ARTICLE IN PRESS

Expert Systems with Applications xxx (2011) xxx–xxx

Contents lists available at ScienceDirect

Expert Systems with Applications

journal homepage: www.elsevier.com/locate/eswa

Re-examining information systems user performance: Using data mining to identify properties of IS that lead to highest levels of user performance

Boontaree Kositanurit [a], Kweku-Muata Osei-Bryson [b,*], Ojelanki Ngwenyama [c]

[a] Fiscal Policy Office, Ministry of Finance, Thailand
[b] Information Systems Research Institute, School of Business, Virginia Commonwealth University, Richmond, Virginia, USA
[c] Institute of Innovation and Technology Management, Ted Rogers School of Management, Ryerson University, Toronto, Canada

ARTICLE INFO

Keywords:
Data mining
Decision tree
Information systems
End-user performance

ABSTRACT

As competitive pressures increase, managers try to realize every bit of productivity from people, business processes and new information technologies (IT). This leads one to ask, how can managers configure information systems to achieve higher levels of performance from end users? In this regard, managers continually seek advice on how to meet the promises and expectations of continued increases in productivity through the use of IT. However, results from research on how to achieve higher performance through the use of IT in organizations has been mixed. Consequently, it has been difficult for IS researchers to give managers any advice on investing in specific aspects of IS that would lead to the highest performance possible. We focus on this question in this research. We use a data mining approach to tease out information about specific characteristics of IS that managers can manipulate to achieve desired outcomes with regards to individual performance. Our findings offer both researchers and managers significant new knowledge that can make a difference to IT user performance research theory and the practice of user performance management. Further, our research method offers a novel approach to linking theory and practice in IS research, a problem that is of great concern to many IS researchers. The approach is generalized and can be implemented by academic or industry researchers who are interested in generating hypotheses from data for the purpose of theoretical or applied research.

1. Introduction

Achieving higher performance in the use of IT in organizations is a continuing problem within information systems research. While firms have continued to invest in information technology (IT), realizing the promises and expectations that IT would provide increasing productivity gains has been difficult (Ward, 2002). As competitive pressures increase, managers of all types are looking to wring every possible bit of productivity out of their investments in IT. The fundamental question for every manager is how to get better performance out of end-users of IT applications. While the question of end-user performance has been much researched, and some answers have been provided, the situation is still unclear. Information systems researchers continue to have difficulty telling managers what they need to do to achieve the highest level of performance from end users of IT applications. As a practical matter, managers want to be able to identify the characteristics of an information system that can be managed to obtain the highest end-user performance. Although this question is implied in user performance studies, it has not be been investigated directly. The answer requires identification and analysis of relationships that may exist between systems characteristics and individual performance. Previous studies of user performance have not systematically examined this issue. In this paper, we pursue the question by trying to identify those properties of IS which tend to lead to the highest levels of individual end-user performance. We apply a data mining-based approach in this investigation that involves the use of decision trees (e.g. Samoilenko & Osei-Bryson, 2008). Our reason for using this method is that we wanted a formal approach for reasoning from the data to derive both hypotheses for future testing and actionable rules that managers can use. In this paper, we use decision tree (DT) analysis of questionnaire data to explore the impact of certain properties of IS on individual performance.

2. Review of relevant research

There are many studies that have investigated end-user performance with information systems (Cf. Table 1). This body of literature can be divided into two types of inquiry, (a) Task-technology fit studies, and (b) User satisfaction studies, each category approaching the study of end-user performance from a different

* Corresponding author.
E-mail address: Kweku.Muata@isy.vcu.edu (K.-M. Osei-Bryson).

0957-4174/$ - see front matter © 2010 Elsevier Ltd. All rights reserved.
doi:10.1016/j.eswa.2010.12.011

Table 1
Studies relating to end-user performance.

Focus of the study	Method of data collection	Method of data analysis	Citations
TTF: the effect of task demands and graphical format on information processing strategies	Experiment	ANOVA	Jarvenpaa (1989)
TTF: the fit between job and PC capabilities	Surveys (questionnaires)	Partial Least Square analysis	Thompson et al. (1991)
TTF: computer graphs and fit with question types and question complexity levels	Laboratory experiment	Two-way analysis of variance and Wilcoxon matched pairs signed-ranks test	Wilson (1994)
TTF:	Surveys (questionnaires)	Regression analysis	Goodhue (1995)
TTF: model validation	Surveys (questionnaires)	Regression analysis	Goodhue and Thompson (1995)
TTF	Surveys (questionnaires)	Establishing instrument validity	Goodhue (1998)
TTF	Laboratory experiment	Regression analysis	Mathieson and Keil (1998)
TTF and fitness-for-use (FFU)	Surveys (questionnaires)	Regression analysis and Path analysis	Dishaw and Strong (1998)
TTF and TAM	Surveys (questionnaires)	Path analytic technique	Dishaw and Strong (1999)
TTF	Experiment and questionnaire	Regression analysis and Logistic Regression	Goodhue et al. (2000)
TTF: CASE-task fit and software developer's performance	Surveys (questionnaires)	Hierarchical regression analysis	Lai (1999)
User satisfaction	Surveys (questionnaires)	Measurement development	Bailey and Pearson (1983)
User satisfaction	Surveys (questionnaires)	Measurement development	Ives et al. (1983)
User satisfaction	Surveys (questionnaires)	Measurement development	Doll and Torkzadeh (1988)
User satisfaction	Surveys (questionnaires)	Establishing instrument validity	Torkzadeh and Doll (1991)
User satisfaction	Surveys (questionnaires)	Establishing instrument validity	Doll et al. (1994)
User satisfaction	Surveys (questionnaires)	Establishing instrument validity	Hendrickson et al. (1994)
User satisfaction	Surveys (questionnaires)	Establishing instrument validity, structural equation model, regression analysis	Etezadi-Amoli and Farhoomand (1996)
User satisfaction	Surveys (questionnaires)	Partial Least Square Testing	Igbaria and Tan (1997)
User satisfaction	Surveys (questionnaires)	Structural equation based on Partial Least Square	Blili et al. (1998)
User satisfaction and TAM	Surveys (questionnaires)	Structural equation model using LISREL	Al-Gahtani and King (1999)
User satisfaction	Surveys (questionnaires) and observation through meta-monitoring system analysis that automatically, tracked and recorded users' activities.	Z-tests	Downing (1999)

perspective. The task technology fit approach postulates that when the user's task and the technology are congruent, user performance will be high (Dishaw & Strong, 1998; Goodhue, 1995; Goodhue & Thompson, 1995; Mathieson & Keil, 1998). Consequently, studies falling under this approach try to define task and technology characteristics and what is "*goodness of fit*" between specific technologies and end-user tasks (Dishaw & Strong, 1998; Goodhue, Klein, & March, 2000; Mathieson & Keil, 1998). On the other hand, user satisfaction studies investigate the extent to which certain IS properties, such as system quality, information quality, and system use and user satisfaction can influence user performance (Bailey & Pearson, 1983; Doll & Torkzadeh, 1988). Numerous user satisfaction studies have been conducted in the last decade which attempt to identify the factors of the information systems that lead to high user performance (DeLone & McLean, 1992; Doll, Xia, & Torkzadeh, 1994; Hendrickson, Glorfeld, & Cronan, 1994; Torkzadeh & Doll, 1991).

Our research question places this study at the intersection of TTF and user performance studies, because the constructs, "information systems characteristics" and "user performance", that we are interested in are commonly theorized in both categories of studies. In this regard, our review of the literature will focus on outlining those constructs (and variables) that are relevant to our investigation.

2.1. Task-technology fit

Several researchers have used the task-technology fit (TTF) model to explain the impact of information systems and task characteristics on individual performance (Dishaw & Strong, 1998; Ferratt & Vlahos, 1998; Goodhue & Thompson, 1995). This model is founded on the notion that when user task characteristics and characteristics of the information system fit well together, both utilization of the system and user performance will be high. As Goodhue and Thompson state; "...TTF is the correspondence between task requirements, individual abilities, and the functionality of the technology" (Goodhue & Thompson, 1995). In their study, they find empirical support for the relationships TTF and Performance, and Utilization and Performance, moderate support for the relationships Task Characteristics and TTF, and Technology Characteristics and TTF, and no support for the relationship TTF and Utilization (cf. Fig. 1). The specific information systems properties/technology characteristics they tested for were Information Quality, Locatability, Authorization, System Reliability and Ease of Use. While the TTF model does not tell us, what characteristics of information systems lead to highest levels of user performance, it does suggest some constructs relevant to the investigation of our question.

2.2. User satisfaction and performance

The second category of studies, user satisfaction, focuses on identifying the conditions under which users are satisfied with the systems. Doll and Torkzadeh (1988) define user satisfaction as "the affective attitude towards a specific computer application by someone who interacts with the application directly". The fundamental argument of the user satisfaction approach is that high levels of user satisfaction lead to high levels of user performance. Bailey and Pearson (1983) conducted a literature review in an early study to identify influencing factors. They developed and tested a questionnaire for investigating user satisfaction. Ives, Olson, and Baroudi (1983) replicated and extended Bailey and Pearson's

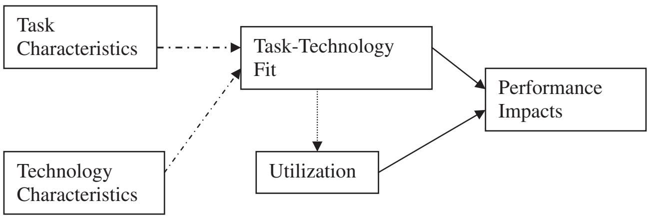

Fig. 1. The TTF model proposed and tested by Goodhue and Thompson (1995).

(1983) study to provide evidence of validity of the instrument. Reliability, content validity, predictive validity and construct validity were tested. Doll and Torkzadeh (1988) also developed an instrument to measure end-user computing satisfaction. This instrument included several constructs relating to information systems properties such as information content, format, accuracy and ease of use.

These early works paved the way for other studies that linked the constructs of user satisfaction, system characteristics and user performance. Some of this research has also focused specifically on clarifying and confirming the relationship between user satisfaction and end-user performance (DeLone & McLean, 1992). This argument is also the central point of Igbaria and Tan (1997) nomological net model. In another important study, DeLone and McLean (1992) also postulated but did not test the existence of relationships between the constructs, system quality, information quality, use, user satisfaction, and the constructs individual and organizational performance. Later, Etezadi-Amoli and Farhoomand (1996) developed a questionnaire instrument and empirically tested the relationship between end-user satisfaction and user performance. These researchers also validated constructs relevant to our research question, these are, *System Documentation*, *Functionality* and *Ease of Use*.

Taken together, the TFT and User satisfaction and performance literature offers a rich set of validated constructs for collecting data relating to information systems properties and user performance. However, what is lacking is a model (or set of models) that explains the relationships between information systems characteristics and user performance. We use these prior studies (and their inventory of validated constructs) as a starting point for the investigation of our question: what are the properties of information systems that lead to the highest end-user performance?

3. Overview on decision tree induction

A decision tree (DT) is a tree structure representation of the relationship between input variables and the target variable such that each non-leaf node is associated with one of the input variables, each branch from a non-leaf node is associated with a subset of the values of the corresponding input variable, and each leaf node is associated with a value of the target (or dependent) variable. There are two main types of DTs: (1) classification trees, and (2) regression trees (e.g., Breiman, Friedman, Olshen, & Stone, 1984). For a classification tree, the target variable takes its values from a discrete domain (i.e., ordinal, categorical, binary), and for each leaf node the DT associates a probability for each class (i.e., value of the target/dependent variable). The class that is assigned to a given leaf node of the classification tree is the one that provides the largest class probability. In this paper, we will focus on the classification tree because our target is ordinal, and so henceforth the term decision tree refers to a classification tree.

Associated with each leaf of a DT is a set of IF–THEN rules or rule-set (e.g. "IF FOR1 = [5–7] THEN **PERF03**={[5–7] with probability 0.939}).

The generation of a DT involves partitioning the relevant dataset into at least two parts: the training dataset and the validation dataset. There are two major phases of the DT generation process: the *growth phase* and the *pruning phase* (e.g., Kim & Koehler, 1995). DTs are built in the *growth phase* using greedy algorithms in a top-down manner that involves a recursive target dependent partitioning (i.e., splitting) of the relevant training data, where the partitioning is done by a component of the DT induction algorithm known as the splitting method. It is known that the use of different splitting methods on the same dataset can lead to DTs with different rule-sets. Our interest is in identifying actionable rules that are associated with high end-user performance. There are many such rules, some of which might not be included in the rule-set of a particular DT, and so we generate multiple DTs that have different rule-sets by varying parameters such as the choice of splitting method (e.g. entropy, gini, chi-squared).

Compared to statistical techniques such as regression models, DTs have three primary advantages:

1. DTs provide an interpretable model in the form of interpretable and actionable rules.
2. DTs do not require that ordinal variables be treated as interval variables. In fact, DTs can directly handle ordinal, interval, binary and categorical variables without requiring the use of dummy variables. It should be noted that for our dataset, the majority of variables take their values from an ordinal Likert scale.
3. DTs can handle missing data without requiring imputation or exclusion of the relevant observation. It should be noted that for our dataset, several of the variables were missing values.

4. Research approach

Approaches to analyzing statistical data can be classified as either confirmatory or exploratory. Confirmatory approaches require the explicit specification of one or more hypotheses by the researcher followed by the testing of these hypotheses. Exploratory analysis involves the attempt, by an automated process, to conduct data analysis in order to identify useful patterns without predetermined hypotheses about the nature of these patterns.[1]

Most previous approaches to analyzing questionnaire data on user performance have been of a confirmatory nature, involving the use of traditional statistical analysis such as regression analysis, structural equation modeling and ANOVA (cf. Table 1). It should be noted that even in the cases where exploratory factor analysis is used to identify relevant factors, that this analysis is often part of a two-stage process in which the second stage involves confirmatory analysis such as regression. These confirmatory analysis approaches have at least two major limitations that can be overcome using the data mining approach proposed in this paper:

1. In some situations, it is burdensome and almost impossible for the researcher to specify and evaluate all relevant hypotheses. Thus, the researcher cannot discover additional important relationships that may exist in the data if they were not explicitly included in the set of hypotheses.
2. The use of these traditional statistical techniques involves the implicit assumption that non-binary variables with numeric values take their values from an interval (cardinal) scale. However, in many cases the relevant evaluations were done using

[1] This approach to scientific enquiry is not new; it starts with observations (data) followed by hypothesis generation, upon which testing carried out (Good, 1983; Tukey, 1980). The objective of this approach to enquiry is to propose alternative models which enable the advancement of science (Chalmers, 1999; Mulaik, 1984; Popper, 1959; Tukey, 1969).

Please cite this article in press as: Kositanurit, B., et al. Re-examining information systems user performance: Using data mining to identify properties of IS that lead to highest levels of user performance. *Expert Systems with Applications* (2011), doi:10.1016/j.eswa.2010.12.011

Table 2
Procedural approach to this research.

Step		Description
Identification of potential predictors		This involves using relevant extant literature to identify variables appear to be potential predictors of user performance. We utilized well known validated instruments from the previous related (i.e. Goodhue and Thompson's (1995) task-technology fit instrument, Etezadi-Amoli and Farhoomand's (1996) end-user computing satisfaction instrument (EUCS), and Doll and Torkzadeh's (1988) EUCS instrument)
Instrument Development		This involved integrating validated instruments from the previous relevant studies
Data collection		
Exploratory data analysis:	DT induction	Our interest is in identifying actionable rules that are associated with high end-user performance. There are many such rules, some of which might not be included in the rule-set of a particular DT. Therefore we generate several DTs by varying parameters such as the Splitting Criterion (i.e. Chi-Square, Entropy and Gini)
	Hypothesis generation & evaluation	Hypothesis are generated in two ways: • A single rule that is considered to be 'strong' because its posterior probability exceeds a specified threshold • A set of sibling rules for which the differences in the relevant posterior probabilities are considered to be statistically significant
	Abduction of model	This involves integrating the set of causal links that are associated with the abducted hypotheses analysis. This theoretical model describes the independent and dependent variables and the newly hypothesized relationships
Theoretical justification of model		This includes review of relevant extant literature to find theoretical support for the causal relationships generated in the exploratory data analysis step

the ordinal Likert scale. These statistical techniques thus treat the variables as if the difference between the ordinal values 1 and 2 is the same as the difference between the ordinal values 6 and 7.

In this paper we use a data mining-based approach to investigate our research question: what properties of IS lead to the highest level of end-user performance? This data mining approach uses a decision tree (DT) technique that does not require the specification of hypotheses by the researcher. As such, it is a form of exploratory data analysis that aims to expose relationships that exist within the data without the use of theoretical preconceptions. Our research approach consists of the steps described in Table 2.

5. Data collection and analysis

5.1. Data collection

In collecting data for our research, we integrated and utilized well known validated instruments from the previous studies. The three research instruments that were utilized in this study are Goodhue and Thompson's (1995) task-technology fit instrument, Etzadi-Amoli and Farhoomand's (1996) end-user computing satisfaction instrument (EUCS), and Doll and Torkzadeh's (1988) EUCS instrument (cf. Appendix A). Using these survey questionnaires, we collected data from many sources (different organizations) from two countries (US and Thailand). No incentives were given to the respondents. However, we promised anonymity, to protect the respondent's identity and to ensure that the answers provided are truthful. Consequently, we collected no data that could identify the respondent. Instead, we used a case identifier for each response. Questionnaire items were added to get demographic and support information (items 42–49; see Appendix A). These additional questions helped us to access the industry type, users' level of knowledge about their organizations and users' familiarity with the systems they use. Since our interest is core business information systems (e.g., accounting, order-processing, and customer information systems), questionnaires of the non-ERP users in which respondents identified computer applications they use such as Internet Explorer, Microsoft Office, and AUTOCAD were omitted from the study. On this account 36 non-ERP users' responses were omitted. The total number of usable questionnaires was 653 (349 from the US and 304 from Thailand).

Different media for data collection were used in the United States and Thailand. While an on-line internet survey was used in collecting data in the US, the more traditional method (paper and pencil) was used in Thailand. A total of twenty-five organizations participated in the study, fifteen from the U.S., and ten from Thailand. Of the fifteen US organizations participating in the study, 12 responded only to the ERP survey; two others responded to both ERP and non-ERP surveys; and one responded only to the non-ERP survey. For the overall response rate, 442 ERP and non-ERP users from 15 US organizations visited the on-line survey website. Of these, 349 respondents completed the survey representing 78.96% of the total users who visited the website. Among 300 ERP users who visited the website, 255 (85%) respondents completed the survey. Among the 142 non-ERP users who visited the website, 94 (66.19%) respondents completed the survey. The missing value rate of the on-line survey was extremely low for the items related to the core information. Only five questionnaire items (CONT2, CONT4, FUNC1, EOU2U, and ACCU1) had missing values (see Appendix A). Beside ACCU1, which had two missing values, the other items had only one missing value each. According to Tabachnick and Fidell (2001), if the missing values are 5% or less in a large dataset with no specific pattern, the problem is not critical and any procedure can be used to handle missing values. For the US dataset, the missing values for the items related to the core information were replaced by the mean of that item. As the demographic and support information is mainly used to have a better understanding of the data (i.e., performing the descriptive statistics), missing values are left as they are.

Four hundred and forty questionnaires were distributed to respondents in ten organizations in Thailand. Three hundred and forty questionnaires were returned, representing an overall response rate of 77.27%. Of these, 240 questionnaires were distributed to respondents in six ERP organizations with 209 returned, representing 87.08%. Of the four non-ERP organizations, 200 questionnaires were distributed with 130 returned, representing 65.5% (see Table 3). There were more missing values for the Thai responses than for the US. Questionnaires missing more than 20% of their values were omitted from the study. However, the missing value rate was very low among the 39 questionnaire items (i.e., the core information). Only the questionnaire item regarding the support from vendor and other sources had a missing value rate (i.e., 6.9%) of greater than 1%. This can be explained by the fact that for the non-ERP users, if using systems made in-house, the support from vendors or other sources is irrelevant. Therefore, it is not surprising that all the missing values of this item except one came from the non-ERP user responses. Missing data for each questionnaire item relating to the proposed theoretical model were replaced by the mean of that questionnaire item. For the same reason as the US data, missing values of the demographic and support information are left as they are.

Table 3
Responses classified by industry type.

Industry	Number of Responses					
	USA			Thailand		
	ERP	Non-ERP	Total	ERP	Non-ERP	Total
Financial Service Provider/Banking	13	16	29	0	45	45
Health Care	15	0	15	0	0	0
Higher Education and Research	101	67	168	0	0	0
Insurance	6	0	6	0	0	0
Manufacturing	9	0	9	45	0	45
Oil and Gas	12	0	12	53	0	53
Public sector	23	0	23	0	0	0
Retail	28	11	39	0	0	0
Telecommunication	1	0	1	46	0	46
Utilities	47	0	47	35	37	72
Engineering and Construction	0	0	0	0	18	18
Others	0	0	0	25	0	25
Total Responses	**255**	**94**	**349**	**204**	**100**	**304**

5.2. Exploratory data analysis

As stated previously, our major research question is: what are some properties of IS that tend to lead to the highest levels of individual end-user performance? Given that we have three performance measures (i.e., PERF01, PERF02, PERF03), we associate one prediction problem with each. As will be seen later, the utilization variable UTIL2 (i.e., preference to use the system) was identified as an important predictor in each of these problems. Utilization is not a property of the IS but is more of a reaction of the end-user to properties of the IS and, as such, would be considered to be a mediator variable. We attempted to identify system properties that are important predictors of UTIL2. We were also interested in knowing whether there were rules associated with high performance that did not include utilization. For each of our performance variables, we generated DTs in which utilization was not considered as a predictor variable. We thus ended up with seven prediction problems.

We used the SAS Enterprise Miner (EM) software to generate a pair of DTs for each prediction problem. Our interest in generating multiple DTs for each prediction problem was to explore multiple ways to look at the data in order see if the additional insights might be obtained. Following the traditional data mining approach for supervised learning, we partitioned the model dataset into training and validation (sometimes called Test). For the generation of each DT, we used a stratified sampling approach to partition our dataset of 653 cases such that, approximately 70% of the data (457 cases) was used for Training and approximately 30% (196 cases) was used for Validation. For each DT we used two variables, COUNTRY, and the relevant target variable (i.e., PERF01, PERF02, PERF03, or UTIL2) as stratification variables to ensure that characteristics of both training and validation data sets are close to each other. In order to ensure even further variation in our experimentation, we also varied the Splitting Criterion (i.e., Entropy, Gini) thus resulting in two DTs for each problem. For pre-pruning, we set the Minimum Number of Observations per Leaf at 20, and the Minimum Number of Observations Required for a Split Search at 40. Although the default cutoff posterior probability for the majority is typically 0.50, given our interest in stronger rules, we use a cutoff posterior probability of 0.80.

5.2.1. Rules associated with high end-user performance

Each of the three performance variables takes their values from the 7-point ordinal Likert scale. Given our interest in the system characteristics that would lead to the higher levels of individual end-user performance, we created a binary partitioning of this scale of the higher performance levels (i.e. 5, 6, 7) and the lower performance levels (i.e. 1, 2, 3, 4). In generating this set of DTs, we included all variables (except of course the performance measures) as possible predictors of performance.

5.2.2. Prediction IS Utilization: UTIL2 (preference to use the system)

Although the rule-sets of the DTs used to predict performance (i.e., PERF01, PERF02, PERF03) are different, whenever UTIL2 is allowed to be a predictor, it is selected in each rule of each rule-set.

Table 4
Examples of relationships and supporting 'strong' rules (*Threshold* = 0.80).

Relationship		Rule
Predictor	Target	
Information Quality	Performance	IF FOR1 = [5-7] THEN **PERF01** = {[5-7]: 90.8%} IF CONT1 = [6-7] & FOR1 = [3-4] THEN **PERF01** = {[5-7]: 80.5%} IF FOR1 = [5-7] THEN **PERF02** = {[5-7]: 87.2%} IF FOR1 = [5-7] THEN **PERF03** = { [5-7]: 93.9%} IF FOR1 = [6-7] & FOR2 = [4-7] THEN **PERF01** = {[5-7]: 93.8%} IF CONT1 = [6-7] & FOR1 = [1-4] & FOR2 = [4-7] THEN **PERF01** = {[5-7]: 80.5%} IF FOR2 = [5-7] THEN **PERF03** = { [5-7]: 93.5%}
Information Quality	Utilization	IF (FOR1 OR FOR2) = [5-7] & EOU2T = [4-7] & FOR2 = [2-4] THEN **UTIL2**={([5-7]: 80.8%} IF FOR1 = [7] & EQU2T = [6-7] THEN **UTIL2** = { [5-7]: 93.0%} IF FUNC4 = [6-7] & FOR2 = [5-7] THEN **UTIL2** = {([5-7]: 91.7%}
System Quality	Performance	IF CONT1 = [6-7] & FOR1 = [3-4] THEN **PERF01** = {[5-7]: 80.5%} IF CONT1 = [6-7] & FOR1 = [1-4] & FOR2 = [4-7] THEN **PERF01** = {[5-7]: 80.5%}
System Quality	Utilization	IF (FOR1 OR FOR2) = [5-7] & EOU2T = [4-7] & FOR2 = [2-4] THEN **UTIL2**={[5-7]: 80.8%} IF FUNC4 = [6-7] & FOR2 = [5-7] THEN **UTIL2** = {[5-7]: 91.7%}
Utilization	Performance	IF UTIL2 = [5-7] THEN **PERF01** = {[5-7]: 96.3%} IF UTIL2 = [5-7] THEN **PERF02** = {[5-7]: 94.8%} IF UTIL2 = [5-7] THEN **PERF03** = { [5-7]: 96.7%}

Table 5
Examples of Local hypotheses that can guide management decision making.

Pair	Pair of Sibling Rules	Hypothesis
1	IF ACCU1 = [1-4] & MODULE ∈ {2, 3, 8, 9} & FOR2 = [1-4] & UTIL2 = [2-4] THEN **PERF02** = { [5-7]: 30.0%} IF ACCU1 = [5-7] & MODULE ∈ {2, 3, 8, 9} & FOR2 = [1-4] & UTIL2 = [2-4] THEN **PERF02** = { [5-7]: 70.0%; }	*Given* MODULE ∈ {2, 3, 8, 9} & FOR2 = [1-4] & UTIL2 = [2-4] Then ACCU1 has a statistically significant impact on PERF02 ** *Accepted* **
2	IF DOC5 = [1-2] & UTIL2 = [1-2] THEN **PERF03** = { [5-7]: 27.3%}; N = 33. IF DOC5 = [3-7] & UTIL2 = [1-2] THEN **PERF03** = { [5-7]: 61.3% }; N = 31.	*Given* UTIL2 = [1-2] *Then* DOC5 has a statistically significant impact on PERF03 ** *Accepted* **
3	IF RELIA1 = [1-3] & FOR2 = [5] & UTIL2 = [2-4] THEN **PERF02** = { [5-7]: 35.0%}; N = 20. IF RELIA1 = [4-7] & FOR2 = [5] & UTIL2 = [2-4] THEN **PERF02** = { [5-7]: 57.1%}; N = 21.	*Given* FOR2 = [5] & UTIL2 = [3-4] *Then* RELIA1 has a statistically significant impact on PERF02 ** *Rejected* **
4	IF CONT1 = [1-5] & FOR1 = [1-4] & FOR2 = [4-7] THEN **PERF01** = {[5-7]: 42.9%}; N = 21. IF CONT1 = [6-7] & FOR1 = [1-4] & FOR2 = [4-7] THEN **PERF01** = {[5-7]: 80.5%}; N = 41.	*Given* FOR1 = [1-4] & FOR2 = [4-7] *Then* CONT1 has a statistically significant impact on PERF01 ** *Accepted* **

Since utilization is not a characteristic of the IS but the user's a reaction to the IS, and such reaction is based both on the characteristics of the IS and the characteristics of the user. Thus it is important to identify rules that are associated with various levels of utilization.

5.2.3. Hypothesis generation & analysis

As noted previously an hypothesis can be generated in two ways: (1) based on 'strong' rules; and (2) based on a set of sibling rules. Table 4 identifies predictor and target constructs associated with our strong rules (i.e., training posterior probability was at least 0.80). As stated earlier, it is burdensome, if not impossible, for the researcher to generate all relevant hypotheses. In the DT based phase, the automatically generated rules could be used to formulate hypotheses that could be subjected to traditional hypotheses testing. One type of hypothesis that is generated by our DT-based approach has the form: If *stated condition* applies, then the *target event* (e.g., PERF01 is in the [5–7] interval) occurs with *probability* p_0 (e.g., 95%). An example of this hypothesis is "IF FOR1 = [5–7] THEN PERF01 = [5–7] occurs with probability 0.908".

However, there is also another type of hypotheses that can be obtained from the DT rules. Consider the first pair of rules in Table 5. The condition components of both rules are the same except for the conditions that are based on ACCU1 (i.e., ACCU1 = [1–4], ACCU1 = [5–7]). The posterior probabilities appear to be very different (i.e., 30.0%, 70.0%), with the higher probability associated with the higher value of ACCU1. This could suggest the hypothesis: "Given MODULE ∈{2,3,8,9} & FOR2 = [1–4] & UTIL2 = [2–4] THEN ACCU1 has a positive impact on PERF02". A hypothesis of this type can be considered to be a local hypothesis with the localizing condition event, "Given MODULE ∈{2,3,8,9} & FOR2 = [1–4] & UTIL2 = [2–4]". The corresponding global hypothesis would be "ACCU1 has a positive impact on Performance", with the main difference between the two being that the global hypothesis has no localizing condition event. Local hypotheses may hold for a particular region of the problem space, but not hold over other regions,. Thus it is possible that while a global hypothesis might not be supported by empirical data, the local hypothesis might be supported.

Local hypotheses that are supported by data can be of interest to managers as they can provide guidance for action. It is, however, likely that some local hypotheses may not be conceptualized by the researcher and as such may not be subjected to confirmatory data analysis. We constructed a difference of proportions test on the hypothesis, "Given MODULE ∈{2,3,8,9} & FOR2 = [1–4] & UTIL2 = [2–4] THEN $p_{[5-7]} > p_{[1-4]}$ (i.e., ACCU1 has an impact on PERF02)" was accepted at the $\alpha = 0.05$ level of significance, where $p_{[5-7]}$, $p_{[1-4]}$ are the probabilities of high performance given ACCU1 = [5–7] and [1–4], respectively. We did similar tests on the local hypotheses derived from the other pairs of rules in Table 5, but the result was that while the second and fourth local hypotheses were accepted, the third was rejected.

5.2.4. Abduction of the model

We obtained our theoretical model by integrating the set of rules that are associated with our DTs. Given our variable descriptions, one can associate variables in our rules with the system quality (e.g., CONT1, EQU2T, RELIA1, DOC5), information quality (e.g., ACCU1, FOR1, FOR2), information quality, utilization (e.g., UTIL2), and performance (i.e., PERF01, PERF02, PERF03) constructs. Fig. 2 provides a graphic description of the relationships between the constructs that have been identified from our set of DTs using the 'strong' rules displayed in Table 4 and the local hypotheses displayed in Table 5. The relationships in this model have been hypothesized by other researchers (e.g., DeLone & McLean, 1992), and several studies have attempted empirical verification of one or more of these relationships. But to date no single study has attempted to verify all of these relationships (see DeLone & McLean, 2002).

Each of the causal links in our abducted model were postulated by DeLone and McLean (1992) and subsets of them have been empirically tested by other researchers in various studies. However, to date no single study has tested nor demonstrated the exis-

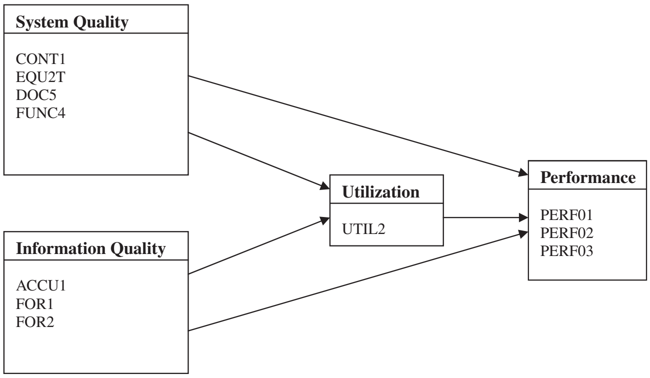

Fig. 2. Links between Characteristics of IS and user performance.

tence all of these relationships for ERP systems or for other types of information systems. Those causal links that have been empirical tested and supported are: (1) the causal link between independent variable Information Quality and the dependent variable Utilization (Igbaria & Tan, 1997); (2) the causal link System Quality and Utilization (Igbaria, Zinatelli, Cragg, & Cavaye, 1997; Taylor & Todd, 1995); (3) the causal link between Utilization and Performance (Goodhue & Thompson, 1995; Guimaraes & Igbaria, 1997; Igbaria & Tan, 1997; Teng & Calhoun, 1996; Torkzadeh & Doll, 1991; Yuthas & Young, 1998); (4) the causal link between Information Quality and Performance (Etezadi-Amoli & Farhoomand, 1996; Seddon & Kiew, 1994; Teo & Wong, 1998); and (5) System Quality and Performance (Etezadi-Amoli & Farhoomand, 1996; Goodhue & Thompson, 1995; Seddon & Kiew, 1994; Teo & Wong, 1998). While these other studies only investigated subsets of the causal relationships of our model, they provide evidence that corroborate our findings and the efficacy of our research approach.

6. Contributions to theory and practice

This research makes several contributions to the theory and practice of information systems. This study offers the following: (1) a theoretical contribution to the body of knowledge on IS properties and user performance, in the form of a new model and hypotheses for testing; (2) a contribution to the practice of information systems management, specifically, an approach to identifying IS properties that managers can manipulate to improve user performance; (3) a contribution to information systems research methodology, specifically a induction tree approach to exploratory data analysis and model generation; (4) an illustration of how new generation information technologies can be used to assist in making IS research rigorous and relevant to managerial problems; and (5) an application of data mining to solve managerial problems. We will discuss the first three below.

6.1. Contribution to body of knowledge on IS properties and user performance

We obtained a theoretical model that is consistent with the IS Success model that was postulated but not tested by DeLone and McLean (1992). While various subsets of the causal links of that model were tested by other researchers, this is the first study to test all of the links for information systems in general, and ERP systems in particular. Further our research approach did not require the assumption that it was appropriate to use the ordinal Likert scale as if it were an interval scale, nor for us to conjecture hypotheses. While our results are consistent with the DeLone and McLean (2002) conceptual model and empirical findings of some of the relationships, in following the abductive approach we did not impose the DeLone & McLean model, conjectured any a priori hypotheses, or imposed methodological assumptions of other researchers. In this regard, the findings of other empirical research using different methods and the corroboration of the DeLone and McLean (2002) conceptual model provides mutual support for the legitimacy of both our results and research method.

6.2. Contribution to the practice of information systems management

Our DT-based approach can lead to the identification of actionable rules that managers could use to guide their decision actions, as they focus on areas for configuring the relevant IS in order to achieve high end-user performance. Given the rules that have been

Table 6
Comparison of the ideal model of scientific and our hybrid approach.

Ideal model of scientific inquiry		Hybrid process for empirically based theory development
Phase	Description	
Empirical observation	Observer (gather data about) some phenomena of interest	1a: Use existing theory to identify variables that are likely to be relevant to the phenomena of interest 1b: Based on *Substep 1a* above, gather data related to the phenomena of interest
Hypothesis generation	Using these observations (data) invent one or more hypotheses that might explain the phenomena	2a: Use data mining approach to do automatic generation & preliminary testing of hypotheses 2b: Based on the results of *Substep 2a*, generate a preliminary model that appears to explain the phenomena of interest 2c: The researcher examines & of necessary revised the preliminary model that was generated in *Substep 2b*. This revision may be based on the researcher's knowledge of existing theory
Design of experiments	Using the hypotheses, design an experiment to test the logical consequences of the hypotheses	3: Design an experiment to test the logical consequences of the hypotheses Conventional data analysis approaches may be included in the experimental design
Empirical testing	Having designed the experiment, collect observations about the phenomena and examine them to see if the predictions prove to be true or false	4a: Collect observations about the phenomena 4b: Conduct measurement validity 4c: Determine if hypotheses of the current model are supported based on data analysis of the given dataset This phase should be repeated since no amount of testing can ever guarantee the truth value of a theory about phenomena but only gradually increasing confirmation of the theory

identified, the manager can identify courses of action (i.e., condition components of rules that include decision variables) that could lead to high end-user performance (e.g., IF UTIL2 = [5–7] THEN **PERF01** = {[5–7]: 96.3%}; IF FOR1 = [5–7] THEN PERF01 = {[5–7]: 90.8%} & PERF02 = {[5–7]: 87.2%} & **PERF03** = {[5–7]: 93.9%}) and/or high system utilization (e.g., IF FUNC4 = [6–7] & FOR2 = [5–7] THEN **UTIL2**={[5–7]: 91.7%}). Given the set of rules and different costs associated with different system configuration decisions (e.g., FOR1 = [5–7]; FUNC4 = [6–7] & FOR2 = [5–7]), the manager could conduct a cost/benefit analysis to determine the most appropriate system configuration decision.

It should be noted that it may be unnecessary to identify the complete set of DTs if the IS manager is mainly interested in identifying a set of strong rules that could be used to provide guidance in configuring the IS in order to achieve high end user performance. It should also be noted that the fact that a given variable was not included in the rule-set of any of the DTs does not mean that it could not be a useful predictor. Rather, this suggests that good predictions can be made even without using the given variable.

6.3. Contribution to IS research methodology

We proposed the use of a decision tree induction as an exploratory data analysis technique for generating theoretical models (illustrated in Table 6). This approach does not require the researcher to speculate a priori about the nature of the relationships between potential predictor and target variables. This approach uses existing theory to identify variables that appear to be potential direct or indirect predictors of end-user performance. As such, we were able to generate and provide preliminary confirmation of a predictive model. Our approach is consistent with the exploratory model of scientific inquiry that starts with observation (i.e., gathering data about phenomena of interest) followed by hypothesis generation, experimental design and testing of the implications of the hypothesis (Good, 1983; Mulaik, 1984; Peirce, 1902; in Collected Papers 1931–1935; Popper, 1959; Tukey, 1969, 1980).

Our approach is also consistent with the grounded theory method of Glaser and Strauss (1967) that is used by many IS researchers. The grounded theory method employs a strategy of collecting, coding and analyzing data that allows descriptive categories and relationships to emerge from the data without the use of theoretical preconceptions or prior theory (Corbin & Strauss, 1990). Finally, our data mining approach could be used with a confirmatory approach in the following hybrid process for empirical-based theory development.

7. Conclusion

We have presented a DT-based approach to generating and doing preliminary verification of a model that describes the relationship between IS properties and end-user performance. This approach can also be used in conjunction with confirmatory analysis (e.g., regression) in a multi-stage data analysis process. It is general and can be implemented by any academic or industry researcher who is interested in generating hypotheses from data for theoretical or applied research. Many DM software packages (e.g., C5.0, SAS Enterprise Miner, IBM Intelligent Miner) provide facilities that make the generation of DTs a relatively easy task. Given this fact, the major decision to be made by the researcher is the determination of the target events (e.g., PERF01 is in the [5–7] interval) that are of interest. Once this decision has been made, many DM software applications provide convenient facilities for discretizing the target variable (e.g., PERF01) into two or more distinct events (e.g., PERF01 is in the [5–7] interval, PERF01 is in the [1–4] interval). Alternately, the discretization could be done outside the DM tool in other widely available software such as EXCEL. Once this has been done, the research can conveniently generate multiple DTs by varying the choice of splitting method (e.g., Gini, Entropy) and other parameters.

It should be noted that our data mining-based approach could have used constructs instead of individual items. A construct's score is based on a weighted linear combination of the scores of the relevant individual items, where the weights are the relevant factor loadings. Some decision tree construction algorithms allow splits to be based on weighted linear combinations of the individual input variables, and so could accommodate the use of constructs. We chose to use individual items rather than constructs primarily for the following reasons: (1) The individual items take their values from an ordinal Likert scale. Doing factor analysis involves the implicit (but not automatically valid) assumption that the ordinal Likert scale is an interval scale. Our data mining based approach does not require this assumption. (2) A construct's score is not easily interpretable (because it is based on a weighted linear combination of the scores of the relevant individual items). Thus, rules that are based on constructs would not be easily interpretable, particularly for decision makers. One goal of this research project is to identify characteristics of information systems that could be used by managers to configure the system in a manner that would lead to high end-user performance. Therefore, rules that are based on constructs rather than individual variables would likely be less useful to such managers.

Appendix A. Definition of variables: (variable-questionnaire item)

(1) CASEID – is a unique number for each case/record.
(2) COUNTRY – (1) USA (2) Thailand.

Other variables are 7 points Likert scale: 1 Strongly Disagree rightarrow 7 Strongly Agree.

A.1. TTF instrument

(3) CURR – The data provide by the system is up-to-date enough for my purposes.
(4) RDATA – The system available to me is missing critical data that are very useful to me in my job.
(5) RDETAIL – The system maintains data at an appropriate level of detail for my group's tasks.
(6) MEAN – The exact definition of data fields relating to my tasks is easy to find out.
(7) AUTH1 – Data that would be useful to me are unavailable because I do not have the right authorization.
(8) AUTH2 – Getting authorization to access data that would be useful in my job is time consuming and difficult.
(9) RELIA1 – The system I use is subjected to unexpected or inconvenient down times which makes it harder to do my work.
(10) RELIA2 – The system I use is subject to frequent system problems and crashes.
(11) EOU1T – It is easy to learn how to use the system.
(12) EOU2T – The system I use is convenient and easy to use.
(13) TRAIN – There is not enough training for me or my staff on how to find, understand, access or use the system.

A.2. User satisfaction instrument of Doll and Torkzadeh

(14) CONT1 – The system provides the precise information I need.
(15) CONT2 – The information contents provided by the system meet my needs.

(16) CONT3 – The system provides reports that seem to be exactly what I need.
(17) CONT4 – The system provides sufficient information to my needs.
(18) ACCU1 – The system is accurate.
(19) ACCU2 – I am satisfied with the accuracy of the system.
(20) FOR1 – The output is presented in a useful format.
(21) FOR2 – The information is clear.
(22) TIME – the system provides me the information I need in a timely manner.

A.3. User satisfaction instrument of Etezadi-Amoli and Farhoomand

(23) DOC1 – The content of the user manual is useful.
(24) DOC2 – The index of the user manual is useful.
(25) DOC3 – The user manual is current (i.e. up-to-date).
(26) DOC4 – The user manual is complete.
(27) DOC5 – The user manual is easy to understand and follow.
(28) EOU1U – The description of the functions/ commands displayed on screen is clear to me.
(29) EOU2U – The function/command names of the are easy to remember.
(30) FUNC1 – The system provides complete features I need.
(31) FUNC2 – I am satisfied with the speed of interacting with the system.
(32) FUNC3 – It is easy to detect possible errors in the systems.
(33) FUNC4 – It is easy to correct errors that happen in the systems.
(34) FUNC5 – It is easy to change the output format.
(35) SUPP1 – I am satisfied with the amount of support provided by vendor or other sources.
(36) SUPP2 – I am satisfied with the availability of information systems staff for consultation.

A.4. Utilization

(37) UTIL1 – Currently, I cannot accomplish my tasks without the system.
(38) UTIL2 – If I have a choice to use any systems to perform my tasks, I still prefer to use the current system I use.

A.5. Performance

(39) PERF01 – The system helps me to be more effective.
(40) PERF02 – The system has a positive impact on my productivity in my job.
(41) PERF03 – The system is an important aid to me in the performance of my job.

A.6. Demographic and support information

(42) INDUS – Industry type.
(43) EDUC – Education level.
(44) LWCOMP – Years work in the company.
(45) LWJOB – Years work in the current job.
(46) LWSYS – Years work with the system in consideration.
(47) MGRLEVEL – Management level.
(48) SYSTEM – Similar to ID but more detail in that non-are decomposed into software package, in-house system, and customize package.
(49) MODULE – The system module that participants use the most.

References

Al-Gahtani, S. S., & King, M. (1999). Attitudes, satisfaction and usage: factors contributing to each in the acceptance of information technology. *Behaviour & Information Technology, 18*(4), 277–297.

Bailey, J. E., & Pearson, S. W. (1983). Development of a tool for measuring and analyzing computer user satisfaction. *Management Science, 29*(5), 530–545.

Blili, S., Raymond, L., & Rivard, S. (1998). Impact of task uncertainty, end-user involvement, and competence on the success of end-user computing. *Information and Management, 33*, 137–153.

Breiman, L., Friedman, J., Olshen, R., & Stone, C. (1984). *Classification and regression trees*. California: Wadsworth & Brooks.

Chalmers, A. F. (1999). *What is this thing called Science?* Hackett Publishing.

Corbin, J., & Strauss, A. (1990). Grounded theory method: Procedures, cannons, and evaluative criteria. *Qualitative Sociology, 13*, 3–21.

DeLone, W. H., & McLean, E. R. (2002). Information systems success revisited. In *Proceedings of the 35th Hawaii international conference on system sciences*.

DeLone, W. H., & McLean, E. R. (1992). Information systems success: The quest for the dependent variable. *Information Systems Research, 3*(1), 60–95.

Dishaw, M. T., & Strong, D. M. (1998). Assessing software maintenance tool utilization using task-technology fit and fitness-for use models. *Journal of Software Maintenance Research and Practice, 10*(3), 151–179.

Dishaw, M. T., & Strong, D. M. (1999). Extending the technology acceptance model with task-technology fit constructs. *Information and Management, 36*(1), 9–21.

Doll, W. J., & Torkzadeh, G. (1988). The measurement of end-user computing satisfaction. *MIS Quarterly*(June), 259–274.

Doll, W. J., Xia, W., & Torkzadeh, G. (1994). A confirmatory factor analysis of the end-user computing satisfaction instrument. *MIS Quarterly*, 453–461.

Downing, C. E. (1999). System usage behavior as a proxy for user satisfaction: An empirical investigation. *Information and Management, 35*, 203–316.

Etezadi-Amoli, J., & Farhoomand, A. F. (1996). A structural model of end user computing satisfaction and user performance. *Information and Management, 30*, 65–73.

Ferratt, T. W., & Vlahos, G. E. (1998). An investigation of task-technology fit for managers in Greece and the US. *European Journal of Information Systems, 7*(2), 123–136.

Glaser, B., & Strauss, A. (1967). *The discovery of grounded theory: Strategies for qualitative research*. Chicago: Aldine.

Good, I. J. (1983). The philosophy of exploratory data analysis. *Philosophy of Science, 50*, 238–295.

Goodhue, D. L. (1995). Understanding user evaluations of information systems. *Management Science, 41*(12), 1827–1844.

Goodhue, D. L. (1998). Development and measurement validity of a task-technology fit instrument for user evaluations of information systems. *Decision Sciences, 29*(1), 105–138.

Goodhue, D. L., Klein, B., & March, S. T. (2000). User evaluations of IS as surrogates for object performance. *Information and Management, 38*, 87–101.

Goodhue, D. L., & Thompson, R. L. (1995). Task-technology fit and individual performance. *MIS Quarterly*, 213–236.

Guimaraes, T., & Igbaria, M. (1997). Client/server system success: Exploring the human side. *Decision Sciences, 28*(4), 851–875.

Hendrickson, A. R., Glorfeld, K., & Cronan, T. P. (1994). On the repeated test-retest reliability of the end-user computing satisfaction instrument: a comment. *Decision Sciences, 25*(4), 655–667.

Igbaria, M., & Tan, M. (1997). The consequence of information technology acceptance on subsequent individual performance. *Information and Management, 32*, 113–121.

Igbaria, M., Zinatelli, N., Cragg, P., & Cavaye, A. (1997). Personal computing acceptance factors in small firms: A structural equation model. *MIS Quarterly, 21*(3), 279–305.

Ives, B., Olson, M. H., & Baroudi, J. J. (1983). The measurement of user information satisfaction. *Communications of the ACM, 26*(10), 785–793.

Jarvenpaa, S. L. (1989). The effect of task demands and graphical format on information processing strategies. *Management Science, 35*(3), 285–303.

Kim, H., & Koehler, G. (1995). Theory and practice of decision tree induction. *Omega, 23*(6), 637–652.

Lai, V. S. (1999). A contingency examination of CASE-task fit on software developer's performance. *European Journal of Information Systems, 8*, 27–39.

Mathieson, K., & Keil, M. (1998). Beyond the interface: Ease of use and task-technology fit. *Information and Management, 34*, 221–230.

Mulaik, S. A. (1984). Empiricism and exploratory statistics. *Philosophy of Science, 52*, 410–430.

Peirce, C. S. (1931–1935). *Collected papers of Charles Sanders Peirce*, In C. Hartshorne, P. Weiss, & A. Burks (Eds.), Vol. 1–8. Harvard University Press.

Popper, K. R. (1959). The logic of scientific discovery. Harper Torch Books.

Samoilenko, 1., & Osei-Bryson, K.-M. (2008). Increasing the discriminatory power of DEA in the presence of the sample heterogeneity with cluster analysis and decision trees. *Expert Systems with Applications, 34*(2), 1568–1581.

Seddon, P., & Kiew, M.-Y. (1994). A partial test and development of the DeLone and McLean model of IS success. In *Proceedings of the international conference on information systems, Vancouver, Canada (ICIS 94)* (pp. 99–110).

Tabachnick, B. G., & Fidell, L. S. (2001). *Using multivariate statistics* (4th ed.). Boston: Allyn and bacon.

Taylor, S., & Todd, P. (1995). Assessing IT usage: The role of prior experience. *MIS Quarterly, 19*(4), 561–570.

Teng, J., & Calhoun, K. (1996). Organizational computing as a facilitator of operational and managerial decision making: An exploratory study of manager's perceptions. *Decision Sciences, 27*(4), 673–710.

Teo, T. S. H., & Wong, P. K. (1998). An empirical study of the performance impact of computerization in the retail industry. *Omega: The International Journal of Management Science, 26*(5), 611–621.

Thompson, R. L., Higgins, C. A., & Howell, J. M. (1991). Personal computing: Toward a conceptual model of utilization. *MIS Quarterly, 15*(1), 125–143.

Torkzadeh, G., & Doll, W. J. (1991). Test-retest reliability of the end-user computing satisfaction instrument. *Decision Sciences, 22*, 26–37.

Tukey, J. (1969). Analyzing data: Sanctification or detective work? *American Psychologist, 24*, 83–91.

Tukey, J. (1980). We need both exploratory and confirmatory. *The American Statistician, 34*(1), 23–25.

Ward, S. (2002). Companies squander billions on tech. USA Today, May 20.

Wilson, E. V. (1994). An investigation of the relative presentation efficiency of computer-displayed graphs. *Information and Management, 26*, 105–115.

Yuthas, K., & Young, S. (1998). Material matters: Assessing the effectiveness of materials management IS. *Information & Management, 33*, 115–124.