn't explain much about the term "pretest," it may include pretest, pilot study and pilot test. Because our results show the more often implementation of the pretest, it can be interpreted as the higher recognition of its importance.

Another important aspect of the quality of survey research is whether the questionnaires were pretest and how they were pretested. Table13 indicates that 42 studies did not pretest the questionnaire and seven studies did not mention the questionnaire. Table14 reports the methods of pretest. This very large number of studies (30.67%) used questionnaires that were tested with sample s of different respondents without pretesting them again. On the other hand, some studies (2.8%) apply pretest questionnaires from expert to similar respondents of other samples.

Table 13		
Times	P	%
1	18	24.00%
2	5	6.67%
3	2	2.67%
6	1	14.67%
Not mentioned (with pretest)	7	9.33%
Without pretest	42	56.00%

Table 14		
	P	%
A sample of the population	23	30.67%
Experts	2	2.67%
Student	6	8.00%
Not mentioned(with pretest)	5	6.67%

In our database, the researchers perform their pretest study more frequently than perform the pilot study. The sample of pretest is often collected from target population (30%). Yet, there are twenty percent of surveys use about 10 subjects. However, there are four papers extend the meaning of pretest to pilot study while these study report the result of pretest.

Sampling Procedures- Sample frame

In our database, only 13% of the papers did not describe the sample frame. Most of the sample frames refer to geographic region (37%), company worker (24%)or commercial list (21%).

Table 15		
Sample Frame	P	%
Clients	2	2.67%
Commercial List	16	21.33%
Company Worker	18	24.00%
Geographic Region	28	37.33%
Members of an Association	8	10.67%
Population	2	2.67%
Students	2	2.67%
Other	1	1.33%
Not Mentioned	10	13.33%

Sampling method

The database indicates that there is 20 studies used go-through list sampling method and 17 studies used random sampling method. Usage of convenience and judgment sampling procedure are 14 studies (table16).

Table 16		
	P	%
Cluster	1	1.33%
Convenience	14	18.67%
Go through list	20	26.67%
Judgment	14	18.67%
Quota	1	1.33%
Random	17	22.67%
Snowball	2	2.67%
Stratified	3	4.00%
Not Mentioned	5	6.67%

It should get more concerned about the sampling methods. Usually, textbooks or papers about the research methodology would recommend probabilistic sampling methods in order to reduce sampling bias or errors. However, our study shows that over a half of papers used non-probabilistic sampling methods. Those researchers should aware of problems caused by the sampling bias. As GLD has commented that, it is almost impossible to perform a perfect survey in the read world. For the limitation of budget, scale of research design and the difficulty to reach right respondents for right answers, non-probabilistic sampling might not add serious harm as long as the researchers keep alert on the possible biased errors. In addition, the purpose of survey research would rather explore the unverified phenomena or confirm the presumed theoretical models than the search of the general opinions or attitudes.

Sample size

Table17 shows the distribution of delivered questionnaire, responded questionnaire, valid questionnaire and response rate in each paper. The average response rate is 48%, the average number of delivered questionnaire is 560, and the average number of responded questionnaire is 250(valid questionnaire is 240). For each sample (in table18), the response rate is 51%, average delivered questionnaire is 470, and the average number of responded questionnaire is 200(valid questionnaire is 220). Based on these data, the sample size of three journals of MIS filed is an important criterion of survey quality. Because most important factor in determining the size of a sample needed for estimating a population parameter is the size of the population variance. Often it is claimed that a sample should bear some proportional relationship to the size of the population from which it is drawn.

Table 17		
	P	Avg
Delivered Questionnaires/Paper	70	562.2
Responded Questionnaires/Paper	49	253.7
Valid Questionnaires/Paper	40	242.1
Response Rate/Paper	48	48%

Table 18		
	S	Avg.
Delivered Questionnaires/Sample	83	474.1
Responded Questionnaires/ Sample	61	203.8
Valid Questionnaires/ Sample	43	225.2
Response Rate/ Sample	79	51%

Testing for Sample bias

There are a few researches test the sample bias(see table19 and table20). However, most frequently used method of testing for sample bias is to compare the response and Non-response (about 10%), the testing technology is t-test(about 6%) or Chi-square(about 6%)?Pretesting is in order to detect weakness in the instrument and most studies use two or more pretest. Although many research try to keep pretest condition close to what actual study, there is lack of powerful testing technologies.

Table 19		
Method	P	%
Early vs. Late	4	5.33%
Explanation	3	4.00%
Initial vs. Follow-up	1	1.33%
Response vs. Non-response	7	9.33%
Response vs. Response	4	5.33%
Not Mentioned (With Tests)	1	1.33%
Without Tests	56	74.67%

Table 20		
Testing technology	P	%
Other	5	6.67%
T	5	6.67%
Chi-square	5	6.67%
Not Mentioned (With Tests)	4	5.33%

Table 21		
	P	%
Biased (With Tests)	2	2.67%
Unbiased (With Tests)	17	22.67%

Explanation of External Validity

There are only four studies reports the explanation of external validity. These four studies are published in MISQ.

Data Collection- Data Collection Methods

Table22 presents the distribution of studies among the eight data collection methods used in MIS surveys. Mail survey (54.67%) is the most frequently used data collection methods and 11 studies relied on face-to-face questionnaires (14 percent). Quite surprisingly, there is seldom usage of computer embedded (5.33%) and telephone interview questionnaires(9.33%).

Table 22		
Data Collection Methods	P	%
Ask	1	1.33%
Computer Embedded Questionnaire	4	5.33%
Face-to-face Interview	11	14.67%
Hand out	1	1.33%
Internal Distributed Questionnaire	5	6.67%
Mail	41	54.67%
Sent	2	2.67%
Telephone Interview	7	9.33%
Not Mentioned	7	9.33%

Validity Analysis of Questionnaire Measurement

Table23 displays 40% of the papers have explained the instrument validity. Also, there are many criterion to test validity of questionnaire measurement such as concurrent, content, convergent and discriminant validity that are used frequently. There are 11 studies test concurrent validity, 12 test content validity, 10 test convergent validity and 19 test discriminant validity.

Table 23		
	Paper	%
Adopted Validated Instrument	8	0.107
Concurrent	11	0.147
Content	12	0.160
Convergent	10	0.133
Discriminant	19	0.253
Predictive	1	0.013
Other	3	0.040
Mentioned	30	0.400
Not Mentioned	45	0.600

Reliability Analysis of Questionnaire Measurement

Fifty-three percent (53%) of the papers described the reliability (Table 24).The most popular technology of reliability analysis of questionnaire measurement is Cronbach's alpha (34 of 40 mentioned studies). Some of studies (7 studies) used a validated instrument without validate them again. Although validity and reliability are two of the most emphasized characteristics to indicate instrument quality, there is still about a half of those papers not to mention about them.

Table 24		
	Paper	%
Adopted Validated Instrument	7	0.093
Composite Reliability/SEM	3	0.040
Cronbach's Alpha	34	0.453
Other	1	0.013
Mentioned	40	0.533
Not Mentioned	35	0.467

Data Analysis Method

The last part of the list is data analysis methods. According to our result (table25), descriptive statistics(92%), correlation(52%), factor analysis(28%), and regression(24%) are used most often. Furthermore, in the multivariate statistic methods, discriminant analysis, logistic regression, canonical correlation and cluster analysis are all used once or twice in those papers, except for structural equation modeling that were adopted by nine papers. However, simple statistic methods seem to gain more favor than complex multivariate statistic methods for researchers.

Table 25		
	Paper	%
Descriptive	69	0.920
Correlation	39	0.520
Factor Analysis	21	0.280
Regression	18	0.240
ANOVA Series	8	0.107
Discriminant Analysis	1	0.013
Logistic Regression	1	0.013
Canonical Correlation	1	0.013
Clustering Analysis	2	0.027
EFA	2	0.027
CFA	4	0.053
PLS	6	0.080
Non-parametric Statistic	5	0.067
Others	6	0.080
Total	16	0.213

SMA

The SMA of the studies of JMIS is higher quality than IJIM and MISQ. According to SMA measurement (Table26), the average score of JMIS' studies is 6.1, the IJIM's is 4.1 and the MISQ's is 4.4. The SMA of our study has an average of 4.9 and standard deviation of 1.775. Using t-test to compare with GLD's SMA results (mean=3.133, standard deviation=1.333 and n=227), the t-value is 9.2655 so that our results are significantly different from GLD's results. That means the sophistication of methodology performance has improved in these years.

Table 26			
SMA	IJIM	JMIS	MISQ
1	0	0	2
2	2	1	1
3	7	1	3
4	12	2	3
5	8	2	1
6	3	10	2
7	0	6	3
8	0	5	1
Average	4.1	6.1	4.4

Has the rigor been improved through those years?

Our assessment of survey research in MIS indicates that the quality of survey research methodology is lacking overall. Table 27 summarizes the enhancement and retro- gradation of surveys in MIS. The surveys aimed at explanation, exploration and description generally are improved than Pinsonneault and Kraemer's study. However, there are still some problems in research design and sampling procedures. Four dimensions are particularly enhanced: unit of analysis, pretest, response rate, and pilot test. Two dimensions are particularly weak: research hypotheses and representativeness of the sample. The following session will describe these elements.

Table 27
Summarizes the enhancement and retro- gradation of surveys in MIS

Element/Dimension	Exploration	Description	Explanation
Research design			
Survey type	Adequate	Adequate	Need more longitudinal surveys
Unit(s) of analysis	Clearly defined*	Clearly defined and appropriate for the questions/hypotheses*	Good definition
Respondents	Need to increase the number of respondents	Need to increase the number of respondents	Need to increase the number of respondents
Research hypotheses	Not necessary	Adequate stated*	Adequate stated*
Sampling procedures			
Representativeness of sample frame	Adequate approximation	Need better explanation and justification of choices	Need better explanation and justification of choices
Representativeness of the sample	Adequate	Need more systematic random samples	Need more systematic random samples!!
Sample size	Adequate	Adequate	Adequate
Data collection			
Pretest of questionnaires	With subsample of sample*	With subsample of sample*	With subsample of sample*
Response rate	Not a criterion*	60-70% of targeted population*	60-70% of targeted population*
Pilot Test			
(Mix of data collection methods)	Need more use of multiple methods	Not a criterion	Multiple methods
*The survey research is improved			
!! the survey research is retrograde			

CONCLUSION

Pinsonneault and Kraemer (1993) thought that the volumes of explanatory studies should be increasing in years because the knowledge of MIS has been cumulated. However, our empirical result shows that exploratory and descriptive researches were seventy-six percent of the sample papers, which is contrast to their prediction. The possible reason is that the quick evolution of information technology generates new problems and issues. Researchers need to explore new topics from time to time. The "new" research topics mean there maybe less people have heard about or experienced about it. Therefore, to collect people's opinions by survey would face the limitation of available respondents. The prospect can be supported by another finding that over a half of sample papers adopted nonprobabilistic sampling methods. In addition, as if we believe that the MIS research has grown as PK presumed, multivariate statistics or complex statistics methods were not used as often as we expected. Survey research is based on positivisism paradigm, which suffers from an objectivist illusion in believing that all knowledge is derived from objective facts, and the analytical supposition that the end-result of sociological investigations can be formulated as 'laws' or 'law like' generalizations of the same kind as those established by natural scientists (Bryant, 1985). However, the observations cannot provide an adequate basis for determining the truth or falsity of theories. It simply takes for granted the socially constructed world. Furthermore, positivism cannot account for the way in which social reality is constructed and maintained, or how people interpret their own actions and the actions of others.

The theory means in all empirical science the explicit formulation of determinate relations between a set of variables. The fact that these regularities in the social sciences are restricted in the extent to which they can be generalized, and that they permit prediction to only a limited extent, does not constitute a basic difference between the natural and social sciences. In the MIS field, the volumes of explanatory studies is not increasing in years, a judgment will have to be made about these criticisms. Though synthesis is not possible, consideration of an alternative avenue might be useful, and researchers should develop a means for considering multi-paradigm views together (Gioia, et al., 1990).

Finally, we acknowledge that our use of three journals during four years as data points may not have been sufficient to establish trends, but there do appear to have been some interesting changes occurring between the periods examined in this study. Clearly, this research needs replication in studies using other journals and time periods. Despite these limitations, we hope that we have suggested a conceptual template and data analyzing and analysis methodology for future reviews of trends in MIS field.

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Appendix

LYCHEE Empirical Examination List

♦ **Demographic:**

1. mm(season)/yy [/ 19] Vol. [ ], No. [ ], pp[~]
2. Journal name [MISQ]
3. Research theme
   [computer-supported cooperative work] [decision support and knowledge-based systems]
   [systems projects] [evaluation control]
   [users] [economics and strategy]
   [introduction and impact] [IS research]
   [electronic commerce] [IS ethics]

♦ **Research Design:**

1. Research purpose: [exploratory] [descriptive] [explanatory] [Instrument/measure development]
2. Survey type: [cross-sectional] [longitudinal]
3. Number of hypotheses:
   1 [not mentioned or vague] 2 [hypothesis] 3 [proposition] 4 [Question] [n=]
4. Analysis unit:
   1 [not mentioned] 2 [individual] 3 [department] 4 [organization] 5 [project] 6 [application]
5. Respondent positions:
   1 [not mentioned] 2 [CEO] 3 [CIO] 4 [managers] 5 [IS professionals] 6 [staff professionals] 7 [students]
   8 [project leaders] 9 [not restricted]

♦ **Questionnaire Development**

1. Questions:
   1-1. Open-ended
   1-2. Closed-ended: Question scale: 1 [not mentioned] 2 [Likert-5] 3 [7 point] 4 [other]
2. Pilot study? 1 [yes] 2 [no]
   2-1 Research Method: 1 [experience survey/interview] 2 [focus group] 3 [expertise] 4[panel discussion]
   2-2 Who were the respondents? 1 [not mentioned] 2 [experts] 3 [student] 4 [a sample of the population]
   2-3 How many respondents? [n=]
3. Pretest? 1 [yes] 2 [no]
   3-1 Times: [ ]
   3-2 Who were the respondents? 1 [not mentioned] 2 [experts] 3 [students] 4 [a sample of the population]
   3-3 How many respondents? [n=]
4. Does the paper append the survey instrument? 1 [none] 2 [whole] 3 [part] 4 [measures of R. V.s]

♦ **Sampling Procedures:**

1. Sample frame: 1 [not mentioned] 2 [population] 3 [clients] 4 [members of an association or subscribers to a magazine] 5 [attendees of a conference or seminar] 6 [geographic region] 7 [commercial list] 8 [students] 9 [company workers] 10 [other]

2. Sampling method: 1 [not mentioned] 2 [random] 3 [systematic] 4 [stratified] 5 [cluster]
6 [convenience] 7 [snowball] 8 [quota] 9 [judgment] 10 [go through list]
3. Sample size: | Times N(deliver) N(response) N(Valid)
Response rate
[not mentioned] | [ ] [ ] [ ] [ ] [%]
| [ ] [ ] [ ] [ ] [%]
3-1 Promotion activities to raise response rate and accuracy? [yes] [no]
if yes, 1 [follow up calls/letters/duplicate questionnaires] 2 [gift] 3 [research result will be offered]
4. Testing for sample bias: [not mentioned]
4-1 Test target: 1 [response vs. response] 2 [response vs. non-response] 3 [response vs. population]
4 [Early response vs. late response] 5 [non-response reason] 6 [initial vs. follow-up]
7 [response vs. sample frame]
4-2 Test method: [not mentioned] [t] [x^2] [other]
4-3 Test result: [unbiased] [biased]
5. Explanation of external validity: [yes] [no]

♦ **Data Collection:**

1. Data collection methods: 1 [not mentioned] 2 [face-to-face interview] 3 [telephone interview]
4 [computer embedded questionnaire] 5 [mail] 6 [internal distributed questionnaire]
2. Validity analysis of questionnaire measurement: 1 [not mentioned] 2 [content] 3 [convergent]
4 [discriminant] 5 [concurrent] 6 [predictive] 7 [adopted validated instrument] 8[other]
3. Reliability analysis of questionnaire measurement: 1 [not mentioned] 2 [Cronbach's alpha]
3 [composite reliability/SEM] 4 [adopted validated instrument] 5 [other]

♦ **Data analysis methods:**

1 [descriptive] 2 [correlation] 3 [factor analysis] 4 [regression] 5 [ANOVA/MANOVA/ACOVA/ MACOVA]
6 [discriminant analysis] 7 [logistic regression] 8 [canonical correlation] 9 [clustering analysis]
10 [multi-dimensional scaling] 11 [SEM: EFA CFA PLS] 12 [nonparametric statistics] 13 [others]

*Composite reliability = reliability coefficient = reliability factor /SEM

♦ **Grover's Criteria**

1	2	3	4	5	6	7	8	9

[1] Reports the way to randomize/select samples.
[2] Reports a profile of sample frame.
[3] Reports a profile of respondents.
[4] Uses any combination of personal, telephone, or mail data collection.
[5] Appends the whole/part of questionnaire.
[6] Performs a reliability/validity analysis of item measurement or adopts a validated instrument.
[7] Performs a pretest of instrument.
[8] Reports a response rate.
[9] Performs a statistical test to justify that the loss of data from non-respondents does not harm or bias the survey's findings.

ARTIFICIAL NEURAL NETWORK APPLICATION TO BUSINESS PERFORMANCE WITH ECONOMIC VALUE ADDED

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ABSTRACT

An application of neural networks to classify the performance status of business firms is performed. An artificial neural network (ANN) model is developed using publicly available dataset as input and output variables. Several different neural network topologies are designed and applied to the datasets. A neural network model classifies both high and low business performance status. The ANN model can enhance strategic and managerial insights by providing meaningful financial information.

INTRODUCTION

Since the development of an artificial neural network (ANN) approximately 50 years ago, it has received considerable attention from researchers. Neural network was once viewed as the theoretical foundation of building machine learning systems. It was proven to have many limitations. Recent neural network studies have overcome some previous limitations. ANN has been applied to a variety of problems for classification and prediction. It has been applied successfully for development of non-parametric statistical models. More robust outcome researches have been explored in the topics of pattern classification and pattern prediction. Neural network models are able to identify an existing pattern in data classification in different categories (Archer & Wang, 1993; Hsiao & Huang, 2002; Lotfi et al., 2000; Patuwo et al., 1993; Wang, 1995). Neural networks in business performance applications have been used for audit decision (Hansen et al., 1992; Lenard et al., 1995), initial public offerings (Jain & Nag, 1995), and multi-criteria decision-making (Malakooti & Zhou, 1994).

One of the most difficult issues in the ANN application discipline is to a proper utilization of a neural network model to implement a large-scale financial services research dataset. Moreover, if characteristics of the factors are complicated and complex, finding an optimal alternative is very difficult and may not get the best solution. Many researches have applied a neural network model to classify desired solutions or to improve methodological perspectives. Even though successful applications in ANN models have been made, little interests are given to the economic value added (EVA)-related business performance planning area. The utilization of neural network models in classification issues of management, finance, and other functional areas has been mostly limited to the usage of factors with continuous or ratio variables, rather than categorized values used in socioeconomic settings (Hart, 1992; Lee & Park, 2001; Sharda, 1994; Wilson, 1995).

The purpose of this study is to develop a neural network model to identify a proper classification between high and low business performance status. A neural network model is developed based on the publicly available financial dataset as input and output variables. The proposed model is expected to provide the factors affecting the classification of high/low EVA status, enhance business strategies to meet more appropriately business performance with financial measurement, and support decision-makers with more accurate information to implement.

LITERATURE REVIEW

Early studies have recognized that combining many simple nodes into neural network models is the source of increased computational power. The weights on the neural network are fixed so that the node performs a certain logic function with different nodes performing different functions. The nodes can be arranged into a network to generate any output that can be represented as an aggregation of logic functions. The learning mechanism has been designed for a neural network model. This mechanism is that the strength of the connection between them should be improved, if two nodes are active simultaneously. This idea is similar to the correlation matrix learning mechanism.

Many studies in neural networks have explored in business and financial areas during the last several decades. A study of Wong and Selvi (1998) provides an extensive literature analysis in finance application of neural network models. Neural network application to business performance and/or finance appeared in areas such as bankruptcy models (Chen, 1995; Fletcher & Goss, 1993; Markham & Ragsdale, 1995; Tam & Kiang, 1992), bonding models (Dutta et al., 1994; Quah et al., 1996), loan models (Bansal et al., 1993; Piramuthu et al., 1994), mutual fund models (Chiang et al., 1996; Hung et al., 1996), options models (Hutchison et al., 1994; Kaastra & Boyd, 1995; Swanson & White, 1995), real estate models (Borst, 1991; Collians & Evans, 1994; Worzala et al., 1995), stock prediction models (Wittkemper & Steiner, 1996; Wong & Long, 1995; Wood & Dasgupta, 1996).

A neural network is an imitating mechanism of human intelligence for the purpose of deriving certain performance characteristics. A neural network has been developed as generalization of a nonparametric methodology. A neural network model assumes that nodes have their own values for processing certain data, values are transmitted through nodes over connection links, each link has a weight that multiplies the values conveyed in a neural network, and each nodes applies an activation function to its input to identify the output value.

Assumption of information flow through the network is that a unit time step for data moves from one node to the next. This lead-time allows the network to model some perceptional processes. The most typical single layer network is consisted of an input layer connected by paths with fixed weights to associated nodes. The weights on the connection paths are adjustable. The learning rule of a single layer network uses an iterative weight adjustment. Learning rule can converge to the correct weights if weights allow the network to regenerate correctly all of the learning input and target output pairs. However, the theoretical proof on the convergence in iterative learning mechanism under suitable assumptions represents the limitations regarding what the single layer network type can learn.

A neural network model consists of a number of data processing layers interconnected in a network. Each layer has a mathematical mechanism with computational functions. A layer receives input values from other layers, and synthesizes the values by an input function. The layer creates output values by an output function. Then, the output values transferred to other layers as designed by the neural network architecture.

Characteristics of neural network have the architecture (the pattern of connections between the nodes), training or learning (the method of determining the weights on the connections), and the activation function. Each node is connected to other nodes by direct interaction links, each with an associated weight. This weight represents information used by the network to find a solution. Each node has an activation level that is a function of the inputs. Because a node sends its activation as a value to several other nodes, it can transmit one value at a time, while the value is transmitted to several other nodes.

An alternative learning rule can be used to adjust the connection weights to a unit whenever the unit response is incorrect. The unit response represents a classification of the input pattern. The least-mean-square or delta rule as an alternative learning rule adjusts the weights to reduce the difference between the input and the target output. This results in the smallest mean-squared error (MSE). The learning rule for a single-layer or multi-layers networks is interpreted as an adaptive linear system. The difference in learning rule leads to an improved capability of the neural network model to generalize. Some elaborated studies deal with associative memory neural networks with the development of self-organizing feature maps that use a topology for the cluster units. This feature truncates the linear output to prevent the output from being too large to get an optimal solution as the network iterates.

One of the advanced features is development of a back propagation algorithm (BPA) in a learning mechanism to train multi-layer networks. The BPA has a linear approximation function for the input layer and a logistic function for the output layer. The BPA using the hidden layer allows the data to be classified. A BPA has been developed to overcome the limitation of single-layer networks. It can solve complex problems, lacking a general methodology of learning a multi-layer neural network model. An improved model is derived from a number of neural network model based on fixed weights and adaptive activation. This neural network can use as associative memory networks and can be used to solve constraint satisfaction problems. Stochastic neural networks that weights or activations are changed on the basis of a probability density function incorporate such ideas as simulated annealing and Bayesian decision theory.

MODEL DEVELOPMENT

This study utilizes the financial dataset, which is a longitudinal study dataset of firms with high or low business performance. Information has been gathered on 764 high/low business firms. Pattern characteristics of financial services and changes in these factors over the course of the business can be analyzed for high/low EVA firms. Dozens of variables are selected initially from the original dataset. After controlling these variables, one output variable (dependent variable) and eight input variables (independent variable) are selected after diagnostic controlling them by the variance inflation factor (VIF) method for detecting multicollinearity among input variables. VIF values are less than 1.700 for multicollonearity diagnosis, so that multicollinearity problem is not significant among input variables. Out of 764 cases, valid cases are selected, implying a firm has either on high EVA status or on low EVA status. Selected cases provide valid information based on the responses of specific firms. Thus, cases have completed information on each firm, based on the selected input and output variables. The descriptive statistics for input and output variables are presented in Table 1.

Table 1: Descriptive Statistics of Input and Output Variables

Variables	X-bar	SD	MIN	MAX	N
EVA96	-1216	3764	-1354	13364	73
RDI93	1.420	1.566	0	6.580	73
RDI94	1.449	1.534	0	6.734	72
RDI95	1.549	1.679	0	7.073	68
RDI96	1.505	1.563	0	5.719	48
INV96	-1.433	19.601	-164.654	16.211	73
ROE96	0.030	0.102	-0.538	0.276	73
CAP96	3.048	2.140	0.547	12.008	73
SIZ96	8.676	1.184	6.599	11.975	73

The neural network model developed to classify a current EVA status of high/low business performance firms is the three-layer back-propagation algorithm neural network model. An input layer is used to represent a set of input variables. An output layer is used to represent an output variable. A hidden layer has an arbitrary number of the hidden nodes. Thus, numbers of hidden nodes are chosen arbitrarily and they derive different outcomes. Categorical variables have been recorded. For the first node in the output layer, it is given 0 if the current EVA status is low, and 1 if the current EVA status is high. For the second node in the output layer, the code is assigned to the reversed way. Table 2 presents descriptions about input variables and output variables in the neural network model.

Since no prior information is available as to how layers should be connected in the three-layer network, all nodes in the two adjacent layers are fully connected each other. The neural network model is for classifying the current EVA status of high/low business performance firms. Input layer has 8 nodes: RDI93, RDI94, RDI95, RDI96, INV96, ROE96, CAP96, SIZ96. Each of these variables is entered into the corresponding input layer of the neural network. These values are multiplied by model-generated random numbers so that they become the input values of the hidden layer. Each value is placed in a logistic function that computes the network activation of the hidden layer, becoming input values of the output layer. This value is entered into the same logistic function that computes the activation of the output layer, resulting in the output values: high EVA status or low EVA status. Thus, in actual practice, the output values could be considered as representing the likelihood of high EVA status or low EVA status in the current business performance of each firm.

Table 2: Summary of Input and Output Variables	
Variables	Description
Input Variables	
RDIt	Intensity of R&D(%) where t = 93, 94, 95, and 96
INVt	Tangible Assets Investment(%) at time t
ROEt	Ratio of Return of Equity(%)at time t
CAPt	Intensity of Capital(Korean Won) at time t
SIZt	Firm Size (Korean Won) at time t
Output Variable	Current EVA status (either high status or low status)

The network architecture is designed to be the three-layer BPA networks. After configuring the neural network model, a learning rate, initial weight, and momentum learning epoch are assigned to the model to initiate the learning. Since assigning a learning rate, momentum, and number of epoch is arbitrary, a default value for each of them is assigned to the model. Once the model is designed, a certain percent over total pattern is extracted for the learning set and the test set. Approximation of 10 percent has been randomly extracted from the total pattern. An epoch is considered completed after the network examines all of the input and output patterns for all training sets. Epochs for training set are repeated for 200 times with a learning rate. In order to avoid the overfitting the network, the learning process was stopped when total number of epoch repeated reached at 20,000. A software NeuroShell®2 was used to implement this model (NeuroShell, 1993). Table 3 indicates a model statistics about the BPA neural network model.

Table 3: Model Architecture for the BPA Neural Network	
Neural Network Modeling	Parameters
Total pattern	74
Learning set	61
Test set	13 with 20000 events
Pattern selection	Random
Weight updates	Momentum with 0.1
Learning epoch	200 with learning rate 0.1
Initial weight	0.3
Hidden Nodes	H1=3, H2=7, H3=10, and H4=16

CONCLUSION

This study proposed a neural network model to classify an EVA status of either high or low business performance. Neural network modeling of high/low EVA classification involves the interaction of many diverse factors. The relationships are often complex and complicated so that it makes the classification of outcomes very difficult and contingent.

This study presents an application of neural networks to classify by firms with the EVA status of business performance. A neural network model in classifying both the high and low status of EVA-related business performance is developed. Financial dataset is used in order to demonstrate the neural network's capability.

Neural networks are known to be able to identify relationships even when some of the input data are very complex and complicated. One of the advantages in ANN is to discriminate the linearly inseparable data. Even though neural network have been applied to a variety of areas such as management, finance, and other functional areas, a specific neural network model will be difficult to generalize to apply for a certain business environment with an appropriate interpretation. If the appropriate methodologies in various ANN design models are different, it would be interesting to see what impact would have on classification of high/low EVA firms.

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Manuscripts
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EMPLOYEE PERFORMANCE EVALUATION USING THE ANALYTIC HIERARCHY PROCESS

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ABSTRACT

Managers do not look forward to giving performance reviews and there is no exception to that rule. Every year managers struggle with finding just and fair way to allocate salary increases to their department. They want to find a way that will reward the best performers by given them the largest salary increases for the years. Identifying the best performers is a very subjective task. So, managers are always searching for a way to make this task as objective as possible. This research will utilize the AHP to deal with the performance evaluations and merit increases for a local firm in the state of Indiana. More specifically, the research will help the managers in assigning weights to the most important factors used in the evaluation process.

INTRODUCTION

"The groans of the managers echo the halls as the reminder comes that it's time once again for annual performance reviews,"(Molta, 1997). Managers do not look forward to giving performance reviews and there is no exception to that rule. Every year managers struggle with finding a way to be fair with the salary increases that are allocated to their department. They want to find a way that will reward the best performers by given them the largest salary increases for the years. Identifying the best performers is a very subjective task. So, managers are always searching for a way to make this task as objective as possible

The Analytic Hierarchy Process (AHP) would seem to be an effective tool to use in this decision process. The overall decision process is complex and involves consideration of both objective and subjective factors. AHP would seem to be a useful means to deal with this complexity, force determination of factor weights and evaluations, and provide empirical basis for a sound conclusion. AHP may serve as a means to deal with the current frustration found in this decision-making process and assist managers in making better decisions.

This research will utilize the AHP to deal with the performance evaluations and merit increases for a local firm in the state of Indiana. More specifically, the research will help the managers in assigning weights to the most important factors used in the evaluation process. An application of the technique will be used in the Management Information System (MIS) department of the firm.

ANALYTIC HIERARCHY PROCESS

"AHP is about breaking a problem down and then aggregating the solutions of all the sub problems into a conclusion. It facilitates decision making by organizing perceptions, feelings, judgments, and memories into a framework that exhibits the forces that influence a decision. In the simple and most common case, the forces are arranged from the more general and less controllable. The AHP is based on the innate human ability to make sound judgments about small problems."(Saaty, 1994).

"The analytic hierarchy process is a flexible model that allows us to make decisions by combining judgment and personal values in a logical way," (Saaty, 1994). By reducing the decision to a series of simple comparisons, then calculating the results, the AHP helps arrive at the best decision for allocation of salary increase dollars. In simplified terms the process followed is to determine what factors are significant; place the factors and alternatives in a decision hierarchy; perform calculations to determine the weighted score.

AHP has been applied successfully in many areas of decision-making. The technique has been applied in: synthesizing group decisions (Gass & Rapcsak, 1998); auditing tax declarations (Iwasaki & Tone, 1998); total quality (Wang, Xie, &Goh, 1998); global locations (Badri, 1999); new product screening (Calantone, Benedetto,& Schmidt, 1999); university resource allocations (Kwak & Lee, 1998); and ethical decision making (Ido, 1998) to name just a few. The technique has also been used in the healthcare area such as; choosing a hospital (Javalgi, Rao, & Thomas, 1991); cancer treatment decisions (Kimbore, 1999); and healthcare information resource planning (Lee & Kwak, 1999). Other areas where the technique has been applied include arms control, conflict resolution, security assessments, political candidacy and environmental issues (Saaty & Vargas, 2001).

DECISION HIERARCHY

Each year, executive management announces to managers what the target salary increase for the year will be. This past year was a very tight year so the percentage increase was 2.5%. The director of the MIS department would like to allocate 2.5% of the total salary to the employees in a manner that would give the star performers more and the laggards less.

The decision hierarchy for the employee evaluations has three different levels. The top level describes the overall decision. In our case it would be how to allocate salary increases. The middle level describes the factors to be considered for performance evaluation. The lower level shows the alternatives. In our case the alternatives would be the employees in the MIS department.

Many factors were considered for evaluating employee performance. The list includes adaptability, dependability, initiative, job knowledge, quality of work, quantity of work, planning and organization, oral communications, written communications, and work relationships. The number of factors was narrowed down, by the director, to the following five factors: adaptability, initiative, quality of work, job knowledge, and work relationships. These five factors were selected because they seem to capture the essence of the job functions.

There are more than four employees in the MIS department but for the sake of this research only four employees will be chosen. These four will be chosen because they have the same job title. We will refer to these employees as A, B, C and D.

FACTORS USED

Before we start the evaluation process, we need to develop a clear definition of the factors.

Adaptability	The employee's ability to accept change readily, both in job responsibilities as well as in the work environment. The extent to which employee is able to perform a variety of assignments and manage competing demands within the scope of his/her job duties.
Initiative	The degree of aptitude and ingenuity displayed in carrying out work assignments. The extent to which employee is a self starter in attaining objectives of the job; shows interest and enthusiasm in work; undertakes self-development activities; seeks increased responsibilities; looks for an takes advantages of opportunities for improvements.
Quality of Work	The degree of accuracy and thoroughness in carrying out assignments demonstrated by the employee. The extent to which the employee displays a commitment to excellence.
Job Knowledge	The degree of knowledge and information the employee has with respect to all requirements of the position. It is the total of all work-related knowledge, whether acquired on the job, through training and education, or from previous experience and other jobs. It also encompasses the extent to which the employee exhibits the ability to learn and apply new skills; the amount of interest shown in keeping abreast of current developments; and the amount of supervision required.
Work Relationships	The ability of the employee to communicate, persuade and interface with other employees. The extent to which the employee exhibits tact and consideration; offers assistance and support to co-workers; and displays a positive outlook and pleasant manner.

PAIR-WISE COMPARISONS

A nine-point scale was used to judge the different alternatives. The scale ranges from equally preferred to extremely preferred. See Table 1.

Table 1: Scale Used for Pairwise Comparison

1	Equally preferred
2	Equally to moderately preferred
3	Moderately preferred
4	Moderately to strongly preferred
5	Strongly preferred

6	Strongly to very strongly preferred
7	Very strongly preferred
8	Very to extremely strongly preferred
9	Extremely preferred

Each employee was compared to the other employees one at a time for each of the evaluation factors. These are subjective decisions made by the director based on actions by the employees over the last year. An example of the thought process for the comparison is given in the matrix for adaptability. See Table 2. Employee B is strongly to very strongly preferred to Employee A. Employee C is strongly preferred to Employee A. Employee D is extremely preferred to Employee A.

Table 2: Pairwise Comparison for Adaptability

Adaptability	Employee A	Employee B	Employee C	Employee D		
Employee A	1	0.167	0.02	0.111		
Employee B	6	1	4	0.333		
Employee C	5	0.250	1	0.250		
Employee D	9	3	4	1		
Column Totals	21.000	4.417	9.20	1.694		
Adaptability	Employee A	Employee B	Employee C	Employee D	Factor Evaluation	
Employee A	0.048	0.038	0.022	0.066	0.044	
Employee B	0.286	0.226	0.435	0.197	0.286	
Employee C	0.238	0.057	0.109	0.148	0.138	
Employee D	0.429	0.679	0.435	0.590	0.533	
Check for Consistency						
Adaptability	Employee A	Employee B	Employee C	Employee D	Weighted Sum Vector	Consistency Vector
Employee A	0.044	0.048	0.028	0.059	0.179	4.068
Employee B	0.264	0.286	0.552	0.177	1.279	4.472
Employee C	0.220	0.072	0.138	0.133	0.563	4.080
Employee D	0.396	0.858	0.552	0.533	2.339	4.388
Consistency Index 0.084;	Random Index 0.900;	Consistency Ratio 0.093				

The extreme preference in this comparison is between Employee D and Employee A. Employee D can successfully juggle multiple projects with competing demands, Employee A is very stressed by interruptions from one project while working on another project. If Employee A is forced to switch between projects a lot of time will be wasted in the process of refocusing on the project at hand. Employee D accepts change and many times even suggests it. Employee A resists change at every opportunity. In considering the evaluation factor of adaptability Employee D is extremely preferred to Employee A so a 9 is placed in the matrix for that comparison. A similar thought process for each employee comparison was followed. Throughout the year the director makes notes about significant actions or the employees. These notes were used to assist the director in making the comparisons.

After all pair-wise comparisons were made; the consistency ratio for each pair-wise matrix was calculated. In general, a consistency ratio greater than 0.10 should cause the user to question the results (Saaty, 1994). Although the consistency ratio for the initiative factor was 0.114, we did not think it is far off and completed our analysis. After completing the analysis we returned the matrix on initiative to the director and asked for a new comparison. See Table 3. This resulted in a slight difference in the overall evaluation. See Table 4.

Table 3: Revised Pairwise Comparison for Initiative

Initiative	Employee A	Employee B	Employee C	Employee D		
Employee A	1	0.500	0.200	0.200		
Employee B	2	1	0.250	0.250		
Employee C	5	4	1	0.500		
Employee D	5	4	2	1		
Column Totals	13.000	9.500	3.450	1.950		
Initiative	Employee A	Employee B	Employee C	Employee D	Factor Evaluation	
Employee A	0.077	0.053	0.058	0.103	0.073	
Employee B	0.154	0.105	0.072	0.128	0.115	
Employee C	0.385	0.421	0.290	0.256	0.338	
Employee D	0.385	0.421	0.580	0.513	0.475	
Check for Consistency						
Initiative	Employee A	Employee B	Employee C	Employee D	Weighted Sum Vector	Consistency Vector
Employee A	0.073	0.058	0.068	0.095	0.294	4.027
Employee B	0.146	0.115	0.085	0.119	0.465	4.043
Employee C	0.365	0.460	0.338	0.238	1.401	4.145
Employee D	0.365	0.460	0.676	0.475	1.976	4.160
Consistency Index 0.031;	Random Index 0.900;	Consistency Ratio 0.035				

Table 4: Revised Overall Evaluation						
	Adaptability	Initiative	Quality of Work	Job Knowledge	Work Relationships	Overall Weight
Employee A	0.044	0.073	0.107	0.057	0.116	0.099
Employee B	0.286	0.115	0.043	0.223	0.047	0.077
Employee C	0.138	0.338	0.330	0.244	0.336	0.316
Employee D	0.533	0.475	0.520	0.477	0.501	0.508
Factor weights	0.068	0.134	0.503	0.035	0.260	1.000

FACTOR WEIGHTS

"For technical professionals, the ground rules for performance reviews are changing in sync with changes in the work environment. In the past, technical skills were almost the sole criterion for determining effectiveness of systems programmers and network engineers. In today's environment, much more emphasis is placed on team-oriented skills and communication skills,"(Viehweg, 1997).

The director analyzed the five factors and presented the following descriptions:

Quality of work	This is the most important factor because there is no substitute for accuracy in a technical field.
Work relationships	The programmers/analysts no longer sit in a room alone. They work directly with end-users and even with clients. One must be able to trust the employee to represent the MIS department well with end-user and client interaction.
Initiative	With each employee's unique area of knowledge and responsibility they will see opportunities for improvement the director might never see. The director needs the employees to take advantage of those opportunities or at the least bring them to the director's attention.
Adaptability	The employee needs to be able to juggle multiple projects. Many times they will be working on a project and be interrupted by an emergency or just have to put it on hold while they wait for information from someone else.
Job Knowledge	The knowledge the employee has is important but skills can be taught. Training is provided and employees are encouraged to take advantage of it. The most important aspects of this factor are the ability to learn and the amount of supervision required.

These factors were compared and placed in a matrix to calculate their weights. See Table 5.

Table 5: Factor Weights						
	Adaptability	Initiative	Quality of Work	Job Knowledge	Work Relationships	
Adaptability	1	0.333	0.143	3	0.200	
Initiative	3	1	0.200	5	0.333	
Quality of Work	7	5	1	9	3	
Job knowledge	0.333	0.200	0.111	1	0.143	
Work Relationships	5	3	0.333	7	1	
Column Totals	16.333	9.533	1.787	25.000	4.676	
	Adaptability	Initiative	Quality of Work	Job knowledge	Work Relationships	Averages
Adaptability	0.061	0.035	0.080	0.120	0.043	0.068
Initiative	0.184	0.105	0.112	0.200	0.071	0.134
Quality of Work	0.429	0.524	0.560	0.36	0.642	0.503
Job knowledge	0.020	0.021	0.062	0.04	0.031	0.035
Work Relationships	0.306	0.315	0.186	0.28	0.214	0.260

OVERALL EVALUATION

After all calculations were performed an overall weight is arrived at for each employee. See Table 6. These numbers are used to calculate the amount of increase in salary should be allocated to each employee. See Table 7. We noticed there was a significant difference between these allocations of raises and the way it had previously been allocated. Basically there are two reasons for the differences: 1) weighting of the factors and 2) dealing with a capped salary.

Table 6: Overall Evaluation						
	Adaptability	Initiative	Quality of Work	Job Knowledge	Work Relationships	Overall Weight
Employee A	0.044	0.090	0.107	0.057	0.116	0.101
Employee B	0.286	0.099	0.043	0.223	0.047	0.074
Employee C	0.138	0.333	0.330	0.244	0.336	0.316
Employee D	0.533	0.478	0.520	0.477	0.501	0.509
Factor weights	0.068	0.134	0.503	0.035	0.260	1.000

Table 7: Dollar Allocation for Raises			
Results Using AHP			
	Salary	Overall Weight	Raise
Employee A	31290	0.101	330.73
Employee B	28000	0.074	242.32
Employee C	41693	0.316	1034.77
Employee D	30000	0.509	1666.76
Total	130983	1.000	3274.58
2.5% of Total	3275		
Before			
	Salary	Increase	Raise
Employee A	31290	0.015	469.35
Employee B	28000	0.040	1120.00
Employee C	41693	0.000	0.00
Employee D	30000	0.050	1500.00
Total	130983		3089.35

Factors Weights: Employee A is weaker than Employee B in the areas of adaptability and job knowledge while Employee B is weaker than Employee A in the areas of quality of work and work relationships. Quality of work and work relationships together make up 75% of the total weight. Because Employee B rated low on these two areas it made a significant impact in the amount of raise allocated. Previously when the two employees were compared, the weakness of Employee A in the areas of adaptability and job knowledge left such a great impression on the director's mind that it influenced the raise percentage.

Dealing with a Capped Salary: The salary of Employee C has reached the top of the pay grade for that position so this employee is not eligible for an annual raise. 2.5% of that employee's salary can be distributed to the other employees. To do this using AHP we need to go through the entire process of the paired comparisons using only Employees A, B, and D. Once we arrived at the new weights we would apply them to the same dollars used for this comparison. This seems like a lot of work; however, in the future the director will know this is a constraint and start the process by looking at which employees having a capped salary.

CONCLUSION

There are no panaceas for giving employee performance reviews. Despite some drawbacks in using the AHP in performance evaluation, the technique has many positive points: (1) The *degree of excellence* distributed by one employee will have the affect of challenging all other employees to that level of performance. (2) *Fair distribution of dollars* - the best employees get rewarded more money. (3) *Helps managers objectively* - Distributing salary dollars based on the most important factors. (4) *Can compare employees* of differing job titles based on applying the definitions of the factors to each position. A

AHP applied a sense of objectivity and resulted in a significantly different conclusion from previous methods used in the firm. We believe that this alone is enough to convince the director to use this method for future employee evaluations.

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SAMPLE SIZE AND MODELING ACCURACY OF DECISION TREE BASED DATA MINING TOOLS

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ABSTRACT

Given the cost associated with modeling very large datasets and over-fitting issues of decision-tree based models, sample based models are an attractive alternative - provided that the sample based models have a predictive accuracy approximating that of models based on all available data. This paper presents results of sets of decision-tree models generated across progressive sets of sample sizes. The models were applied to two sets of actual client data using each of six prominent commercial data mining tools.

The results suggest that model accuracy improves at a decreasing rate with increasing sample size. When a power curve was fitted to accuracy estimates across various sample sizes, more than 80 percent of the time accuracy within 0.5 percent of the expected terminal (accuracy of a theoretical infinite sample) was achieved by the time the sample size reached 10,000 records. Based on these results, fitting a power curve to progressive samples and using it to establish an appropriate sample size appears to be a promising mechanism to support sample based modeling for large datasets.

INTRODUCTION

Data mining has emerged as a practical analytical tool primarily on the basis of its ability to deal with the large volume of data available from databases and data warehouses. Rapid increases in processor speed coupled with continuing decreases in the cost of mass storage devices and other computer hardware have made it practical to collect and maintain massive databases. Data mining software is viewed as a tool that can perform undirected or semi-directed analysis and, thus, can be applied to the full length and width of very large data sets at much lower costs than analytical techniques requiring stronger human direction. While data mining tools have typically been applied to the full volume of available data, issues of cost and model over-fitting suggest that use of data mining models based on a sample of available data may be appropriate in many instances. Thus, the relationship between sample size and model accuracy is an important issue for data mining.

Despite the increases in processing speeds and reductions in processing cost, applying data mining tools to analyze all available data is costly in terms of both dollars and time required to generate and implement models. In discussing differences between statistical and data mining approaches, Mannila (2000) suggests that: "The volume of the data is probably not a very important difference: the number of variables or attributes often has a much more profound impact on the applicable analysis methods. For example, data mining has tackled width problems such as what to do in situations where the number of variables is so large that looking at all pairs of variables is computationally infeasible." The above quote suggests that the benefit of data mining tools comes from their ability to deal more effectively with complex interactions among variables rather than from the ability to process massive volumes of instances.

It has been noted that decision tree based data mining tools are subject to over-fitting as the size of the data set increases, Domingos (1998) and Oates and Jensen (1997). As Oates and Jensen [1998] note, "Increasing the amount of data used to build a model often results in a linear increase in model size, even when that additional complexity results in no significant increase in model accuracy." In a similar vein Musick, Catlett, and Russell (1993) suggest that "often the economically rational decision is to use only a subset of the available data." A variety of pruning algorithms have been proposed to deal with this problem, and most commercial data mining software using decision tree based algorithms incorporate the use of pruning algorithms. While pruning helps to limit the proportion by which model complexity increases as the amount of data increases, its effectiveness can only be assessed by examining the responsiveness of model complexity and model accuracy to changes in data set size.

Sampling can also be used as a tool to lower the cost of maintaining data mining based operational models. Lee, Cheung, and Kao (1998) have proposed a dynamic sampling technique to test for changes in a dataset. Their technique suggests using a sample of data to detect when enough change has occurred in the structure of a dataset to justify re-estimation of a model using the full set of available data. In addition to this monitoring role, periodic re-estimation of a decision tree model using a moderate sized sample of data may be the most cost effective way to maintain a reliable predictive model. For example, an organization might find it equally costly to re-analyze a model on the basis of a sample of 10,000 records once a month or to re-analyze the model based on all available data once a year. In such a case, modeling based on a sample will be the most effective strategy if the phenomenon being modeled is relatively dynamic and models based on the sample approximate the accuracy of a model based on all available data. In addition, many practical data mining scenarios may involve purchase of data from third party sources or the generation of supplementary data to directly support a data mining analysis. In these cases, there can clearly be substantial savings from working with a sample of data provided that sample-based results are sufficiently accurate.

Prior studies of sampling in data mining have used public domain data modeling tools and relatively small data sets from the UCI repository. In this paper we describe the results of models generated from the systematic sampling of data from two corporate datasets one of which contained more than 1.5 million records. The target variable for each data set is a binary variable. Models are generated with each of six prominent commercial data mining tools. Statistical analyses across the tools, over varying sample sizes, and with respect to other relevant factors are presented. The results provide an insight into the response of model accuracy with respect to increases in sample size, and also allow us to examine the extent to which that response varies across different data mining tools and across varied data sets.

REVIEW OF PREVIOUS SAMPLING STUDIES

The effectiveness of data mining models based on sampling from datasets has not been widely studied. However, there are a few studies that have addressed this topic which can be used as the starting point for this study. John and Langley (1996) applied arithmetic progressive sampling (e.g. samples of 100, 200, 300, 400, etc.) to 11 of the UCI repository datasets. Because many of the datasets used were small, they first replicated each record 100 times to simulate a large dataset. The inflated data set was used to generate a set of samples whose size was systematically incremented by 100 records between samples. A model was then generated for each sample using a "naive Bayesian classifier." The sample-based models were applied to a holdout set to evaluate their accuracy. A power function based regression equation was estimated as each progressive sample was performed, and sampling was terminated when the accuracy of the current model was within 2 percent of the expected accuracy (based on the regression) for a model using the full dataset. Twenty-five sets of samples and their associated models were produced and tested for each dataset.

Applying this criterion to the 11 inflated UCI repository databases, led to average final sample sizes ranging from 300 to 2,180 all of which were within 2 percent of the accuracy of a naïve Bayesian classifier model built from the entire training set. Limitations of this study include the fact that the results were generated by replicating data from small source datasets and that the models that were compared used naïve Bayesian classifiers.

Frey and Fisher (1999) systematically examined the response of modeling accuracy to changes in sample size using the C4.5 decision tree algorithm applied to 14 datasets from the UCI repository. The datasets used were all relatively small - from 57 to 3,196 observations. This study focused on determining the shape of the learning curve and made no attempt to determine an optimal sample size. For 13 of the 14 datasets, they found that the response of predictive accuracy to sample size was more accurately predicted by a regression based on a power law function than by regressions using linear, logarithmic, or exponential functions. The power coefficient varied rather substantially across the datasets (from +.118 to -1.117).

Provost, Jensen, and Oates (1999) modeled 3 of the larger (32,000 record CENSUS, 100,000 record LED, and 100,000 record Waveform) UCI repository datasets using differing progressive sampling techniques. Progressive sampling begins with a relatively small sample from the dataset. Next, a model is created and run against a holdout dataset to test its accuracy. Then a larger sample is used to generate another model whose accuracy also is tested on the holdout set. The process is repeated for models based on progressively larger samples, until a standard accuracy criteria is met.

The primary aim of their paper was to compare the efficiency of alternative progressive sampling techniques as measured by the computation time required to achieve a standard degree of accuracy. Arithmetic, geometric, and dynamic progressive sampling techniques were evaluated. Arithmetic progressive sampling uses equal absolute increments between samples, for example, increments of 100 (100, 200, 300, 400) or increments of 500 (500, 1,000, 1,500, 2,000). Geometric progressive sampling uses equal proportional increments and an arbitrary initial size. For example, incremental doubling with an initial sample size of 100 would use samples of 100, 200, 400, 800. The dynamic progressive sampling technique used by Provost, Jensen, and Oates involved: (1) initially estimating and testing models based on samples of 100, 200, 300, 400, and 500, (2) estimating a power function based learning curve based on results for those models, and (3) selecting the next sample to be the size required to achieve accuracy criteria according to the learning curve.

The initial accuracy criteria used called for sampling to progress until the average accuracy for the set of the last 3 samples is no more than 1% less accurate than results from a model based on all available data. At that point, the middle sample of the set is designated as the minimum sample meeting the criterion. This criterion was applied to an arithmetic sampling schedule with increments of 1,000. The criterion was met at the level of 2,000 records for the LED dataset, at 8,000 for the CENSUS dataset, and at 12,000 for the WAVEFORM dataset. Since this measure compares sample based models to the accuracy of a model based on the full dataset, it is clearly designed as a test of how accurate models based on various sample sizes are rather than as a method for determining what sample size is sufficient for a dataset whose population has not been modeled.

PLAN OF THE CURRENT STUDY

Our study incorporates sampling structures and evaluation techniques used in prior studies, but applies these techniques to real client data sets and models constructed using alternative commercial data mining tools.

For each data set to be analyzed, a holdout set of records was first removed and then a geometric progression of sample sizes was generated from the remaining training data set. The samples start at a size of 500 records and double for each new sample up to final a sample size of 32000, resulting in sample sizes of 500, 1,000, 2,000, 4,000, 8,000, 16,000, and 32,000. AN RS/6000 Sp/2 system provided to the CDI by IBM was used fro data preparation. For each sample size, a set of four distinct samples was generated with replacement. A model was created for each sample at each size using each of six data mining software tools

The staff of the Center for Data Insight includes student workers responsible for mastering the use of a number of commercial data mining tools supplied by vendor partners. The analyses presented here compare results obtained using decision tree models from the six different commercial data mining tools, and built by the student expert on each tool. Nondisclosure agreements prevent us from identifying the tools in the comparative analyses - they are labeled as tool A through tool F in the analyses presented here.

Our goal has been to apply the sampling structure described above to a variety of data sets associated with "real" business customers of the Center. Initially we present results for two data sets with binary target variables relating to differing aspects of customer relationship management issues. These data sets and target variables are briefly described below.

Dataset 1 consists of data from a company selling computer related products largely to wholesale customers. The target variable for this dataset is a binary flag indicating whether a customer is still "active" or is a "dead" customer based on an appropriate criteria related to the recency of their last purchase. The proportion of active customers was approximately two-thirds. This dataset is relatively narrow (15 explanatory variables) with several of the explanatory variables containing cardinal numeric values. The full dataset includes approximately 50,000 customer records. Because of the relatively small size of dataset 1, a holdout set of 10,000 records was used for testing the models.

Dataset 2 tracks retail customers of a firm selling a broad range of products. The target variable is a binary variable classifying customers as "better than average" or "poorer than average." Customers were considered better than average if their score based on a weighted average of a set of measures of customer value was higher than average. (The measure used was a weighting of the recency of last purchase, frequency of purchases, and monetary value of purchases.) Thus, the target variable is evenly balanced between "better than average" and "poorer than average" customers. This dataset is over 100 variables in width, most of the explanatory variables are categorical, and the full dataset includes about 1.5 million customer records. A holdout set of 50,000 records was used for testing the models of the second dataset.

Since the datasets described above were from prior customers of the Center, the modelers were reasonably familiar with the data. The modelers were encouraged to treat the study as a contest and build the most accurate model possible for their tool using any pruning parameters or other modeling options they felt appropriate. However, they were told to use a common model across all samples. Thus, they applied modeling options based on their a priori experience with the tool and maintained consistent modeling options across the various samples for a given dataset. The proportion of records correctly classified was the criteria for measuring the success of models.

SUMMARY MODEL RESULTS

In examining model results, we will first look at summary measures comparing the performance of each tool at various sample sizes for each dataset. Table 1 and Figures 1 and 2 present averages (across the four samples) of the percentage of cases correctly classified for each tool at each sample size. In general, accuracy tends to increase at a decreasing rate as sample size increases. For dataset 1, tool B performed substantially less well than the others for all sample sizes below 16,000. The remaining 5 tools show relatively stable patterns with accuracy increasing at a decreasing rate. For all of the tools, model accuracy increases only modestly beyond the 16,000 sample size. For dataset 2, all of the tools produced rather smooth curves with accuracy increasing at a decreasing rate and becoming relatively flat for sample sizes of 8,000 or more.

Table 1: Average Percentage Correctly Classified by Tool and Dataset

Sample Size	Tool A	Tool B	Tool C	Tool D	Tool E	Tool F
Dataset 1						
500	82.07	71.82	80.97	80.28	83.41	83.84
1,000	83.88	67.87	83.06	81.18	85.17	83.62
2,000	84.23	66.29	83.48	82.70	85.88	84.60
4,000	84.92	68.96	85.85	83.15	86.31	85.94
8,000	85.24	69.91	85.36	82.98	86.45	82.78
16,000	85.39	85.80	85.84	86.88	86.21	86.48
32,000	85.23	85.80	86.11	87.70	86.51	86.78

Table 1: Average Percentage Correctly Classified by Tool and Dataset						
Sample Size	Tool A	Tool B	Tool C	Tool D	Tool E	Tool F
Dataset 2						
500	86.04	86.78	90.35	82.40	87.41	89.70
1,000	87.38	89.16	93.58	88.33	88.60	89.91
2,000	88.08	90.36	93.19	88.65	89.63	91.19
4,000	90.33	91.45	93.45	89.85	90.63	91.96
8,000	89.92	91.94	93.63	90.10	91.42	92.40
16,000	90.34	92.57	93.07	90.23	91.56	92.87
32,000	90.60	93.11	93.95	90.55	91.61	93.34

Data Mining Figures

Figure 1

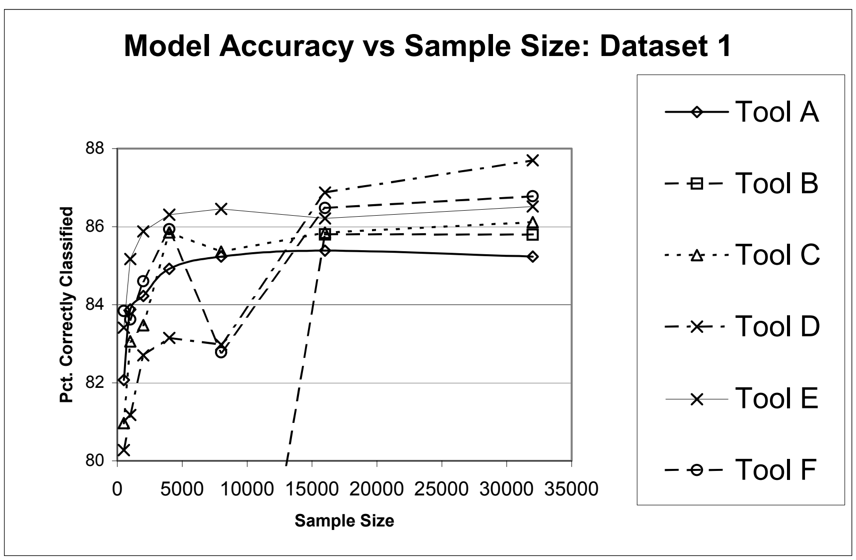
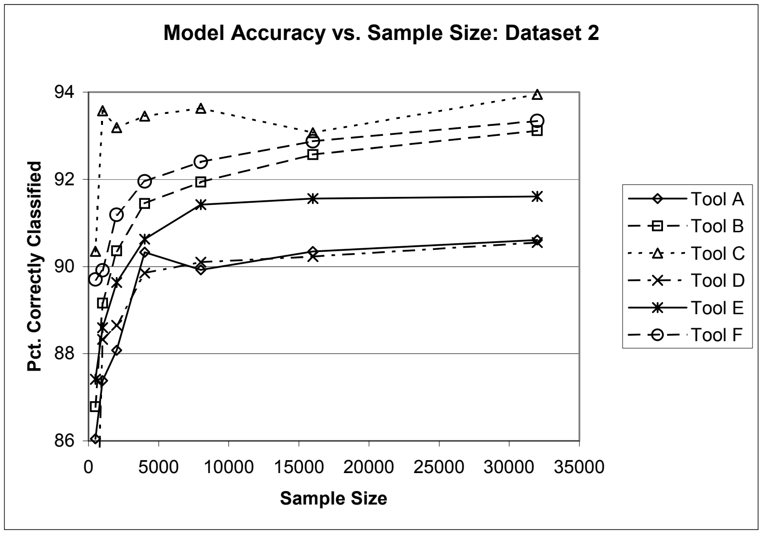


Figure 2



Within a given dataset tools that do well for small sample sizes also tended to do well for larger sizes, however, there was no clear pattern of dominance across the two datasets. Tool E provided the most consistent performance on dataset 1, while tool D showed the best performance at the largest sample sizes. Both of these tools were near the bottom in their performance for dataset 2. At the same time, tool C provided the strongest accuracy for dataset 2 (particularly at small sample sizes), but had average performance for dataset 1.

Table 2 presents summary univariate analysis of variance results for the two datasets. The sample size and the tool used as well as the interaction between those 2 factors were used as explanatory factors. As Table 2 indicates, both factors and their interaction are statistically significant for both datasets.

Also presented are results of the Tukey test for homogeneous subsets for each factor. This test identifies sets of values for each factor whose means do not differ significantly at the .05 level. Results for both datasets show that accuracy increases with sample size. Results for dataset 2 show a plateauing of accuracy - accuracy for all sample sizes above 4,000 fit into the same homogeneous subset. Dataset 1 results place only the 16,000 and 32,000 sample sizes in the final homogeneous subset. This is primarily due to the unusual pattern of results for Tool B. If tool B is excluded for dataset 1, all sample sizes greater than 4,000 once again fit in the same homogeneous subset. The Tukey test for the tool factor shows that there are significant differences in average accuracy, but no strong systematic patterns that hold up across both datasets.

FINDING AN OPTIMAL SAMPLE SIZE

In the previous section all of the data presented was based on average responses across the four separate samples that were generated for each sample size. While this information is of interest, the robustness of the results across individual samples is perhaps of more interest. For someone contemplating using sample data for modeling, knowing that 90 percent of the time a sample of 8,000 records will be accurate to within 0.5 percent of the accuracy of a model based on all available data is likely to be more useful than knowing that the average sample of 8,000 records is only .25 percent less accurate than a model based on all available data. Sampling will be accepted if there is only a small probability that its accuracy will be outside of acceptable bounds. In addition, it is likely that the sample size required to approach the accuracy of a model based on all available data will vary considerably from one dataset to another. This suggests that sampling should ideally be approached on a dataset-by-dataset basis. Under this scheme, a number of progressive samples at relatively small sizes would be used to build models. Some measurement designed to test for convergence in the accuracy of the models would then be applied to determine whether additional larger samples were needed to achieve acceptable model accuracy.

Table 2: Univariate Analysis of Variance Results

	Dataset1		Dataset 2	
Adjusted R-Squared	0.891		0.753	
Source	F Value	Signif.	F Value	Signif.
Corrected Model	34.31	0.000	13.44	0.000
Intercept	332167.86	0.000	818558.80	0.000
Size	42.05	0.000	44.73	0.000
Tool	161.22	0.000	46.37	0.000
Size*Tool	11.61	0.000	1.69	0.024

Tukey Test for Homogeneous Subsets

	Dataset 1				Dataset 2			
Sample Size	Homogeneous Subset				Homogeneous Subset			
	1	2	3	4	1	2	3	4
500	80.40				87.12			
1000	80.80	80.80				89.49		
2000	81.19	81.19	81.19			90.18	90.18	
4000			82.52				91.28	91.28
8000		82.12	82.12					91.57
16000				86.10				91.77
32000				86.36				92.19
Signif.	*0.755*	*0.174*	*0.170*	*0.999*		*0.517*	*0.054*	*0.178*

Table 2: Univariate Analysis of Variance Results								
Tool Used	Homogeneous Subset				Homogeneous Subset			
	1	2	3		1	2	3	4
Tool A		84.42	84.42		88.96			
Tool B	73.78					90.77	90.77	
Tool C		84.38	84.38					93.03
Tool D		83.55			88.59			
Tool E			85.71			90.12		
Tool F		84.86	84.86				91.62	
Signif.		*0.089*	*0.083*		*0.894*	*0.428*	*0.133*	

The models created in this study followed a fixed sampling scheme using progressive samples form 500 to 32,000 records. However, tests of progressive sampling methodologies can be applied ex-post. We can evaluate the sample size that would have been required to meet a particular convergence criterion. Two alternative methods for measuring convergence across progressive samples are presented here. The first is based on using moving averages of model accuracy while the second uses statistical analysis of model results.

Oates and Jensen (1997) used a convergence measure based on examining the improvement in model accuracy as the sample size was progressively increased to test for convergence. Under this scheme, when the improvement in accuracy drops below a prescribed level sampling is terminated. For this criterion to be effective, the improvement in model accuracy as sample size increases needs to be relatively stable and monotonically decreasing in magnitude. If this is the case, it is reasonable to assume that, once the improvement in model accuracy drops below a specified limit, it would stay below that limit for all larger sample sizes as well, and that a plateau in model accuracy has been achieved. To minimize the chance of improperly terminating due to a single non-representative sample, a moving average of the accuracy of the last three samples is maintained and sampling is terminated when the improvement in this moving average drops below a specified convergence criterion (1 percent in Oates and Jensen's paper).

In adapting this technique, we used a weighted average of the last 3 samples. That is, the moving average model accuracy for a given sample sizes is:

$$AccMA_n = (Sz_n*Acc_n + Sz_{n-1}*Acc_{n-1} + Sz_{n-2}*Acc_{n-2})/(Sz_n + Sz_{n-1} + Sz_{n-2})$$

where Acc_n is the measured model accuracy for the nth progressive sample, Sz_n is the size of the nth progressive sample, and $AccMA_n$ is the moving average accuracy measure for the nth progressive sample. The convergence test applied calls for sampling to terminate if

$$AccMA_n - AccMA_{n-1} < \delta$$

where δ is the convergence criterion. For this study, values of both 1 percent and 0.5 percent are used for δ.

Summary results for this convergence criterion (applied to the models generated from each of the four sample-sets for each tool across the two datasets) are presented in Table 3. When a 1 percent convergence criterion is used, convergence is achieved by the time a sample size of 8,000 records is reached in almost every instance across both datasets. When the 0.5 percent criterion is used, there is more variety in the sample size required. However, three-quarters of the sample-set/tool combinations for dataset 1, and over 60 percent of the sample-set/ tool combinations for dataset 2 reached convergence at 8,000 records or less.

Table 3: Moving Average Convergence Results for Sampling Runs

	Using 1% Convergence Criterion				Using 0.5% Convergence Criterion			
	Dataset1		Dataset 2		Dataset 1		Dataset 2	
	Sample size at Convergence							
	Number	Pct.	Number	Pct.	Number	Pct.	Number	Pct.
4,000	14	58.3%	11	45.8%	7	29.2%	5	20.8%
8,000	9	37.5%	13	54.2%	11	45.8%	10	41.7%
16,000	0	0.0%	0	0.0%	3	12.5%	3	12.5%
32,000	0	0.0%	0	0.0%	0	0.0%	4	16.7%
> 32,000	1	4.2%	0	0.0%	3	12.5%	2	8.3%
Unstable*	8	33.3%	2	8.3%	10	41.7%	6	25.0%

* A set of samples is considered unstable if the convergence criterion is met at one sample size but is not met for some larger sample size.

Since this analysis was performed ex-post, we were able to test the stability of sample-sets meeting the convergence criteria at sample sizes less than 32,000. Moving average accuracy values for each sample size up to 32,000 were always computed. If a sample-set meeting the convergence criterion for one sample size would have failed that test at some larger sample size it was classified as unstable. For example, if sample-set 2 for tool C met the 1 percent convergence criterion at a sample size of 8,000, we would look at the change in moving average accuracy from 8,000 to 16,000 and from 16,000 to 32,000. If either of these showed an improvement of more than 1 percent, the model would be classified as unstable for that sample-set. The results of Table 3 show only 2 of 24 models to be unstable for dataset 2 with the convergence criterion set at 1 percent. However one-third of the sample-set/tool combinations show unstable results for dataset 1. When the convergence criterion is tightened to 0.5 percent, unstable results are found for one-quarter of the sample-set tool combinations of dataset 2 and over 40 percent of those for dataset 1.

While the moving average results are interesting, the number of exceptions found is somewhat troubling. Also, there is no means of estimating just how close a sample-based model's accuracy is to the accuracy that could be expected from a model using all available data. To provide such a convergence criterion we need to produce a model of the shape of the response of accuracy to changes in sample size that either provides an upper limit on accuracy as simple size increases or estimates a curve that can be extrapolated to estimate expected accuracy for the total number of records available in the dataset.

Casual observation of Figures 1 and 2 suggests a shape that is consistent with a log-linear model or a power curve model. Power curve models approach a finite limit while log-linear models are theoretically unbounded. Because the dependent variable in this study is the percentage of cases correctly classified, boundedness is an attractive property. In addition, Frey and Fisher's (1999) results cited earlier indicate that the power curve tends to provide a strong fit (stronger than linear, log-linear, or exponential models in 13 of the 14 datasets they modeled). For these reasons, a model based on the power curve was used in analyzing the response of accuracy to sample size.
The form of model used was:

$$\mathrm{acc}(n) = a - be^{nc}$$

where n is the sample size, acc(n) is the expected accuracy of a model whose sample sizes is n, a, b, and c are parameters to be estimated, and e is the natural logarithm. For well-behaved systems the value of b is positive and the value of c is negative. When this is the case, the term be^{nc} approaches 0 as n becomes large. Thus, the value of a can be interpreted as an asymptotic value representing the accuracy that would be produced by the model with an infinitely sized dataset (hereafter terminal accuracy). The values of the b and c parameters interact in determining the shape of the response curve in a way that makes their direct interpretation somewhat difficult. It is of more interest to apply the model and obtain estimates of the sample size required to bring the expected model accuracy within a fixed percentage of the asymptotic accuracy.

Table 4 presents summary results of nonlinear regressions using this model for each sample-set across tools and datasets. Each model is based on all 7 sample sizes from 500 to 32,000. Given the complexity of the non-linear model to be estimated, generation of stable models for samples up to some smaller sample size is problematic. Even with all sample sizes included, the models have only 3 degrees of freedom. R-Squared values are not shown, but generally suggest that the models are rather strong. Sixteen of the 24 models generated from dataset 1 had an R-squared greater than 0.9, while 13 of the models for dataset 2 met this criterion. The column labeled terminal accuracy presents the a parameter, the *estimated* terminal accuracy. In addition, the estimated sample sizes required to come within 1 percent and within 0.5 percent of this level of accuracy are also presented. In two instances, the a parameter was greater than 100 percent leading to an unstable model. Those instances are shown as the starred entries.

It is interesting to note the degree of consistency in the a parameter across sample-sets for each tool. For dataset 1, 3 of the tools had less than 1 percent variation in the a parameter across the four sample-sets, while 4 of the 6 tools met this criterion for dataset 2.

Table 4 also suggests that relatively small samples will often produce models whose accuracy approaches that of an unlimited sample size. For 22 of the 24 models from dataset 2, accuracy came within 0.5 percent of the terminal accuracy at a sample size less than 10,000. For dataset 1, models for tools B and D consistently approach their terminal accuracy only at a substantially higher sample size. Thus, only 15 of the 24 models based on dataset 1 came within 0.5 percent of their terminal accuracy at a sample size less than 10,000.

Overall, the results in Table 4 suggest that relatively small samples can often be used to build models whose accuracy approximates that of models built from the full set of available data. Also, these results are reasonably comparable to those of the Provost, Jensen, and Oates paper that found convergence to 1 percent at sample sizes between 2,000 and 12,000 for selected datasets in the UCI repository. However, the number of exceptions is somewhat troubling. Also, the systematic nature of the exceptions reinforces the idea that the sample size needed to approach terminal accuracy is likely to vary from dataset to dataset.

One could think of the models presented in Table 4 as a procedure to be applied in determining the sample size needed to adequately model a particular dataset. A progressive set of samples for all sizes up a certain limit would be modeled and a power curve estimated. If the power curve suggests that a larger sample is needed to come within a desired limit of terminal accuracy, an additional larger sample would be taken. Additional sampling might be continued on the same basis (double the last sample size used) and the power curve re-estimated until the convergence criterion is met. Alternatively, one additional sample might be generated at the size required to reach the convergence criterion based on the initial power curve estimate.

Table 4: Sample Size Required to Achieve Convergence Across Alternative Tools and Datasets

		Dataset 1				Dataset 2	
Tool	Sample	Sample to approach limit		Terminal	Accuracy	Sample to approach limit	
		within 1 %	within 0.5 %			within 1 %	within 0.5 %
Tool A	1	85.14	1,942	3,083	90.54	4,921	6,778
	2	85.30	1,909	3,271	90.12	2,511	3,515
	3	85.25	2,018	2,761	91.12	4,721	8,199
	4	85.19	788	943	90.09	2,261	2,926
Tool B	1	96.67	95,216	114,669	92.63	3,548	4,739
	2	****	****	****	92.56	4,122	5,854
	3	91.05	57,361	69,785	92.33	3,387	4,810
	4	91.59	54,796	66,055	92.35	2,068	2,608
Tool C	1	85.85	3,565	5,020	94.43	14,541	25,877
	2	85.92	4,046	6,785	****	****	****
	3	85.51	1,249	1,503	93.55	750	875
	4	85.93	2,959	3,977	94.23	593	625

Table 4: Sample Size Required to Achieve Convergence Across Alternative Tools and Datasets

		Dataset 1				Dataset 2	
Tool	Sample	Sample to approach limit		Terminal	Accuracy	Sample to approach limit	
		within 1 %	within 0.5 %			within 1 %	within 0.5 %
Tool D	1	87.11	10,146	13,244	89.92	1,551	1,859
	2	94.93	131,070	165,907	90.59	5,016	9,264
	3	89.30	35,466	47,547	89.92	986	1,119
	4	88.05	21,147	28,494	90.22	1,722	2,242
Tool E	1	86.61	1,549	2,155	91.63	3,656	5,742
	2	86.35	1,216	2,235	90.90	1,142	1,430
	3	86.36	1,179	1,700	91.50	3,046	4,331
	4	86.15	874	1,049	91.71	4,004	5,481
Tool F	1	****	****	****	93.08	5,743	9,088
	2	86.78	4,884	9,368	93.01	5,876	9,519
	3	86.69	4,871	8,137	92.90	3,323	4,804
	4	86.39	3,132	4,351	93.24	3,935	5,587

In our data, assuming that samples up to 32,000 were initially created and modeled, 40 of the 48 sample-set/tool combinations would meet the criterion of coming within 0.5 percent of terminal accuracy at or before the 32,000 sample size. Two of the remaining 8 sample-set/tool combinations did not produce a stable power curve, suggesting either that the full dataset be used for modeling or that the next progressive sample size should be applied and the power curve re-estimated until a stable model meeting the convergence criterion is achieved. For the 6 sample-set/tool combinations whose convergence sample size was larger than 32,000, a new sample at the size required to meet the convergence criterion would be drawn and modeled using the appropriate tool (or the full dataset would be used if the dataset size is less than the sample size to meet the convergence criterion).

The usefulness of the approach outlined in the previous paragraph is evident for the data of dataset 2. For 23 of the 24 sample-set/tool combinations, a model whose expected accuracy is within 0.5 percent of the terminal accuracy was found by running a data mining tool against a total of 65,500 records. The computation time required for this would be substantially less than that required to model against the full 1.5 million record dataset.

SUMMARY

This paper has presented the results of decision-tree models generated using systematic sets of progressive sample sizes. The analyses presented here were applied to 2 sets of actual client data using each of 6 prominent commercial data mining tools.

Comparisons of results across tools indicated significant differences in the effectiveness of the various tools in modeling particular datasets. However, there was not a consistent pattern of tool performance across the 2 datasets. The tools that performed best on dataset 1 were not particularly strong for dataset 2 and vice-versa.

In general, our results suggest that model accuracy tends to increase at a decreasing rate with increases in sample size. In most cases, the results were fit rather well by a model that assumes that the response of accuracy to increases in sample size can be specified by a power curve with a finite terminal value less than 100 percent. The power curve is characterized by a long plateau, with values close to the terminal value at large sample sizes. While rather erratic performance was observed for some of the small samples from dataset 1, accuracy almost universally reached a plateau by the time the 16,000 record sample size was reached. More than 80 percent of the time, accuracy within 0.5 percent of the expected terminal accuracy was achieved by the time the sample size reached 10,000 records. Results for dataset 2 were substantially more consistent than those for dataset 1, reinforcing the idea that the size of sample needed to achieve adequate model performs is likely to vary substantially across dataset and target variable characteristics.

Our results do suggest that systematic progressive sampling often produces models whose expected accuracy is very close to the accuracy expected from a model based on the full dataset. Fitting a power curve to a set of progressive samples and using its results to assess the adequacy of the samples used and determine the appropriate size for an additional sample, if needed, appears to be a promising mechanism for sample-based mining of a large dataset.

This preliminary work suggests a number of avenues for further research. Examination of sampling responsiveness should be extended to broader types of datasets and to non-binary target variables and target variables whose distribution is skewed to varying degrees. Another interesting extension to this study would be the systematic application of bagging of the samples required to produce the accuracy responsiveness estimates, which might provide a low cost means to fully utilize all the samples required to apply this technique.

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RESPONDING TO A ONE -TIME -ONLY SALE (OTOS) OF A PRODUCT SUBJECT TO SUDDEN OBSOLESCENCE

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ABSTRACT

With advancing technologies and shrinking life cycles, today many products are subject to sudden obsolescence. Manufacturers and vendors of products that are subject to sudden obsolescence often announce a one-time-only discount on these products. In this paper, we study a retailer's optimal response to such one-time-only sales (OTOS) of products subject to sudden obsolescence. We build a comprehensive model based on two relevant bodies of literature: the literature on one-time-only sales of non-perishable, non-obsolescent products, and the literature on inventory and pricing decisions for obsolescent products in the absence of any one-time only considerations.

Our model allows for price elasticity, accounts for a various types of inventory holding costs, and deals with obsolescence costs and capital costs separately from the holding costs. Our model also allows for the ordering cost of the special one-time only order to be different from the retailer's regular ordering cost. The model is general enough to accommodate non-obsolescent as well as obsolescent products in situations that do or do not involve an OTOS. A numerical example shows that the use of our model can provide some long-term gain and a particularly attractive short-term improvement in a retailer's profit. Sensitivity analysis shows that the benefits of our model are greatest when the discount is sizable; demand is highly price sensitive; and the retailer's ordering cost for the special order is small.

INTRODUCTION

With rapid advances in technology, abrupt changes in global political situations, and instantaneous dissemination of information in the worldwide market, today product life cycles have decreased dramatically, and a number of products are at risk of becoming obsolete overnight. Swiss watches, computer chips, world maps, breast implants, and Milli Vanilli records are some of the classic examples of this phenomenon. This phenomenon also affects a large number of products whose designs were historically stable for many years, if not decades. For example, fuzzy logic chips have shrunk the lifecycles of such products as washing machines and today's ergonomic focus has rendered obsolescence on older designs of office furniture.

For prudent inventory and pricing decisions on products subject to sudden obsolescence (hereafter called S-Obs products), a retailer must account for the costs of obsolescence carefully. Traditionally, obsolescence costs were treated as a component of the holding costs in the economic order quantity (EOQ) model (Hadley & Whitin, 1963; Naddor, 1966; Silver & Peterson, 1985). Then, some authors dealt with obsolescence costs separately from other inventory carrying costs (Barbosa & Friedman, 1979; Brown, 1982; Hill, Girard & Mabert, 1989). However, these early works were focused on *gradual* rather than *sudden* obsolescence.

Masters (1991) defined *sudden obsolescence* as a situation when a product's lifetime is negative exponentially distributed, and consequently, the probability of obsolescence is constant at any time. Using an *approximate* model, Masters (1991) concluded that for S-Obs products, the use of the EOQ model was appropriate, provided that the obsolescence component was computed as the reciprocal of the product's expected life. Joglekar and Lee (1993, 1996) pointed out that the then current industry practice of estimating annual obsolescence costs at 1 to 3% of a product's cost represented a serious underestimate of the true cost. By Master's (1991) formula even a 3% obsolescence cost implies an expected life of 33 years! Masters (1991) warned that in cases of short-life products, failure to use the proper formula could lead to costs that were five to forty percent higher than the optimal costs.

Masters' (1991) model was an *approximate* one. Using an *exact* formulation, Joglekar and Lee (1993) showed that Masters' model also underestimated the true lifetime costs of his optimal policy while overestimating the optimal order quantity. The associated errors were substantial particularly in the cases of S-Obs products with very short expected lives. Joglekar and Lee (1996) developed a profit maximization model to determine a retailer's optimal order quantity in the face of a manufacturer's quantity discount for S-Obs products. Unlike cost minimization models, a profit maximization model also warns a retailer not to stock a product at all when such a stock results in loss for the retailer.

Not too different from situations of quantity discounts are the commonly observed situations of one-time-only sales (OTOS) of many products. An OTOS occurs because a manufacturer/wholesaler wants to reduce some excess inventory caused by factors such as incorrect forecasts, deliberate excess production, or the threat of impending obsolescence. OTOS allow manufacturers to pass on reduced raw material costs to the reseller, to meet short-term sales goals, to maximize capacity utilization, and/or to add excitement to otherwise mature and mundane products (Abad, 2003). Aucamp and Kuzdrall (1986) have also observed that the situation of an announced permanent price increase, with one last opportunity to buy before that price increase, is mathematically equivalent to an OTOS. Fashion clothes, pop music, and trendy toys are examples of S-Obs products where at the time of a product-introduction, a manufacturer often offers a substantial one-time-only discount to the retailer. Yet, available literature has not studied a retailer's optimal response to such OTOS offers for S-Obs products.

On the other hand, how a retailer should respond to an OTOS of a *non-perishable, non-obsolescent* product has been studied by a number of authors over the last three decades. Using standard EOQ assumptions, earlier works (Naddor, 1966; Brown, 1967; Tersine & Grasso, 1978; Taylor & Bradley, 1985; Lev & Weiss, 1990) developed prescriptive models for determining an optimal special order quantity for a retailer in a variety of OTOS situations. These works assumed a constant demand. Considering price-elasticity, Ardalan (1994; 1995) suggested that, in OTOS situations, in addition to using a special order quantity, a retailer could increase his demand and profits by charging a lower retail price for it. Ardalan (1994) also focused on maximizing the net present value (NPV) of a retailer's cash flows rather than maximizing the per-period profit.

In this paper, we combine Joglekar and Lee's (1996) methodology of analyzing order quantity decisions pertaining to S-Obs products with Ardalan's (1994) approach of simultaneously determining the special price and the special order quantity in the face of an OTOS. In what follows, we establish our notation and develop a model for a retailer's optimal price and order quantity decisions for a price-sensitive S-Obs product in the regular situation, i.e., in the absence of an OTOS. Our model allows for price elasticity, accounts for various types of inventory holding costs, and deals with obsolescence costs and capital costs separately. The model is general enough so that it can be used for obsolescent as well as non-obsolescent products.

Next, we extend the regular situation model to accommodate an OTOS situation. Unlike other available models, we do not assume that a reseller's cost of ordering the special quantity in an OTOS situation will be the same as his regular cost of ordering. We believe that decision-making under special circumstances requires a new model, additional data and greater analytical effort. Hence, the cost of ordering the special quantity is often substantially greater than the regular ordering cost. In order to obtain an accurate estimate of the net advantage of our model's optimal decisions, we use a comparison of the lifetime NPV of the no OTOS situation with the lifetime NPV of a situation involving an OTOS. To gain a clearer perspective on the long term and short-term significance of the net advantage, we look at the net advantage as both, percentage of lifetime NPV and percentage of one cycle NPV.

A numerical example, along with a fairly exhaustive sensitivity analysis, is provided. The numerical example shows that, in many OTOS situations, the use of our model can provide some long-term gain and a particularly attractive short-term improvement in the retailer's NPV. Our analysis also identifies situations where the retailer may be better off not accepting the OTOS discount. The final section provides the conclusion along with some directions for further work.

THE MODEL

Consider a retailer dealing in an S-Obs product characterized by a price sensitive demand function that is time-invariant until obsolescence. Product obsolescence occurs abruptly and completely at a random point in time, which is negative exponentially distributed. At obsolescence, the product is disposed off at a salvage value. Other than these characteristics, standard EOQ assumptions, such as known and constant ordering and carrying costs, zero lead-time, and no stockouts are applicable. In a "regular" situation, i.e., in the absence of an OTOS, the retailer seeks to maximize the NPV of his lifetime cash flows by determining the optimal order quantity and the optimal selling price. Similarly, when faced with an OTOS, a retailer seeks to maximize his lifetime NPV from the special price and order quantity of the OTOS followed by all regular cycles for the rest of the product's life. To evaluate the exact advantage of the optimal OTOS decisions, we look at the difference between these two NPVs.

Throughout this paper, we use the following notation.

A = a constant for the demand function, representing the theoretical maximum demand at zero price

c = retailer's regular unit cost

C_r = retailer's regular ordering cost per order

C_s = ordering cost per order during special cycle

Note: We believe that the commonly used assumption $C_s = C_r$ is unrealistic. C_s is likely to be substantially greater than C_r for three reasons: (i) OTOS policy determination requires the use of a different model, (ii) The OTOS order quantity is likely to be several times the regular order quantity, and (iii) C_s must also include costs of announcing the special retail price, P_s to the retailer's customers.

d = the OTOS discount per unit

H = annual holding costs (such as storage space, and material inspection and handling costs) that are fixed per unit, regardless of the unit cost of the product.

h = annual holding costs (such as deterioration, damage, and pilferage costs) that are fixed per dollar of inventory, but that vary in per unit terms with the unit cost of the product.

Note: Most inventory models assume all holding costs to be of either the H type or of the h type. In real life,one encounters both types. Note also that we deal with the obsolescence costs and the capital costs explicitly and separately. Consequently, neither H nor h includes them.

H_r = total annual holding costs (all except the obsolescence cost) per unit of regular purchase $H_r = [H + (h + i)c]$.

H_s = total annual holding costs (all except the obsolescence cost) per unit of special OTOS purchase

$H_s = [H + (h + i)(c - d)]$.

i = cost of capital per dollar per year (used as both, the cost of capital factor in the inventory holding cost and the discount rate for NPV calculations).

k_r = probability, at the beginning of a regular inventory cycle of Qr/Rr years, that the product does not become obsolete during the cycle. $k_r = e^{-Qr/(RrL)}$ (Joglekar & Lee, 1993, 288).

k_s = probability, at the beginning of the special OTOS inventory cycle of Qs/Rs years, that the product does not become obsolete during the cycle. $k_s = e^{-Qs/(RsL)}$ (Joglekar & Lee, 1993, 288).

L = expected life of the product in years

N_r = NPV factor for a cashflow occurring at the end of a regular inventory cycle. $N_r = e^{-iQr/Rr.}$

N_s = NPV factor for a cashflow occurring at the end of the special OTOS inventory cycle. $N_s = e^{-iQs/Rs.}$

P_r = selling price per unit during regular cycle prior to obsolescence

P_s = selling price per unit during special cycle prior to obsolescence

Q_r = order quantity per order during regular cycle

Q_s = order quantity for the OTOS special order

R_r = demand per year during regular cycle, given by the function $R_r = A - \varepsilon P_r$.

R_s = demand per year during special cycle, given by the function $R_s = A - \varepsilon P_s$.

S_o = salvage value per unit after obsolescence, $S_o < (c - d)$.
t = the time at which the product becomes obsolete
$\Delta\pi_L$ = the difference between the expected lifetime profit resulting from the special OTOS P_s and Q_s policies followed by all regular cycles and the expected lifetime profit of all regular cycles in the absence of an OTOS. $\Delta\pi_L = \pi_{Ls} - \pi_{Lr}$.
ε = price-elasticity constant of the demand function
π_{cr} = expected profit, in NPV terms, from the first regular inventory cycle
π_{Lr} = expected lifetime profit, in NPV terms, from all regular cycles
π_{cs} = expected profit, in NPV terms, from the special OTOS cycle
π_{Ls} = expected lifetime profit, in NPV terms, from the special OTOS cycle followed by all regular cycles

THE REGULAR SITUATION

The following costs and benefits are in terms of a retailer's expected NPV of lifetime cash flows as expected at the beginning of an inventory cycle. First, the ordering costs and the inventory purchase costs are incurred, representing an NPV of

$$C_r + Q_r c \qquad (1)$$

Product revenues and holding costs depend upon whether and when the product becomes obsolete during an inventory cycle. If the product does not become obsolete, the entire order quantity is sold at the regular price. Subtracting the relevant inventory holding costs from these revenues, the corresponding expected NPV is given by:

$$\int_{Q_r/R_r}^{\infty}\Big[\int_0^{Q_r/R_r}\{R_rP_r - (Q_r - xR_r)[H+(h+i)c]\}e^{-ix}\,dx\Big](1/L)e^{-t/L}\,dt$$

Integrating and simplifying this expression by using several equalities established in the notation section, we get

$$P_rR_r(1 - N_r) + H_r[R_rN_r/i + R_r/i - Q_r]\}k_r/i \qquad (2)$$

If obsolescence occurs during the cycle, then the corresponding expected profit contribution is:

$$\int_0^{Q_r/R_r}\Big[\int_0^{t}\{R_rP_r-(Q_r-xR_r)[H+(h+i)c]\}e^{-ix}\,dx+(Q_r-tR_r)S_oe^{-it}\Big](1/L)e^{-t/L}\,dt$$

Integrating and simplifying, this expression can be written as

$$[P_rR_r - Q_rh_r + R_rH_r/i]\,[1 - k_r - 1/(1+iL)]/i \;+ [Q_rS_o + P_rR_rN_rk_r/i + R_rH_rN_rk_r/i^2]/(1 + iL)$$
$$- [R_rL/(1 + iL)^2]\,[H_r + S_o]\,[1 - N_rk_r] \qquad (3)$$

The NPV of the profit provided by a regular cycle, as expected at the beginning of that cycle, is given by

$$\begin{aligned}\pi_{cr} &= (2) + (3) - (1)\\ &= Q_rS_o/(1 + iL) + P_rR_rN_rk_r\,[1/(1 + iL) - 1]/i + [R_rH_rN_rk_r]\,[1 + 1/(1 + iL)]/i^2\\ &\quad + [P_rR_r - Q_rH_r + R_rH_r/i]\,[1 - 1/(1 + iL)]/i\\ &\quad - [R_rL/(1 + iL)^2]\,[H_r + S_o]\,[1 - N_rk_r] - (C_r + Q_rc) \qquad (4)\end{aligned}$$

Given a constant obsolescence rate, and a time-invariant order quantity, the NPV of the product's *lifetime* profit as expected at the beginning of an order cycle is identical to that expected at the beginning of the next order cycle. Hence,

$$\pi_{Lr} = \pi_{cr} + k_r\pi_{Lr}N_r \qquad (5)$$

This can be simplified as

$$\pi_{Lr} = \pi_{cr}/(1 - N_r\,k_r) \qquad (6)$$

The retailer wants to determine his price and order quantity of the regular cycle so as to maximize expected lifetime NPV from all regular cycles. From Joglekar and Lee (1996) we know that this problem is best solved numerically by using the solver function of software such as Excel . Hence, we do not pursue any further manipulation of Equation (6) for a closed form optimization. In our numerical examples, we simply use Excel 's solver function.

THE OTOS SITUATION

We assume that the OTOS discount is available at the beginning of what would have been a regular inventory cycle. Given the discount, the question is whether the retailer should take the discount, and if he does, what special order quantity, he should use, and at what special price he should sell that quantity. We develop a model for calculating expected lifetime NPV of using the special ordering quantity and price at the OTOS followed by regular policies until the end of the product's life. When an inventory cycle of a special order quantity begins, the corresponding ordering costs and the costs of the goods are given by

$$C_s + Q_s(c - d) \qquad (7)$$

Product revenues and holding costs depend upon whether and when the product becomes obsolete during an OTOS cycle. If the product does not become obsolete during the OTOS cycle, all order quantity units of the special cycle will sell at the special price. Subtracting the relevant inventory holding costs from these revenues, we obtain the corresponding NPV by the expression:

$$\int_{Qs/Rs}^{\infty} \left[\int_{0}^{Qs/Rs} \{R_s P_s - (Q_s - xR_s)[H + (h+i)(c-d)]\} e^{-ix} \mathrm{d}x \right] (1/L) e^{-t/L} \mathrm{d}t$$

Integrating and simplifying, this expression can be written as

$$\{P_s R_s (1 - N_s) + H_s [R_s N_s / i + R_s / i - Q_s]\} k_s / i \qquad (8)$$

If obsolescence occurs during the cycle, the corresponding expected profit contribution, in NPV terms, is given by:

$$\int_{0}^{Qs/Rs} \left[\int_{0}^{t} \{R_s P_s - (Q_s - xR_s)[H + (h+i)(c+d)]\} e^{-ix} \mathrm{d}x + (Q_s - tR_s) S_o e^{-it} \right] (1/L) e^{-t/L} \mathrm{d}t$$

Integrating and simplifying, this can be expressed as

$$\begin{aligned} &[P_s R_s / i - Q_s H_s / i + R_s H_s / i^2] [1 - k_s - 1/(1 + iL)] + [Q_s S_o + P_s R_s N_s k_s / i + R_s H_s N_s k_s / i^2]/(1 + iL) \\ &\qquad - [R_s L/(1 + iL)^2] [H_s + S_o] [1 - N_s k_s] \qquad (9) \end{aligned}$$

Thus, the NPV of all the cashflows of the OTOS cycle is given by

$$\begin{aligned} \pi_{cs} &= (8) + (9) - (7) \\ &= Q_s S_o/(1 + iL) + P_s R_s N_s k_s / i\, [1/(1 + iL) - 1] + R_s H_s N_s k_s\, [1 + 1/(1 + iL)^2]/i^2 \\ &\quad + [P_s R_s / i - Q_s H_s / i + R_s H_s / i^2] [1 - 1/(1 + iL)] \\ &\quad - [R_s L/(1 + iL)^2] [H_s + S_o] [1 - N_s k_s] - [C_s + Q_s (c - d)] \qquad (10) \end{aligned}$$

While it is tempting to compare this special cycle NPV with the regular cycle NPV, these NPVs are not comparable since the two cycles involve two different time durations. To determine whether the special order quantity and price policies are more desirable, one must compare the *lifetime* NPV of those special policies followed by regular policies with the expected *lifetime* NPV of using only regular policies throughout.

Expected lifetime NPV from all regular cycles has already been modeled in Equation (6). The expected lifetime NPV of the special OTOS cycle followed by all regular cycles is given by:

$$\pi_{Ls} \quad = \quad \pi_{cs} + \pi_{Lr} k_s N_s \qquad (11)$$

Thus, in the OTOS situation, the retailer wants to determine his special price and order quantity so as to maximize Equation (11). As in the case of the regular situation, we use Excel®'s solver function to solve this problem.

Once the optimized values of the special OTOS cycle are established, the net NPV advantage of the special OTOS policies is given by:

$$\Delta\pi_L = \pi_{Ls} - \pi_{Lr} \tag{12}$$

If the net advantage is negative, the retailer would reject the OTOS discount. Only if net advantage is positive, the optimal price and order quantity values will be implemented. In that case, for a long-term perspective, we examine the net advantage as a percent of the lifetime NPV with all regular policies. For a short-term perspective, we examine the net advantage as a percent of the NPV resulting from the first regular inventory cycle. It is these values that provide the proper perspective on both the long-term and the short-term gains associated with the use of our model in an OTOS situation. As we see it, while a long-term positive gain is important, the relative magnitude of the short-term gain is the most important consideration. After all, by definition, an OTOS is a one time, short-run deal.

NUMERICAL EXAMPLE

Consider a product with the following parameters:

c = \$10/unit	C_r = \$100/order	H = \$1/unit/year	L = 1 year	h = 5%/year
i = 12%/year	S_o = \$2/unit	R_r = 100,000 - 6,000P_r	A = 100,000 units/year	
ε = 6,000 units/\$.				

We believe these parameter values are fairly realistic. The unit cost and the demand constant are arbitrary and may be different from situation to situation. An ordering cost of \$100/order is within a range of values observed in real life. Together, the assumed holding costs (both fixed and variable) and the assumed cost of capital, result in an assumption of an annual inventory cost (excluding the cost of obsolescence) of 27% of the value of inventory. This is also well within the observed range of values in real life. Because we are focusing on S-Obs products, we assume a salvage value of only 20% of the unit cost and we assume an expected life of only 1 year. We consider a price-elasticity constant implying a reduction 6,000 units in demand for every dollar increase in price. We believe this is also within typically observed range of price-elasticity values.

Table 1

Assumptions, Decisions, and Lifetime Profits of Regular and OTOS Situations

Assumptions:

c = \$10/unit, C_r = \$100/order, H = \$1/unit/year, h = 5%/\$/year, i = 12%/year,
ε = 6000 units/\$, S_o = \$2/unit, L = 1 year, C_s = \$500/order,
d = \$1/unit (or 10% of regular unit cost)

Optimal Decisions and Results

Regular Decisions		Regular Results			OTOS Decisions		OTOS Results				$\Delta\Pi_L$ as % of	$\Delta\Pi_L$ as % of
P_r	Q_r	R_r	Π_{cr}	Π_{Lr}	P_s	Q_s	R_s	Π_{cs}	Π_{Ls}	$\Delta\Pi_L$	Π_{Lr}	Π_{cr}
13.43	516	19,419	1,545	52,706	13.16	2,097	21,031	6,456	53,592	886	1.68%	57.33%

As Table 1 shows, under our parameter values, in the regular situation, the retailer's optimal retail price works out to be \$13.43/unit. The corresponding demand is 19,419 units/year, and the optimal order quantity is 516 units/order (or less than two weeks' supply). These optimal decisions result in a regular cycle profit (in NPV terms) of \$1,545 and a lifetime NPV of \$52,706.

Now, assume that the manufacturer has offered an OTOS discount of \$1/unit (i.e., 10% of the regular unit cost), available at the time of the retailer's next order. Also assume that because it requires the use of a different model and involves the need to communicate a special price to the customers, the retailer's ordering cost for the special order, is \$500, instead of the regular \$100. Table 1 shows that, in this situation, the retailer's special order quantity would be 2,097 units and his special selling price would be \$13.16/unit. Given the special price, during the OTOS cycle, the retailer would experience a demand rate of 21,031 units/year. Thus, the special order quantity will last for approximately five weeks. The retailer's profit (in NPV terms) from the OTOS cycle will be \$6,456.

However, this special cycle NPV is not directly comparable with the regular cycle NPV of \$1,545 since the two cycles involve different lengths of time. The product's lifetime NPV from the special cycle followed by all regular cycles is \$53,592. Thus, the retailer's net increase in lifetime NPV due to the OTOS is \$886. In comparison to the NPV of all regular cycles (\$52,706), this net advantage looks small (1.68%). However, \$886 is 57% of a single regular cycle's NPV of \$1,545. This short-term advantage is very attractive. After all, the OTOS decisions are short term, one-cycle decisions. In short, our numerical example shows that if a retailer adopts our model, he would obtain some long-term gain and a particularly attractive short-term gain.

Of course, conclusions from a numerical example are only as valid as the assumed parameters. Hence, in what follows, we provide an analysis of the sensitivity of our results to each one of the assumed parameters. The numerical example in Table 1 serves as the base case for this sensitivity analysis.

SENSITIVITY ANALYSIS

The only parameter we hold constant throughout the sensitivity analysis is the retailer's regular unit cost of the product. However, changes in some of the other parameters could be seen as relative changes in the unit cost.

Table 2

Sensitivity to *d*, the OTOS Discount Per Unit

	Regular Decisions		Regular Results			OTOS Decisions		OTOS Results				$\Delta\Pi_L$ as % of Π_{Lr}	$\Delta\Pi_L$ as % of Π_{cr}
d	P_r	Q_r	R_r	Π_{cr}	Π_{Lr}	P_s	Q_s	R_s	Π_{cs}	Π_{Ls}	$\Delta\Pi_L$		
0.4	13.4	516	19,419	1,545	52,706	13.33	1,098	20,049	3,060	52,629	-77	-0.15%	-4.98%
0.8	13.4	516	19,419	1,545	52,706	13.22	1,746	20,698	5,248	53,202	496	0.94%	32.11%
1.0	13.4	516	19,419	1,545	52,706	13.16	2,097	21,031	6,456	53,592	886	1.68%	57.33%
2.0	13.4	516	19,419	1,545	52,706	12.87	4,170	22,776	13,811	56,746	4,040	7.66%	261.48%

Holding other assumed parameters at their values in Table 1, in Table 2 we vary the assumed amount of discount offered by a supplier to the reseller. As can be seen, when the discount is only \$0.40 (or 5% of the normal unit cost), using special OTOS policies would result in a net loss to the reseller. Thus, the reseller is better off continuing to use his regular policies during the OTOS period and simply benefiting from the windfall gain from the discounted cost. However, as the amount of discount (and its percentage of normal unit cost) increases, the OTOS strategies become increasingly attractive, both, from the long term and the short-term perspective. When the discount is as large as 25% of the normal unit cost, the reseller may want to use a special order quantity that is 8 times his regular order quantity and pass on more than a fourth of his unit cost saving to his customers. Such a one-time opportunity can increase the reseller's lifetime NPV by 7.66% and his single cycle net advantage can be several times his normal single cycle profit.

Similarly, we carried out a detailed examination of the sensitivity of our results to each one of the parameters of our model. In Table 3, we provide a brief summary of the alternative values of parameters used, the resulting indices of long term and short-term advantage of the optimal OTOS strategies. As would be expected, the results are highly sensitive to the price elasticity. The greater the price elasticity, the greater are the advantages of optimal OTOS strategies.

Table 3

Sensitivity Analysis			
Changed Parameter	**$\Delta\Pi_L$ as % of Π_{Lr}**	**$\Delta\Pi_L$ as % of Π_{cr}**	**Comment**
ε = 5,000	1.09%	41.72%	The results are highly sensitive to this parameter. The greater the price elasticity of demand, the greater are the short term and long term advantages of optimal OTOS decisions.
ε = 6,000	1.68%	57.33%	
ε = 7,000	2.75%	80.48%	
C_s = 200	2.25%	76.74%	The results are highly sensitive to this parameter. The greater the cost of ordering an OTOS order, the smaller are the short term and long term advantages of optimal OTOS decisions.
C_s = 500	1.68%	57.33%	
C_s = 800	1.11%	37.91%	
L = 0.75	1.80%	51.46%	The results are moderately sensitive to this parameter. As the *expected life of the product* increases, long term advantages of optimal OTOS decisions decrease while short term advantages increase.
L = 1.00	1.68%	57.35%	
L = 1.50	1.47%	64.46%	
S_o = 1.00	1.55%	54.67%	Short term results are not too sensitive to this parameter. However, long term results are rather sensitive. As the *salvage value of the product* increases, both short term and long term advantages of optimal OTOS decisions increase.
S_o = 2.00	1.68%	57.35%	
S_o = 3.00	1.83%	60.24%	
C_r = 50	1.25%	60.16%	Short term results are not too sensitive to this parameter. However, long term results are rather sensitive. As the ordering cost of a regular order increases, long term advantages of optimal OTOS decisions increase, but short term advantages decline.
C_r = 100	1.68%	57.33%	
C_r = 200	2.41%	58.08%	
H = 0.5	1.82%	60.01%	The results are not too sensitive to this parameter. The greater the *fixed holding cost per unit* of inventory, the smaller are the short term and the long term advantages of OTOS optimal decisions.
H = 1.0	1.68%	57.33%	
H = 1.5	1.56%	54.85%	
h = 0.02	1.75%	58.53%	The results are not too sensitive to this parameter. The greater the *fixed holding cost per dollar* of inventory, the smaller are the short term and the long term advantages of optimal OTOS decisions.
h = 0.05	1.68%	57.33%	
h = 0.08	1.62%	56.17%	
i = 0.08	1.77%	59.95%	The results are not too sensitive to this parameter. The greater the *annual cost of capital,* the smaller are the short term and the long term advantages of optimal OTOS decisions.
i = 0.12	1.68%	57.35%	
i = 0.16	1.61%	54.96%	

The results are also highly sensitive to the ordering cost of the special order. As the ordering cost of the special order increases, the advantage of the special OTOS policies declines. From a practical point of view this is rather important to understand. In the past, researchers have assumed that, in an OTOS, there would be no change in the ordering cost. That assumption is not only unrealistic; it inflates the advantage attributable to optimal OTOS policies.

The results are moderately sensitive to the product's expected life. As expected life increases, the short-term advantages of the OTOS policies increase while the long-term advantages decline. Note also that as a product's salvage value increases the OTOS decisions are increasingly advantageous both in the long run and in the short run. Thus, it seems that OTOS decisions are more beneficial for non-obsolescent products than they are for obsolescent products.

Finally, Table 3 indicates that, from both, the long-term and the short-term perspectives, the results are not very sensitive to changes in regular ordering costs, holding costs, or cost of capital.

CONCLUSION

Today many products are characterized by price elasticity, sudden obsolescence, and short expected lives. Drawing on the relevant literature, first we built a model for a retailer's optimal price and order quantity decisions for such products in the regular situation, i.e., in the absence of a one-time-only discount. Our model is comprehensive. It allows for price elasticity, accounts for a variety of types of inventory holding costs, and deals with obsolescence costs and capital costs in precise and theoretically correct manner. Because manufacturers and vendors of S-Obs products often offer a one-time-only discount for such products, we then extended our model to accommodate the OTOS situations. Because a special order requires the use of a different model and additional costs of announcing a price change, our model used an explicitly different ordering cost for the special OTOS order. A numerical example showed that the use of our model could provide some long-term gain and a particularly attractive short-term improvement in a retailer's profit. A retailer stands to benefit the most from our model if the discount is substantial, the product demand is highly price sensitive, and the retailer's ordering cost for the special order is substantial. Also, it seems that OTOS decisions are more beneficial for non-obsolescent products than they are for obsolescent products.

There are several directions for further work on this topic. First, we assumed a linear and deterministic demand function. A non-linear function is likely to be more realistic in most situations. An extension of our model to a non-linear demand relationship should be straight forward, particularly since we do not derive any closed-form solutions but depend on Excel® to solve the problem. Also, a stochastic demand function is more likely to be encountered in real life. An extension to allow for a stochastic demand function would be relatively more complicated but doable.

A critical assumption in our model is that the fact that a manufacturer has offered an OTOS does not in itself change a retailer's assessment of the product's life expectancy and/or salvage value. In real life, a retailer may assume, often correctly, that an OTOS is a signal of an imminent obsolescence. Thus, in view of the OTOS, a retailer's perceived life expectancy and/or salvage value for the product may be reduced. On the other hand, as we have pointed out, an impending price increase with one last opportunity to buy at the lower price is a situation that is mathematically equivalent to an OTOS. In such situations of impending price increase, a retailer may deduce that the product's life expectancy may be greater than his original estimate of that expectancy. In any case, an extension of our model to allow for such a change in the perceived life expectancy of a product offered on an OTOS would also be an interesting and productive direction for further work. Finally, two recent models of OTOS situations for non-obsolescent products suggest that a retailer's optimal strategy is not to sell the entire special order quantity at the special price. Instead, a retailer should sell only a portion of his special order quantity at a special price, reverting to his regular selling price for the remaining portion of the special order quantity (Abad, 2003; Arcelus, Shah & Srinivasan, 2003). It seems that this type of a strategy may be optimal also for products subject to sudden obsolescence.

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SIX SIGMA AND INNOVATION

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ABSTRACT

Innovation is a proven success factor for many firms, specifically 3M. However, some feel that the impending implementation of the six sigma strategy may hinder the innovative process present at 3M. This paper looks at these concerns and makes recommendations regarding its inclusion within the strategic framework of one of the world's most innovative firms.

INTRODUCTION

In today's high-tech world, innovation has become a driving force for individual firms and entire economies (Bixler, 2002). Long-term success requires that the customer be excited by innovations provided by a company's product and services, hence continued survival requires continuous innovation (Pyzdek, 1999a). Success is about putting innovation at the heart of the company (Mazur, 2002). One such company meeting this description is Minnesota Mining and Manufacturing (3M). In fact, 3M exemplifies the use of innovation as a distinctive competency.

3M began its tradition of innovation in the 1920s, when it introduced waterproof sandpaper. That tradition has lasted 100 years, introducing such products as masking tape, Scotchgard, Post-It Notes, and even astronaut Neil Armstrong's boots. 3M now has 7,100 research and development (R&D) employees in 71 laboratories around the world ("Innovation has been…," 2002). In keeping with tradition, 3M has a unique policy allowing scientists to spend up to 15% of their time working on unauthorized projects of their own creation (Haeg, 2002; Pyzdek, 1999b).

Despite this background of innovation, some analysts believe that 3M's performance is still relatively "lackluster" in comparison to its potential. In response, 3M's new CEO, W. James McNerney has implemented the management technique/philosophy six sigma. Under the auspices of six sigma, McNerney has vowed to slash inefficiencies, implement an employee performance ranking system, and reduce the company's workforce by 7%. He rationalizes that, while 3M has outperformed other companies in its industry, it has always been an underachiever (Mullin, 2001). Specifically, McNerney expects to reach these goals by improving the prioritization of investments, reducing cycle times, and improving areas such as sourcing, indirect costs, and e-business. (Mullin, 2001).

However, not everyone sees this as good news. There are some who feel that a rigorous process such as six sigma actually detracts from creativity. Some of 3M's most prominent names, Art Fry, inventor of the Post-It Note and former 3M CEO, Lewis Lehr, for example, are concerned that six sigma's structure will stifle employee creativity (Haeg, 2002). So, are companies implementing six sigma destined to suffer from a lack of future innovations? Is six sigma too structured and controlling for processes such as R&D? This possibility is the key issue of this paper. We look at the innovation process and the potential impact of six sigma upon this process. After discussion of the issues, recommendations are made for 3M and others who wish to incorporate the six sigma process.

WHAT IS SIX SIGMA?

A cost-saving, inefficiency-slashing program, six sigma is a business concept that touts improving quality and business processes. Specifically, it is "a disciplined method of using extremely rigorous data-gathering and statistical analysis to pinpoint sources of errors and ways of eliminating them" (Harry & Schroeder, 1999). The Greek letter sigma (s) represents a standard deviation from the mean or average. The objective is to reduce process variation so that plus or minus (±) six standard deviations lie between the mean and the nearest specification limit (Statistical six sigma definition, 2003). This translates to no more than 3.4 defective parts per million opportunities. Hence, six sigma implementation begins by measuring defects per million opportunities, allowing only 3.4 defects. Most companies do no better than three sigma (Arndt, 2002) and are pleased with their performance. However, even four sigma performance would still allow 500 incorrect surgical operations per week, 20,000 incorrectly filled pharmaceutical prescriptions each year, and 2,000 lost articles of mail each hour (Marash, 2000). Six sigma companies then set aggressive short-term objectives but strive toward long-term goals.

A six sigma project succeeds by reducing subjective errors in the assessment of problems. Six sigma firms follow a five step process which includes defining a process measuring the process to assess current performance, analyzing information to determine where the errors lie, improving the process and eliminating the errors, and finally setting up controls to prevent future errors (Arndt, 2002).

Developed by Motorola in the 1980s, the six sigma philosophy has spread to other companies such as GE, Allied Signal, and Texas Instruments. The difference between six sigma and previous quality philosophies is that six sigma is being promoted by top management, not just by quality managers. It is being touted not only in technical journals but also on the business pages of newspapers and magazines (Marash, 2000).

There are definitely some success stories. Dow Chemical, DuPont, GE Plastics, Air Products and Chemical, Avery Denison, Great Lakes Chemical, Honeywell, (Schmitt, 2002), W.R. Grace (Sauer, 2001) and Rockwell International (Hasek, 2000) have all embraced six sigma, with quick monetary results. Allied Signal saved $1.5 billion through 1998 and was looking at a subsequent $600 million per year savings thereafter ("Six sigma secrets," 1998).

Six sigma is not limited to manufacturing processes alone. Advocates feel it may also be applied to functions such as accounts receivable, sales, and research and development. While more difficult to evaluate areas in which processes are not standardized, six sigma can still be applied (Arndt, 2002).

THE INNOVATION PROCESS

Innovation is defined as "an iterative process initiated by the perception of a new market and/or new service opportunity for a technology-based invention which leads to development, production, and marketing tasks striving for the commercial success of the invention" (Garcia & Calatone, 2001). Once a product moves through the production and marketing phases and enters the marketplace, it's status moves from invention to innovation (Garcia & Calatone, 2001). As the product becomes an innovation, value is provided to customers. "Value consists of the performance characteristics and attributes that a company offers in the form of a good or service for which customers are willing to pay" (Hitt, Ireland & Hoskisson, 2001). The effect of value is felt in a company's bottom line; therefore, creating value in a good or service is necessary for a firm's competitive success.

Students of innovation argue that a firm's ability to innovate is a function of its local environment (Afuah, 1998). A study of creativity among corporate research scientists found that environment was a critical factor in stimulating or blocking creativity (Kiely, 1997). Badawy (1997) states that "in order to stimulate and reinforce creativity [innovation], appropriate organizational climates [environments] should be established." A review of innovation literature reveals that an environment conducive to innovation is marked by the absence of three factors present in most highly structured or hierarchical organizations: fear of uncertainty, fear of failure and productivity measurement. Uncertainty, failure and measurement, as they pertain to innovation, are now discussed.

Uncertainty

There seems to a general consensus, in the literature, that innovation is unpredictable and characterized by uncertainty (Brown, 2001; Afuah, 1998; Badawy, 1997, Peters, 1997). As such, unexpected occurrences can be good sources of innovation (Afuah, 1998). For example, when Upjohn was testing minoxidil for treatment of high blood pressure, they found hair growth to be a side effect. The result was the marketing of Rogaine (minoxidil) to treat baldness.

Failure

Manners, Steger and Zimmerer (1997) say that "people who have spent their lives building self-esteem based upon technical competence will go to great lengths to avoid losing that fragile base." Badawy (1997) goes further to warn that engineers are professional individuals who demand special treatment and cannot be managed like other labor. Others (Pyzdek, 2001b) even feel that the big risk is not fear of failure but the failure to risk. Examples of "successful failures" include Art Fry's failed superglue experiment (Post-it Notes) and James Wright's failed attempt at developing a synthetic rubber for airplane tires and soldiers' boots (Silly Putty). Other "failure" discoveries include X-rays, Frisbees, Velcro, penicillin, Coca-Cola and the slinky (Niemann, 2003).

Measurement

Innovation is the result of creative activity not of analysis (Pyzdek, 1999a). Creativity cannot be achieved "by the numbers" (Pyzdek, 1999a) nor can it be measured (Kiely, 1997). Pyzdek, (1999a, 1999b) points out that the creative organization is one that exhibits variability, resource redundancy, quirky design and slack. Trying to measure and control all aspects of the innovation process causes engineers and scientists to restrict the depth of their exploration, leaving little room for pursuit of novel ideas (Katz & Allen, 1997). Therefore, an organization that is tolerant of a large variety of deviation from the norm is more likely to enhance creativity (Shapero, 1997).

SIX SIGMA AND THE INNOVATION PROCESS

The current rapid rate of change in technology places a higher premium on being able to quickly offer [new] goods and services to the marketplace. "With the rapid and widespread diffusion of technologies used to produce goods and services, speed to market may be the only source of competitive advantage" (Hitt, Ireland & Hoskisson, 2001). As innovation is pushed into this rapid product development cycle, heightened expectations of the marketplace call for better tools to improve the productivity of the innovation process. Six sigma, often viewed as a toolbox full of new devices (Sauer, 2001), is seen by some as potentially helpful to the innovation process.

Christensen (2002) believes that innovation isn't random; its outcomes only appear to be random because we don't understand all the factors, such as management strategies, degree of company integration, capabilities, and resources, that affect successful innovation. If we can use six sigma to master these variables, the products, processes, and services created will have more predictable outcomes. This implies that six sigma can also serve to eliminate waste of time and resources in the conception process by linking it directly to customer wants and needs. Barry Siadat, AlliedSignal's chief growth officer feels that six sigma will shorten cycle time and increase speed to market, and finally, it will reduce costs ("Six sigma secrets," 1998). These sentiments are reflected by Daniel Laux, president of Six Sigma Academy, who feels that six sigma can now be applied to all industries and all functions and can even be used in R&D to find innovative products (Gilbert, 2002).

At one time, product development generally occurred by happenstance (Six sigma secrets, 1998). In the chemical industry, research scientists produced a new substance, while analytical chemists performed measurements and added specifications later (Sauer, 2001). For discrete products, the conventional R&D approach started from a developer and proceeded to design and prototype through build and test iterations, later resulting in design changes and wasteful rework (Management innovation…, 2000). With a six sigma approach, researchers first find what the customer wants and then look at the process capability study (Sauer, 2001). Then the customer's need and problems can be clearly defined and non-value work eliminated (Management innovation…, 2000), thereby shortening the innovation process.

Studies showing that as much as 80% of quality problems originate in design (Who needs…, 2002) have led firms to look to six sigma's toolbox for design improvement. An aerospace firm experienced a mismatch between the part dimensions represented in the model itself and the measurement specified by designers. Because of the design error, the first products were consistently wrong. Each individual model was always fixed but because the design process that produced the error was not fixed, the error continued to occur and had to be continually fixed; at a cost of $150,000 each time. Proper use of six sigma could have avoided this fiasco (Finn, 2000).

Successful examples include AlliedSignal who used six sigma to reduce variation in performance in the "upfront" design of their AS900 engine. This resulted in reductions of 30% in work-hours, 50% in fan module variability, and 9 months in time-to-certification (Six sigma secrets, 1998). A major innovation in metal injection molding material, developed by a Honeywell six sigma team, enabled the production of a new variable-weight golf putter for a customer, capturing $1 million in sales for Honeywell (Six sigma plus, 2001). Both Dell Computer and IBM utilized six sigma to evaluate products before the first shipment, resulting in savings from detection of manufacturing and design issues (Design for six sigma…, 2002). Even 3M has already realized $1 million savings after a six sigma review found that a dental ceramic wasn't being properly cured (3M: A lab for growth, 2002).

Despite these success stories, the application of six sigma to innovation has its detractors. Johnson (2002) states that "R&D activities involve inquiry, analysis, synthesis and other activities that naturally reshape and change as they proceed-and so naturally defy systematic improvement efforts." Thomas Pyzdek , a regular columnist for Quality Digest adds that You would kill the creativity of research if you tried to apply six sigma there" (Dusharme, 2001). Craig Hickman and Christopher Raia (2002) use the terms convergent and divergent thinking systems to further illustrate this contrast. They (Hickman & Raia, 2002) state that "convergent thinking system, which include most established business organizations, survive on order, measurement, and predictability. In contrast, most innovations result from divergent thinking environments that thrive on disorder, imagination, and ambiguity."

"Not so successful" stories include a multinational firm that upon achieving six sigma success in one division, decreed that the entire company should follow suit. Six sigma worked fine in areas of high volume or repeatable processes, but low volume departments had to go looking for data to feed the tool. Often, this data had little or no relevance to customer satisfaction, yielding a distorting effect on quality management (Six sigma-A true story, 2003). While IBM focused on reducing defects and making incremental improvements using six sigma, EMC Corp. and Cisco Systems, Inc. were pioneering innovations that took the leading position in their markets away from IBM (Gilbert, 2002).

A more than cursory look at these success stories will reveal that six sigma's utilization seems to be ensuring success during the development process after the innovation is conceived; what is known as application development. But what about the actual conception of the idea behind the product, the application itself?

Can a company such as 3M, one whose most well-known attribute is innovation, afford to "tinker" with success? Not according to Thomas Pyzdek. Pyzdek (2001) feels that companies that apply six sigma wall-to-wall are going about the philosophy in the wrong manner. He believes that management should not take the idea (six sigma) too far and try to apply it "across the board" (Dusharme, 2001). R&D departments should apply six sigma to the development aspect but never to the research aspect, as six sigma brings too much organization to a process that should be rather casual and disorganized (Dusharme, 2001; Pyzdek, 1999a).

Six sigma is methodical and organized, rigorous and structured, which seems in contrast to the productive innovation environment. Pyzdek (2000) feels that the greatest enemy of creativity is hierarchy. An overly-structured R&D organization with numerous levels of hierarchy, an abundance of rules and regulations, and a flow of paperwork can sap energy that would otherwise be used for the creation, application, utilization and generalization of knowledge (Pasmore, 1997).

For all firms, six sigma seems to result in compressed product-development times and products that have a much higher hit rate, i.e., are more successful in the marketplace (Stevens, 1998). And six sigma can generate increased sales through better customer relations that promote improvements and innovations (Schmitt, 2002). But a misdirected focus of six sigma in R&D may make an organization less creative, crushing the innovation that is the essence of R&D's contribution to the success of the firm (Johnson, 2002). Hence, a number of recommendations are in order.

RECOMMENDATIONS

As applied to R&D and innovation, six sigma's usefulness lies in solving quality problems that can be reduced to sub-problems; projects can then be planned with a more narrow focus. Six sigma's power is optimized when applied to "inside the box" problems" (Spanyi & Wurtzel, 2003) as encountered in the product development stage. Were six sigma to be applied during these early design phases, it would catch design problems early on, instead of much further in the process. American firms spend about 95% of R&D budgets on product technology and only 5% on process technology. Conversely, the Asian automobile industry spends about 75% of R&D on process technology and only 25% on product (Treichler, Carmichael, Kusmanoff, Lewis & Berthiez, 2002). If more companies adopt a six sigma framework stressing process technology more than product and significantly reducing manufacturing defects in the process, they can expect to save significant costs, increase product life cycles, and reduce warranty and other service costs (Treichler et al., 2002).

However, care should be taken to ensure that creativity, the backbone of any innovative company, is not stifled. In order to ensure this, the creative environment must be protected. Manners et. al (1997) relates that "In research work, the basic tenet of protection typically means protection from the consequences of failure. In order to keep work excitement and openness high, the manager must communicate that you take some risks and I will protect you if you fail."

In addition to protection from the fear of failure, firms should take steps to ensure that R&D employees are protected from the fear of uncertainty. Instead of building a product simply because we have the technology and the wherewithal to do so, should we only consider products that have a ready market? But did customers really know they wanted or needed Post-It Notes? Innovation does not always produce a product or concept that is readily embraced by a market. Peters (1997) claims that throughout the history of successful corporate innovation, neither the first nor the second prototype has ever worked. Hence, procedures should not be so strict that experimentation is hindered (Johnson, 2002) or R&D departments alienated (Treichler et al., 2002). Use methods that establish appropriate protocols but be careful not to overcontrol in such a way that inhibits experimentation and innovation (Johnson, 2002).

Finally, don't try to manage innovation "by the numbers." Innovation thrives in chaos (Peters, 1997) so productivity is difficult if not impossible to quantify. Why shackle it with a measurement system, especially if measurement adds little or no value to the outcome. Don't be afraid to build variability, slack and redundancy into an organization (Pyzdek, 1999a). Remember, an organization that is tolerant of deviation is more likely to enhance creativity (Shapero, 1997).

Utilizing the discussion on fear of failure and uncertainty and measurement, the innovation process can be described as in Figure 1. The innovation-conducive environment, when coupled with rigorous structure and hierarchy results in the results emphasized earlier: sapped energy, decreased knowledge generation and utilization and decreased creativity. The innovation-conducive environment coupled with protection from fear of failure and uncertainty and unnecessary measurement results in increased motivation to perpetuate innovation via creation, application, utilization and generalization of knowledge.

Figure 1
The Effect(s) of Protection and Structure on the Innovation-Conductive Environment

Innovation-Conducive Environment Fear of Failure Fear of Uncertainty Measurement	+	Protection	=	↑Motivation
	+	Structure	=	↓Creativity ↓Knowledge Creation ↓Knowledge Application ↓Knowledge Utilization ↓Knowledge Generalization

CONCLUSION

Innovation perpetuates an organization. Employees are interested in the future of their company and like to work to ensure it. From innovation you get esprit de corps and fulfillment. Innovation is exciting. It is crucial to sustaining the enterprise (Stevens, 1998). It can't always be judged in terms of costs and benefits, especially if it is critical to sustaining the firm. Successful innovation includes the right to fail (Mazur, 2002), uncertainty and measurement slack, something six sigma does not allow.

For firms generating "improved" products or advances in existing technology, six sigma may be appropriate to the research and creation process. However, for firms, such as 3M, that rely almost exclusively on "new" and previously unconceived of products and services, six sigma may prove to be a detriment to the creative process. Therefore, while six sigma is a useful management philosophy, it should not be applied across the board in these organizations.

Six sigma can vastly reduce development time, generate increased sales through better customer relations (Schmitt, 2002), contain costs, create alignment between strategic planning and operations (Sauer, 2001), create an infrastructure of change agents not employed in the quality department (Pyzdek, 2001a) and unleash the creativity of everyone in the organization, providing a flood of ideas along with a method to manage the flood. Just don't let it dry up the flood.

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