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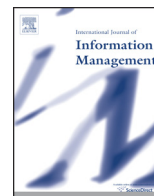
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Citizens as consumers: Profiling e-government services' users in Egypt via data mining techniques



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ABSTRACT

This study uses data mining techniques to examine the effect of various demographic, cognitive and psychographic factors on Egyptian citizens' use of e-government services. Data mining uses a broad family of computationally intensive methods that include decision trees, neural networks, rule induction, machine learning and graphic visualization. Three artificial neural network models (multi-layer perceptron neural network [MLP], probabilistic neural network [PNN] and self-organizing maps neural network [SOM]) and three machine learning techniques (classification and regression trees [CART], multivariate adaptive regression splines [MARS], and support vector machines [SVM]) are compared to a standard statistical method (linear discriminant analysis [LDA]). The variable sets considered are sex, age, educational level, e-government services perceived usefulness, ease of use, compatibility, subjective norms, trust, civic mindedness, and attitudes. The study shows how it is possible to identify various dimensions of e-government services usage behavior by uncovering complex patterns in the dataset, and also shows the classification abilities of data mining techniques.

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1. Introduction

One of the most intractable problems for anyone dealing with government is the sheer complexity of its organizational structure. For example, it has been estimated that the average government has between 50 and 70 different departments, agencies and regulatory bodies (Silcock, 2001). A number of government's different agencies may be involved in simple matters such as registering the birth of a child. Fortunately, advances in technology, particularly the advent of the Internet, has made it possible for local governments to deliver their services to citizens via a single portal known as e-government. e-Government has been regarded as a 'paradigm shift' or a catalyst for government administrative reform resulting in improved quality of service, cost savings, wider political participation and more effective policies and programs (Helbig, Gil-Grcia, & Ferro, 2009). e-Government has also been proposed as a solution for increasing citizen communication with government agencies and, ultimately, political trust (Chadwick & May, 2003).

In several countries there has been a growing pressure for governments to move online. In the Arab world, Dubai pioneered e-voting in elections for half the members of the United Arab Emirates' consultative assembly (The Economist, 2008). In Bahrain the

e-government authority of Bahrain (E-GA) has recently launched the Enterprise Architecture Project (EAP) initiative, which is considered to be the first of its kind in the Arab world. The initiative aims at streamlining government procedures by unifying the standards and procedures among all government entities in all matters related to information communication technology (Bahrain Tribune, 2009). Finally, in Egypt e-government currently provides 85 services to citizens including government forms, public policy information and tax filing (Hamed, 2008). Two main reasons are behind governments' decision to move online. First, a more enlightened view has begun in the ranks of government to treat the citizen like a consumer where transaction satisfaction is important. Second, pressures for governments to do more with less will force governments to provide services in a more efficient way. In fact, e-government offers substantial performance gains over the traditional model of government. For example, based on the analysis of 49 empirical studies, Danziger and Andersen (2002) concluded that there were positive e-government impacts on data access and efficiency and productivity of government performance in both internal operations and external service functions. In fact it has been argued that a significant portion of the benefits created by e-government services are obtained by the government itself in terms of efficiency gains (Tung & Rieck, 2005). For example, the U.S. government generates around US\$ 3 billion on its Web site (Clark, 2003).

While several terms are synonymous with e-government such as digital government, e-governance and e-democracy, authors

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generally use a broad conceptualization for e-government to encompass all government roles and activities shaped by information and communication technologies (Brown, 2005). There are three relationships in the e-government interactive processes: government to government (G2G), government to business (G2B) and government to citizen (G2C). For the purpose of this study, only G2C relationship will be discussed. e-Government progress has also been divided into three phases: the first phase is to *publish*, in which e-government has only limited digital presence through limited published information. The second phase is to *interact*, where citizens can interact with government via electronic media such as emails and chat rooms. The third stage is to *transact*, where citizens participate in government services via the government's digital portal (Lau, Aboulhoson, Lin, & Atkin, 2008).

2. Research objectives

Profiling e-government services users is very important because the first step in planning the target marketing strategy is to segment the market and develop profiles of the resulting market segments. In fact, the usefulness of market segmentation hinges upon accurate profiling. Relatively low accuracy in forecasting segment membership will result in ineffective marketing programs and potential negative impact due to targeting unintended segment members. Despite the importance of profiling e-government services users, researchers have largely ignored specific circumstances under which citizens adopt e-government services. From a public policy standpoint, it is important to know what motivates individuals to use e-government services if a pro-digital government change policy is to be successfully implemented. Using intelligent modeling techniques, this research aims at profiling e-government services users versus non-users. More specifically, the aim of this study is two-fold: (1) to investigate the influence of various demographic, cognitive and attitudinal factors on e-government services usage behavior in Egypt; and (2) to compare the classification performance of data mining techniques against the more traditional techniques such as LDA within the context of e-government services usage behavior.

3. Literature review and hypotheses development

Drawing on research from North America, Europe and Australasia there is a wealth of evidence that suggest that a wide variety of factors influence e-government services usage behavior. These can be characterized as perceived usefulness, perceived ease of use, compatibility, subjective norms, trust, civic mindedness and attitudes.

3.1. Perceived usefulness

Perceived usefulness has consistently been a strong determination of the intention to use a technology. In the technology acceptance model (TAM), Davis (1989) used the term "perceived usefulness" to refer to the prospective user's subjective probability that using a specific application system, in this case e-government services, will increase his or her performance within an organization. Perceived benefits from e-government services occur when the new system is perceived as more beneficial than the paper-based system it supersedes. In their empirical exploration of e-government service adoption, Bretschneider et al. (2003) found that perceived benefit is the major factor in using e-government services. The perceived benefit factor is closely related to perceived usefulness in the TAM theoretical model. Raman and Leckenby (1998) used the concept of utilitarianism to explain online behavior. They found a positive link between utilitarianism and duration

of visit of web ads. This construct, too, seems to be closely related to perceived usefulness identified in TAM. Rogers (1995), in his diffusion of innovation paradigm, also posits that the perceived benefit or relative advantage of innovation positively influences adoption rate. In a meta-analysis in the innovation research literature, Tornatzky and Klein (1982) concluded that relative advantage was positively related to adoption. In a similar vein, King and He (2006), in a meta-analysis of the TAM, found a strong positive link between perceived usefulness and behavioral intention ($\beta = 0.505$). It follows that

H1. Perceived usefulness of e-government services positively influences users' intention to use these services.

3.2. Perceived ease of use

Perceived ease of use refers to the degree to which a prospective user expects the target system to be free of effort (Davis, 1989). TAM further suggests that perceived ease of use is instrumental in explaining the variance in perceived usefulness. This dimension is similar to the complexity or the perceived ease of adoption in the diffusion of innovation paradigm. Perceived ease of adoption can affect adoption behavior since an innovation that is easy to use can considerably reduce the time and effort required by the user and, thus, increase the likelihood of adopting the technology (Wang & Qualls, 2007). Most studies on technology acceptance showed that perceived ease of use directly influenced attitude toward use (e.g., Ahn, Ryu, & Han, 2004; Bruner & Kumar, 2005; Chen, Gillensen, & Sherrell, 2002). King and He (2006), in a meta-analysis of the TAM, found a strong positive link between perceived ease of use and behavioral intention ($\beta = 0.186$). In a study of technology adoption in government agencies, Hamner and Qazi (2009) found a statistically significant association between perceived ease of use and attitude, indicating the important role of the ease of use in the formation of users' attitudes. It follows that

H2. Perceived ease of use of e-government services positively influences users' intention to use these services.

3.3. Compatibility

Compatibility was originally one of the factors determining the diffusion of innovation rate in the diffusion of innovation paradigm. It refers to the degree to which the use of the new technology is perceived to be consistent with the potential users' existing values, previous experience and needs (Nan, Xun-hua, & Guo-qing, 2007). Prior studies indicated that compatibility had strong direct impact on behavioral intention in areas such as using group support systems (Van Slyke, Lou, & Day, 2002), adopting new methodology for software development (Hardgeave, Davis, & Riemenschneider, 2003) and using university smart card systems (Lee & Cheng, 2003). In a recent study of e-payment adoption in China, He, Duan, Fu, and Li (2006) found that only compatibility has a significant effect on respondents' intention to adopt the system. Compatibility may also influence behavioral intention through performance expectancy and effort expectancy (Schaper & Pervan, 2007). For example, Chau and Hu (2002) showed that compatibility of telemedicine technology exerted a significant effect on perceived usefulness. It follows that

H3. Perceived compatibility of e-government services positively influences users' intention to use these services.

3.4. Subjective norms

Subjective norm (also called social norm) refers to users' perception of whether other important people perceive they should

engage in the behavior (Schepers & Wetzels, 2007). While TAM does not include subjective norm, the theory of reasoned action (TRA) identifies attitudes and subjective norms as the sole determinants of behavioral intention (Fishbein & Ajzen, 1975). The theory of planned behavior (TPB), an update of TRA, also included subjective norms. Venkatesh and Davis (2000) acknowledged this and updated the TAM (TAM2) by integrating subjective norms. Several studies found a positive relationship between subjective norms and behavioral intention (e.g., Lu, Zhou, & Wang, 2009; Yi, Jackson, Park, & Probst, 2006). In a study examining culture-specific enablers and impediments to the adoption and use of the Internet in the Arab world, Loch, Straub, and Kamel (2003) found that both social norms and the degree of technological culturation can impact the individual and organizational acceptance and use of the Internet. It follows that

H4. Subjective norms positively influence users' intention to use e-government services.

3.5. Trust

Perceived risk features prominently in the e-service research. For example, Chadwick (2001) asserts that e-commerce risk can be conceptualized as a function of data protection and system reliability. Perceived risk was defined as "consumer's belief about the potential uncertain negative outcomes from the online transaction" (Kim, Ferrin, & Rao, 2008, p. 546). In the case of Web shopping, Bhatnagar, Misra, and Rao (2000) identified three types of risk: financial risk, product risk, and information risk (security and privacy). O'Cass and French (2003) demonstrated that the risk in using the technology was a significant factor in determining the intention to use. In the e-service literature trust was found to be one of the most effective tools for reducing uncertainty and risks (e.g., Pavlou, 2003) and generating a sense of safety (e.g., Suh & Han, 2002). Prior empirical research incorporated trust into TAM in several ways. For example Shih (2003) extended TAM by adding the perceived Web security construct and found that high perceived Web security directly increases consumer attitudes toward e-shopping. Results also support trust as an antecedent of usefulness (Pavlou, 2003), ease of use (Pavlou, 2003), attitude (Chen & Tan, 2004), and behavioral intention (Gefen & Straub, 2003). Few studies explored the role of trust in e-government adoption. For example, Warkentin, Gefen, Pavlou, and Rose (2002) found that trust in the organization using the technology and trust in government as responsible for the introduction of electronic services are important determinants of e-government services adoption. It follows that

H5. Trust in e-government systems positively influence users' intention to use e-government services.

3.6. Civic mindedness

The concept of civic mindedness is central to any analysis of e-government services adoption (Dermody & Hanmer-Lloyd, 2004). Civic mindedness encompasses three aspects: social contact, prior interest in government, and media use for public affairs (Dimitrova & Chen, 2006). As cyberdemocracy represents an extension of democracy into the realm of information technology and electronic communication, it is expected that the use of electronic means by citizens to interact with government to be an extension of their civic and political involvement via traditional channels (Katchanovski & La Porte, 2005). Prior research on e-government suggests that e-government users are similar to those who use government traditional services and are more engaged in civic affairs (Dimitrova & Chen, 2006). It follows that

H6. Civic mindedness positively influences users' intention to use e-government services.

3.7. Attitudes

The social psychology literature on behavioral research has established attitudes as important predictors of behavior, behavioral intention, and explanatory factors of variants in individual behavior (Kotchen & Reiling, 2000). Attitude is defined as an individual's overall evaluation of performing a behavior (Lu et al., 2009). Prior e-services research has established a positive link between attitudes and behavioral intention (e.g., Agarwal, Sambamurthy, & Stair, 2000; Aggelidis & Chatzoglou, 2009). It follows that

H7. Attitude toward e-government services positively influences users' intention to use e-government services.

4. Method

4.1. Sample

The empirical study involved the administration of self-completion questionnaire to citizens in three Egyptian cities. Data were collected using the drop-off, pick-up method (Craig & Douglas, 1999). This data collection method is widely used in studies conducted in the Arab world because of research difficulties such as obtaining random samples and reaching respondents using mail questionnaires (Robertson, Al-Khatib, & Al-Habib, 2002). A total of 1500 questionnaires were distributed. Confidentiality of responses was emphasized in the cover letter with the title "Confidential survey" and in the text. To reduce social desirability artifacts, the cover letter indicated that the survey seeks "attitudes toward e-government services" and nothing else. In total 812 responses were received by the cut-off date, but 36 questionnaires were discarded because the respondents failed to complete the research instrument appropriately. The effective sample size, thus, was 776 with a response rate of 52%.

4.2. Measures

All questionnaire items, originally published in English, were translated into Arabic using the back translation technique (Brislin, 1986). The perceived usefulness scale was adapted from Tung, Chang, and Chou (2008). This scale includes five items (e.g., "using electronic government services would increase my productivity"). The reliability of this scale in this study was $\alpha = 0.834$. The perceived ease of use scale was also adapted from Tung et al. (2008). This scale includes three items (e.g., "I find that the human interface of electronic government system clear and easy to use"). The reliability of this scale in this study was $\alpha = 0.758$. The perceived compatibility scale was adapted from Wu and Wang (2005). This scale includes three items (e.g., "Engaging in online transactions via e-government system is perceived as consistent with my existing values, beliefs and needs"). The reliability of this scale in this study was $\alpha = 0.706$. The subjective norms scale was adapted from Al-Gahtani, Hubona, and Wang (2007). This scale includes two items (e.g., "most people who are important to me think I should use e-government services"). The reliability of this scale in this study was $\alpha = 0.790$. The civic mindedness scale was adapted from Kabashima, Marshall, Uekami, and Hyun (2000). This scale includes four items (e.g., "politics and government are so complicated that sometimes I cannot understand what's happening"). The reliability of this scale in this study was $\alpha = 0.398$. The perceived trust scale was adapted from Kim et al. (2008). This scale includes four items (e.g., "the e-government system may share my personal information with other entities without my authorization"). The reliability of this

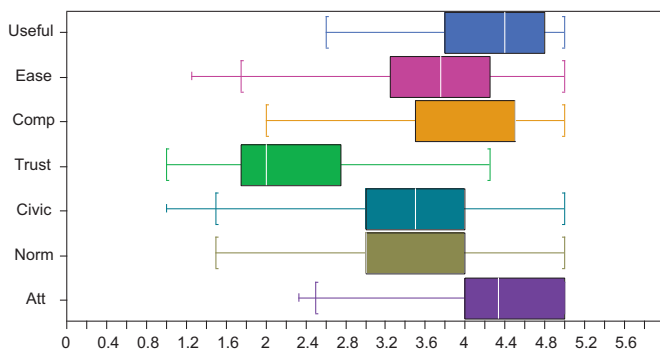


Fig. 1. Boxplots of variables used in the study.

scale in this study was $\alpha = 0.722$. Finally, the attitudes scale was adapted from Yoh, Damhorst, Sapp, and Laczniak (2003). This scale includes three items (e.g., “using electronic government services is good idea”). The reliability of this scale in this study was $\alpha = 0.866$. Fig. 1 shows the boxplots of the variables used in the study.

5. Results

5.1. Discriminant analysis

To compare e-government services users and non-users the traditional LDA was used using the SPSS 16.0 package. Classification with LDA involves classifying subjects into one of several groups on the basis of a set of measurements. LDA has a long tradition in the marketing literature for providing solutions to problems involving discrete outcomes, such as choice or classification (Heilman, Kaefer, & Ramenofsky, 2003) and for its competency in predicting choice as a function of past behavior (Mela, Gupta, & Lehmann, 1997). LDA assumes certain statistical characteristics of the data, such as multivariate normality and homogeneity of variance/covariance matrices. In a preliminary analysis of the data, a case analysis was conducted to identify possible outliers and violations of the LDA assumptions. No serious violations of the assumptions were detected.

Given that the optimal ordering of variables was not known a priori and the purpose was to determine the extent to which certain variables each contributed to prediction of user status, the discriminant functions were computed using simultaneous estimation of all independent variables. In the LDA if there are G groups, G-1 discriminant functions can be estimated. Since this study considers two groups, one function was generated to predict group membership. The function was found to significantly differentiate between users and non-users based on usefulness, ease of use, compatability, trust, subjective norms, civic mindedness, and attitudes as shown in Table 1 (Wilks' lambda = 0.558, $p < 0.001$). The canonical correlation was found to be 0.665, indicating that these variables explain 0.44% of the variance in e-government services usage behavior. The group centroids (-2.780 versus .284) further illustrate the separation between the two groups.

In order to examine the relative importance of each variable in discriminating between which citizens become users versus non-users of e-government services, discriminant loadings were obtained and are presented in Table 2. Variables are ordered by the absolute size of heir correlation with the discriminant function. Each independent variable's canonical discriminant function coefficient is also presented in Table 2. Respondents' attitudes had the greatest influence in determining whether respondents become users or non-users. Respondents' trust scores were next in importance, followed by compatability and usefulness.

Table 1
Discriminant analysis group means for non-users and users.

Independent variable	Non-users			Users			Sig.
	Mean	SD	n	Mean	SD	n	
Sex	0.542	.502	72	.452	.504	704	n.s ^a
Age	31.556	9.101	72	31.236	8.905	704	n.s
Education	2.653	.479	72	2.696	.484	704	n.s
Usefulness	3.425	.999	72	4.227	.704	704	.00**
Ease of use	3.107	.508	72	3.747	.741	704	.00
Compatability	3.125	.803	72	4.088	.809	704	.00
Trust	1.250	.000	72	2.184	.759	704	.00
Attitudes	2.875	1.033	72	4.339	.626	704	.00
Civic mindedness	2.9167	1.603	72	3.294	.936	704	.00
Subjective norms	3.134	1.314	72	3.405	.905	704	.00

^an.s = not significant.
^{**} $p < 0.01$.

Table 2
Discriminant loadings.

	Function 1
Structure matrix	
ATT	.711
TRUST	.422
COMP	.390
USEFUL	.356
EASE	.252
CIVIC	.122
NORM	.092

Pooled within-groups correlations between discriminating variables and standardized canonical functions variable ordered by absolute size of correlation within function.

In order to assess the overall fit of the discriminant function classification results were examined. In combination, the discriminant function achieved 94.3% classification accuracy. This result was cross-validated using the jackknife procedure, which repeatedly re-estimates the discriminant function eliminating one observation at a time; 92.8% of cross-validated group cases were correctly classified as shown in Table 3. This validation procedure indicated that the overall model results were robust and were not specific to the sample used in estimation. Classification results in both samples were also higher than the proportional chance criterion and the maximum chance criterion. Press's Q statistic confirmed that the predictions in both samples were significantly better than chance ($p < 0.001$).

Table 3
LDA classification results.

	Use	Predicted group membership		Total
		0.00	1.00	
Classification results^{b,c}				
<i>Original</i>				
Count	.00	67	5	72
	1.00	39	665	704
%	.00	93.1	6.9	100.0
	1.00	5.5	94.5	100.0
<i>Cross-validated^a</i>				
Count	.00	67	5	72
	1.00	51	653	704
%	.00	93.1	6.9	100.0
	1.00	7.2	92.8	100.0

Cross validation is done only for those cases in the analysis. In cross validation, each case is classified by the functions derived from all cases other than that case. 94.3% of original grouped cases correctly classified. 92.8% of cross-validated grouped cases correctly classified.



Fig. 2. Correct classification rate (CCR) for the MLP neural network.

5.2. Multi-layer perceptron neural network

Given its usefulness in data mining (Smith & Gupta, 2000), MLP is a logical choice for the problem studied here. In fact, Zahavi and Levin (1997) highlighted MLP models as a promising and effective alternative to conventional response modeling in database marketing for targeting purposes. McKechnie (2006) have proposed that NN and data mining techniques should be used to classify customers into distinct segments based on their past behavior, cluster data to establish specific customer type and use this knowledge to tailor marketing efforts. Furthermore, MLP has been employed in the context of competitive market structuring and segmentation analysis (Reutterer & Natter, 2000).

MLP was first developed to mimic the functioning of the brain. It consists of interconnected nodes referred to as processing elements that receive, process, and transmit information. MLP consists of three types of layers: the first layer is known as the input layer and corresponds to the problem input variables with one node for each input variable. The second layer is known as the hidden layer and is useful in capturing nonlinear relationships among variables. The final layer is known as the output layer and corresponds to the classification being predicted (Baranoff, Sager, & Shively, 2000).

There are many software packages available for analyzing MLP models. We chose NeuroIntelligence package (Alyuda, 2003). This software applies artificial intelligence techniques to automatically find the efficient MLP architecture. Typically, the application of MLP requires a training data set and a testing data set (Lek & Guegan, 1999). The training data set is used to train the MLP and must have enough examples of data to be representative for the overall problem. The testing data set should be independent of the training set and is used to assess the classification accuracy of the MLP after training. Following Lim and Kirikoshi (2005), a quasi-Newton algorithm with weight updates occurring after each epoch was used for MLP training. The learning rate was set at 0.1. After 100 iterations the correct classification rate (CCR) reached 99.8% as seen in Fig. 2. Table 4 reports the properties and predictive accuracy of the MLP model. As can be observed, the MLP classifier predicted training sample with 99.8% accuracy and validation sample with 98.3% accuracy.

5.3. Probabilistic neural network

The MLP is the most frequently used neural network technique in pattern recognition (Bishop, 1999) and classification problems (Sharda, 1994). However, numerous researchers document the disadvantages of the MLP approach. For example, Calderon and Cheh (2002) argue that the standard MLP network is subject to problems of local minima. Swicegood and Clark (2001) claim that there is no formal method of deriving a MLP network configuration for a

Table 4
MLP NN properties.

Parameter	Value
Architecture	[10-5-2]
Input activation function	Logistic
Classification model	Confidence limits
Accept/reject level	0.5
Training algorithm	Quasi-Newton
Number of iterations	100
Number of Weights	269
Fitness	65
Akaike Information Criterion (AIC)	-238.4
Output error	Cross-entropy
Network error (training)	0.012
Network error (validation)	0.000
Error improvement	0.000
CCR % (training)	99.8
CCR % (validation)	98.3

given classification task. Thus, there is no direct method of finding the ultimate structure for modeling process. Consequently, the refining process can be lengthy, accomplished by iterative testing of various architectural parameters and keeping only the most successful structures. Wang (1995) argues that standard MLP provides unpredictable solutions in terms of classifying statistical data.

An alternative NN architecture, the PNN is non-linear, nonparametric pattern recognition modeling technique that was originally introduced to the neural network literature by Specht (1990). PNNs require no assumptions about distributions of random variables used to classify; they even can handle multi-modal distributions. They train quickly and as well as, or better than MLP networks. They have the ability to provide mathematically sound confidence levels and are relatively insensitive to outliers (Singer & Bliss, 2003). While the MLP network requires a validation data set (i.e., wasted cases) to search for over-fitting, PNNs use all available data in model building.

PNNs feature a feed-forward architecture and supervised training algorithm similar to back-propagation. The training pattern is presented to the input layer. The main role of the input layer is to map all the external signals into hidden layers by a scaling function through which each input neuron normalizes the range of external signals into a specific range that the neuron network can process. The neurons in hidden layer aim to add flexibility to the performance of the PNN so as to recording the knowledge of classification extracted from the training pattern. There must be, at least, as many neurons in the hidden layer as the number of training patterns (Tam, Tong, Lau, & Chan, 2005). The summation layer consists of one neuron for each data class and sums the outputs from all hidden neurons of each respective data class. The output layer has one neuron for each possible category. The network produces activation, a value between zero and one in the output layer corresponding to the probability density function estimated from that category. The output with the highest value represents the most probable category.

PNNs are used for classification problems where the objective is to assign cases to one of a number of discrete classes (Hunter, 2000). Theoretically, the PNN can classify an out-of-sample data with the maximum probability of success when enough training data is given (Enke & Thawornwong, 2005). The PNN has been extensively used in various pattern classification tasks across several domains due to ease of training and sound statistical foundation in Bayesian estimation theory. For example, Yang and Marjorie (1999) utilized a PNN to predict the financial crisis in oil industry companies in the USA. Jin and Srinivasan (2001) proposed a new technique for freeway incident detection using PNN. Hajmeer and Basheer (2002) used PNN to study the classification of bacterial growth. Chen, Leung, and Daouk (2003) applied PNN to stock

Table 5
PNN properties.

Parameter	Value
Configuration	PNN category predictor
Independent category variables	2 (sex, education)
Independent numeric variables	8 (age, usefulness, ease of use, compatability, trust, attitude, civic mindedness, subjective norms)
Number of cases (training)	621
Number of trials (training)	55
% Bad predictions (training)	0.000
Mean incorrect probability % (training)	0.000
SD of incorrect probability % (training)	0.000
Number of cases (testing)	155
% Bad predictions (testing)	0.000
Mean incorrect probability % (testing)	0.000
SD of incorrect probability % (testing)	0.000

index forecasting. Huang (2004) applied PNN to predict the class of leukemia and colon cancer. Gerbec, Gasperic, Smon, and Gubina (2005) used PNN to classify consumers' electricity load profiles. Xue, Zhang, Liu, Hu, and Fan (2005) classified 102 active compounds from diverse medicinal plants with anticancer activity. Jin and Englande (2006) used PNN to classify whether a condition in a lake is safe to swim or not. Wilson (2006) successfully tested the PNN on 209 seizures obtained from an epilepsy-monitoring unit. Laskari, Meletioui, Tasoulis, and Vrahatis (2006) evaluated the performance of PNN on approximation problems related to cryptography. These applications show that while PNN has been applied to many areas, little attention has been paid to applying PNN to consumer profiling and market segmentation problems.

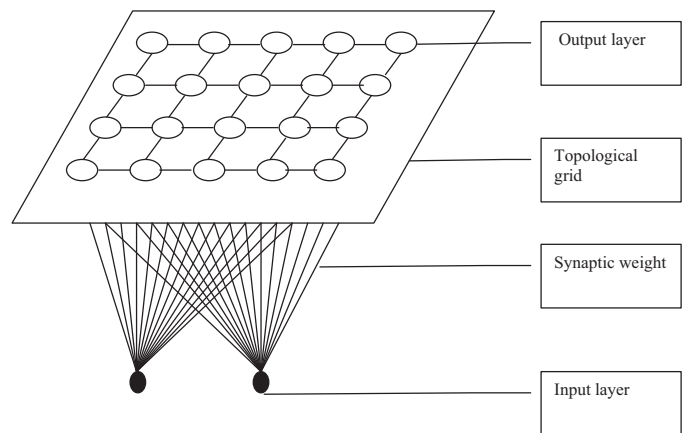
There are many computer software packages available for building and analyzing NNs. Because of its extensive capabilities for building networks based on a variety of training and learning methods, NeuralTools Professional package (Palisade Corporation, 2005) was chosen to conduct PNN analysis in this study. This software automatically scales all input data. Scaling involves mapping each variable to a range with minimum and maximum values of 0 and 1. NeuralTools Professional software uses a non-linear scaling function known as the 'tanh', which scales inputs to a (-1, 1) range. This function tends to squeeze data together at the low and high ends of the original data range. It may thus be helpful in reducing the effects of outliers (Tam et al., 2005).

Table 5 reports the properties and predictive accuracy of the PNN model. As can be observed, the PNN classifier predicted both training and testing samples with 100% accuracy.

5.4. Self-organizing maps

The SOM, also called Kohonen map, is a heuristic model for exploring and visualizing patterns in high dimensional datasets. It was first introduced to the neural networks community by Kohonen (1982). SOM can be viewed as a clustering technique that identifies clusters in a dataset without the rigid assumptions of linearity or normality of more traditional statistical techniques. Indeed, like *k*-means, it clusters data based on an unsupervised competitive algorithm where each cluster has a fixed coordinate in a topological map (Audrain-Pontevia, 2006). The SOM is trained based on an unsupervised training algorithm where no target output is provided and the network evolves until convergence. Based on the Gladyshev's theorem, it has been shown that SOM models have almost sure convergence (Lo & Bavarian, 1993).

The SOM consists of only two layers: the input layer which classifies data according to their similarity, and the output layer of radial neurons arranged in a two-dimensional map (Fig. 3). Output neurons will self-organize to an ordered map and neurons

**Fig. 3.** The SOM architecture.

with similar weights are placed together. They are connected to adjacent neurons by a neighborhood relation, dictating the topology of the map (Moreno, Marco, & Olmeda, 2006). The number of neurons can vary from a few dozen to several thousand. Since the SOM compresses information while preserving the most important topological and metrical relationships of the primary data elements on the display, it can also be used for pattern classification (Silven, Niskanen, & Kauppinen, 2003).

Due to the unsupervised character of their learning algorithm and the excellent visualization ability, SOMs have been recently used in myriad classification and clustering tasks. Examples include classifying cognitive performance in schizophrenic patients and healthy individuals (Silver & Shmoish, 2008), mutual funds classification (Moreno et al., 2006), speech quality assessment (Mahdi, 2006), vehicle routing (Ghaziri & Osman, 2006), network intrusion detection (Zhong, Khoshgoftaar, & Seliya, 2007), anomalous behavior in communication networks (Frota, Barreto, & Mota, 2007), compounds pattern recognition (Yan, 2006), market segmentation (Kuo, Ho, & Hu, 2002) and classifying magnetic resonance brain images (Chaplot, Patnaik, & Jagannathan, 2006).

There are many software packages available for analyzing SOM models. We chose SOMine package version 5.0 (Viscovery Software GmbH, 2008). This software applies artificial intelligence techniques to automatically find the efficient SOM clusters. To visualize the cluster structure, some authors use the unified distance matrix (*U*-matrix) (e.g., Vijayakumar, Damayanti, Pant, & Sreedhar, 2007). However, this method does not give crisp boundaries to the clusters (Worner & Gevrey, 2006). In this study a hierarchical cluster analysis with a Ward linkage method was applied to the SOM to clearly delineate the edges of each cluster. The number of neurons is chosen to be 2000. There are two learning algorithms for SOM (Kohonen, 2001): the sequential or stochastic learning algorithm and the batch learning algorithm. In the former, the reference vectors are updated immediately after a single input vector is presented. In the latter, the update is done using all input vectors. While the batch algorithm does not suffer from convergence problems, the sequential algorithm is stochastic in nature and is less likely trapped to a local minimum. Following Ding and Patra (2007), we choose the sequential learning algorithm to train the SOM. Fig. 4 shows the cluster indicator. This figure clearly shows that the SOM converges successfully after 50 iterations.

The SOM cluster results are shown in Fig. 5. This two-dimensional hexagonal grid shows clear division of the input pattern into three clusters. Since the order on the grid reflects the neighborhood within the data, features of the data distribution can be read off from the emerging landscape on the grid. For example, it can be seen that the green-colored cluster is the smallest cluster

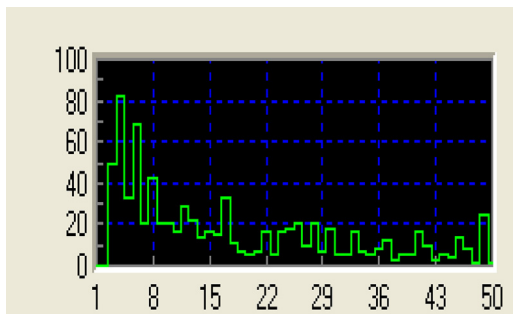


Fig. 4. SOM cluster indicator.

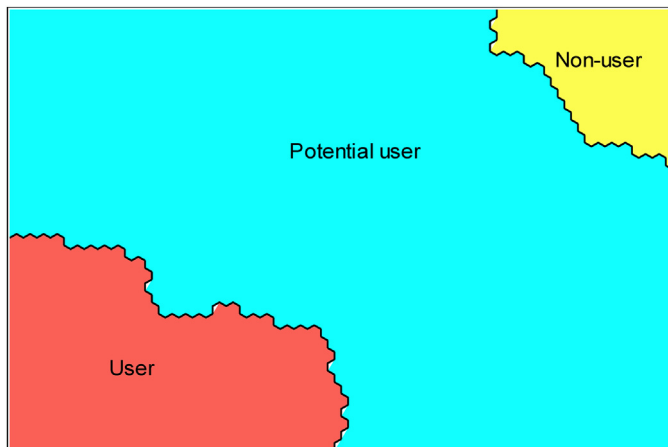


Fig. 5. SOM-Ward clusters.

with a frequency of 9.28%. This is the non-users cluster. Respondents in this cluster are characterized by low perceived usefulness, ease of use and compatibility of e-government services and less favorable attitudes toward e-government services. Surprisingly, this cluster includes individuals who are more civically minded. The red-colored cluster represents the users cluster. This cluster accounts for 19.33% of respondents. The respondents in this cluster are characterized by high perceived usefulness, ease of use compatibility, and favorable attitudes toward e-government. Table 6 summarizes the basic information in each cluster.

Based on the SOM-Ward clusters, feature or component maps can be constructed (Vesanto, 1999). These maps are also known in the literature as ‘temperature maps’ (Churilov & Flitman, 2006). On these maps, the nodes which share similar information are organized in close color proximity to each other. Fig. 6 shows the feature maps for every cluster and for all input attributes. Feature maps show the distribution of values of the respective input component over the map. Relationships between variables could be inspected by visually comparing the pattern of shaded pixels for each map; similarity of the patterns indicates strong monotonic relationships between the variables. The name of the displayed input component appears on top of each map. The color scale at the bottom of the component window shows that blue is used for low values, green for mid-range values and red for high values. From the feature maps we note, for example, that the extreme values represented in

red in the e-government feature map in the users’ cluster matches those extreme values found in the perceived usefulness, ease of use and compatibility feature map. Interestingly, the non-user cluster includes the highest constellation of red pixels in the civic mindedness attribute. Through the use of colors, one can immediately see that the trust portion is significantly larger than the rest in the trust window for the users cluster – thus implying that trust is positively related to e-government services usage – a result that was previously confirmed by other researchers (e.g., Bélanger, 2008). In essence, these colorful maps reveal the existence of previously theorized assumptions and it can even create new ones. The maps also make it possible to find subgroups that do not follow the main theoretical assumptions. For example, when red dots are found in the middle of the green area, this signals the presence of deviant subgroups. When either blue or red nodes are forming two clearly separated areas, this might be considered as a sign of non-linear correlation (Thneberg & Hotulainen, 2006).

5.5. Classification and regression trees

CART is a nonparametric technique developed by Brieman, Friedman, Olshen, and Stone (1984) to classify group observations based on a set of characteristics into distinct groups, using the decision tree methodology. The technique was introduced to overcome the inherent limitations in the automatic interaction detector (AID) and the chi-square automatic interaction detector (CHAID) techniques. Unlike AID or CHAID, CART can work in classification tree mode with categorical predictor variables, or in regression tree mode with interval or ratio scaled predictors. CART recursively splits a dataset into non-overlapping subgroups based on the independent variables until splitting is no longer possible (Baker & Song, 2008).

CART has been widely applied in various fields of research such as mortgage default (Feldman & Gross, 2005), reliability (Bevilacqua, Braglia, & Montanari, 2003), detecting user web search preferences (Pendharkar, 2006), female sexuality (Wiegel, Meston, & Rosen, 2005), detecting change in consumer behavior (Kim, Song, Kim, & Kim, 2005), determining the role of race in capital cases (Berk, Li, & Hickman, 2005), site quality evaluation (Corona, Dettori, Filigheddu, Maetzke, & Scotti, 2005), and auditor change decisions (Calderon & Ofobike, 2008).

In this study CART software version 6.0 (Steinberg & Golovnya, 2006) was used to build classification trees. The Gini index was used in the splitting process while test sample estimation was implemented to evaluate the predictive performance of each classifier. Following D’Alisa et al. (2006), the 10-fold validation approach with re-substitution was adopted. This consists of simulating 10 different samples by subtracting randomly each time 10% of the subjects and duplicating randomly another 10%. After each run, the original sample is restored. The final tree represents the best trade-off between variance explanation and variance stability across 10 “different” samples. Overall correct classification rate obtained from CART was 99.48%.

Fig. 7 depicts the final obtained pruned CART tree. From this figure we see that trust in e-government systems plays the most important role in rule induction. Table 7 summarizes the rules and the classified results from the CART tree. Fig. 8 represents the significant predictors arranged according to their importance in profiling e-government services users. These are the variables proposed by the most widely used CART classification method namely, the Gini reduction method. Other methods such as the symmetric Gini method and the class probability methods reached similar results. From this figure we see that trust, attitudes and compatibility are the most important factors in determining e-government services adoption behavior in Egypt.

Table 6
SOM Ward clusters.

Cluster	Freq. %	Useful	Ease	Comp	Trust	Civic	Norm	Attitude
Cluster 1	19.33	4.401	4.405	4.397	3.005	3.553	4.620	4.478
Cluster 2	71.39	4.179	3.569	4.005	1.962	3.225	3.076	4.301
Cluster 3	9.28	3.425	3.108	3.125	1.250	3.139	3.139	2.873

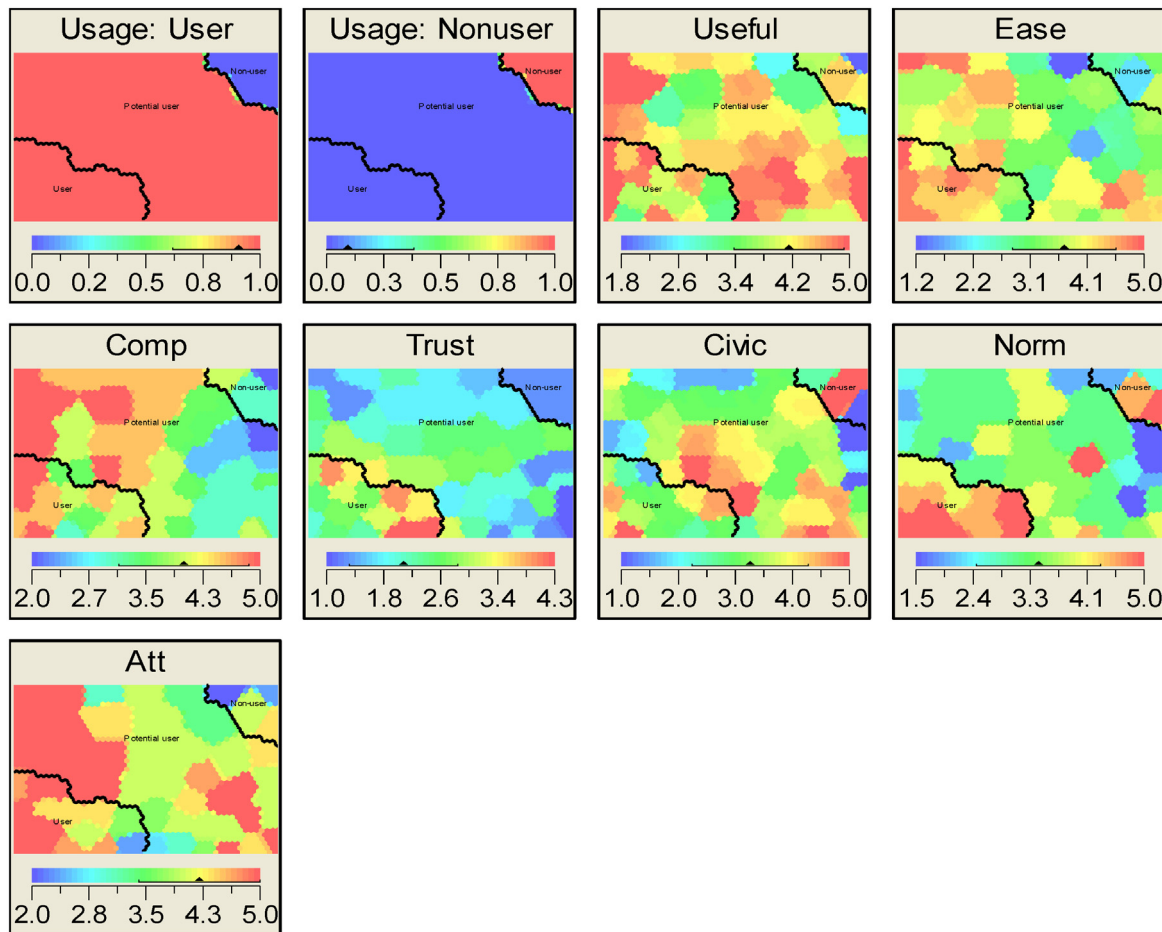


Fig. 6. SOM feature maps of main input attributes.

5.6. Multivariate adaptive regression splines

MARS is a relatively novel data mining technique developed by Friedman (1991). This technique combines classical linear regression, mathematical construction of splines and binary recursive partitioning to produce a local model where the relationship between response and predictors are either linear or nonlinear through approximating the underlying function through a set of adaptive piecewise linear regression termed basis functions (BF) (Jesus & Angel, 2004). MARS develops models in a forward growing stage by adding the BF that is most effective in error-minimizing, while it allows for the detection of interactions by multiplication of a term already entered in the model with another candidate basis function (Flouris & Duffy, 2006). The BF transform makes it possible

Table 7
CART inductive rules.

Terminal node	Basic Rule(s)	Class
1	If age ≤ 19.5	1 (user)
2	If trust ≤ 1.38 & If usefulness ≤ 4.70 & If age ≤ 43.5 & If age > 19.5 & If attitude ≤ 4.66	0 (non-user)
3	If attitude > 4.66 & If age > 19.5 & If age ≤ 43.5	1 (user)
4	If age > 43.5	1 (user)
5	If usefulness ≥ 4.70	1 (user)
6	If trust > 1.38	1 (user)

to blank out certain regions of a variable by making them zero, allowing the model to focus on specific sub-groups of the data deemed important (Ture, Kurt, Kurum, & Ozdamar, 2005).

The power of MARS for building prediction and classification models has been demonstrated in many applications such as information technology productivity studies (Ko & Osei-Bryson, 2006), genetics (York & Eaves, 2001), biomedical analysis (Deconinck, Ates, Callebaut, Van Gysegheem, & Heyden, 2005), network intrusion detection (Peddabachigari, Abraham, Grosan, & Thomas, 2007), credit scoring (Lee & Chen, 2005), finance (Abraham, 2002), software maintainability (Zhou & Leung, 2007) and cancer diagnosis (Chou, Lee, Shao, & Chen, 2004). In this study we used MARS 2.0 package (Steinberg, Colla, & Martin, 1999) to conduct the analysis. Overall correct classification rate obtained from MARS was 99.10% (sensitivity=0.931 and specificity=0.997).

To help interpret the models obtained, we visualize major two-way interactions between independent variables. Fig. 9 is a typical example of such two-way interactions. For example, the lower left part of the graph represents the model's predicted surface for the dependent variable (i.e., e-government services adoption) when only considering the interaction effect between trust and civic mindedness. MARS shifts values on the contribution axis so that the minimum value is 0. Color codes represent different contribution value intervals. From this figure we see that for low levels of trust, the probability of using e-government services rises steeply with civic mindedness and maintains a relatively high probability except for the very low and very high levels of civic mindedness.

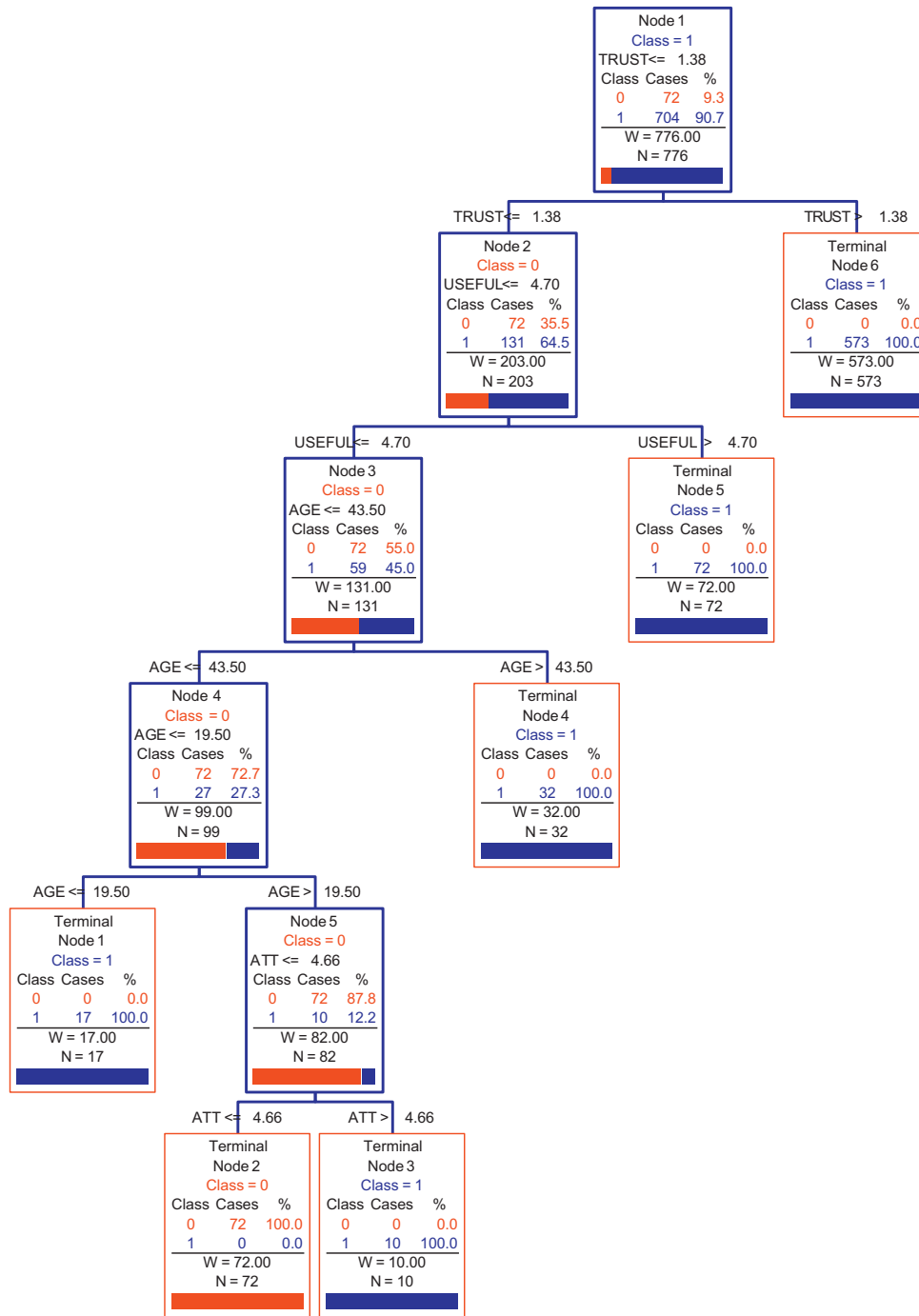


Fig. 7. CART decision tree of e-government services' users.

5.7. Support vector machines

SVMs have been developed by Vapnik (1995) as a novel type of machine learning. SVMs are a set of related supervised

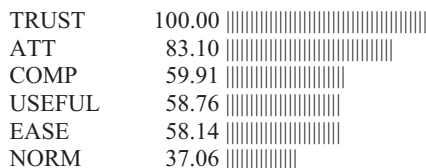


Fig. 8. CART factor importance analysis.

learning methods used for classification and regression. In the case of classification, SVMs obtain the 'optimal' boundary of two classes in a vector space independently on the probabilistic distributions of training vectors in the data set. If the categories are linearly separated, the aim of SVMs is to find the 'optimal' hyperplane boundary which separates both classes, classifying not only the training set but also unknown samples. When the classes are non-linearly separable, the input data are implicitly mapped into a higher dimensional space by a kernel function, e.g., Guassian radial basis function (Berrueta, Alonso-Salces, & Heberger, 2007). An operating model of SVM is shown in Fig. 10. The dashed black line in this figure is the SVM solution. According to this idea, e-government services usage can be viewed as a simple

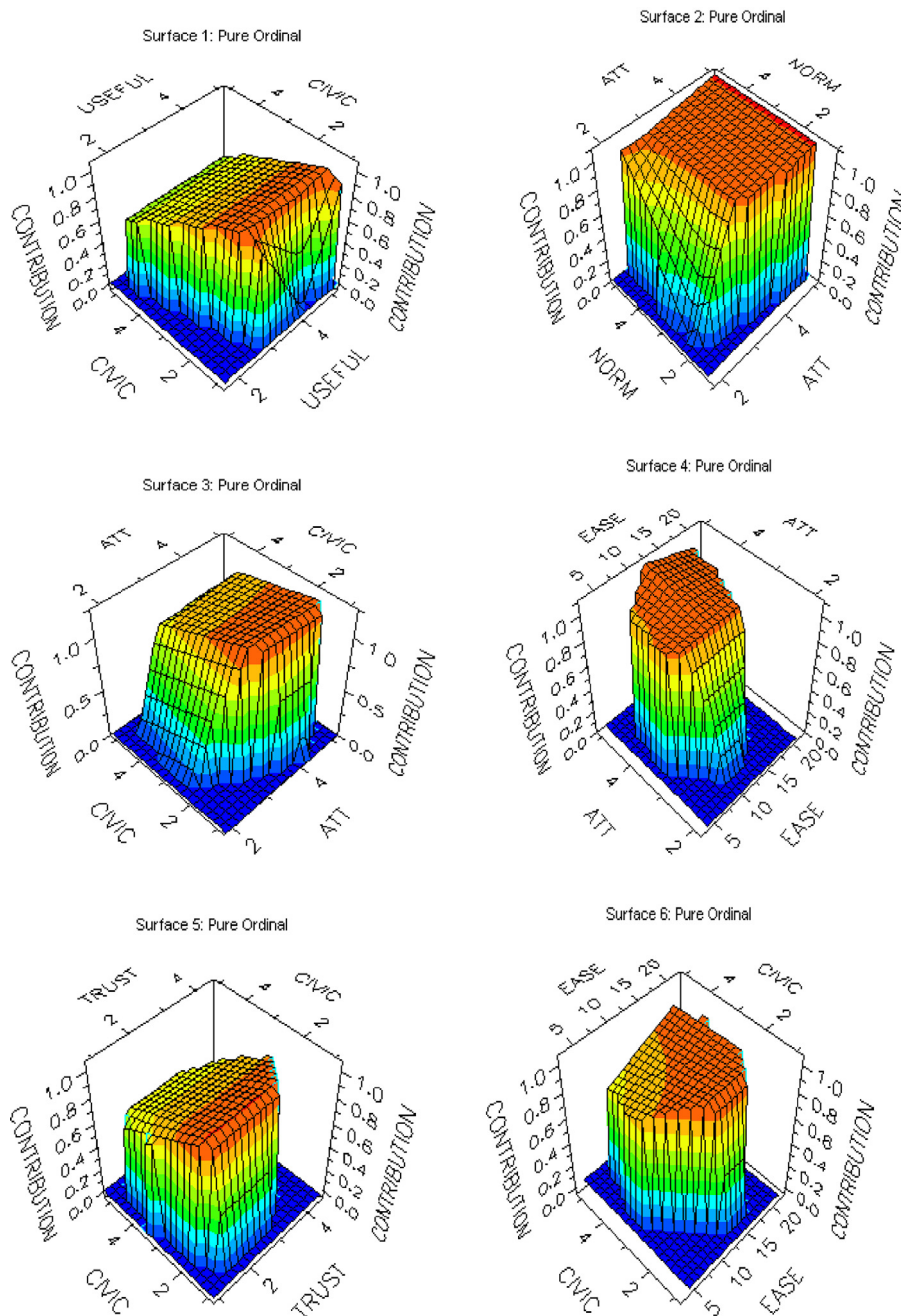


Fig. 9. MARS two-way interactions between independent variables.

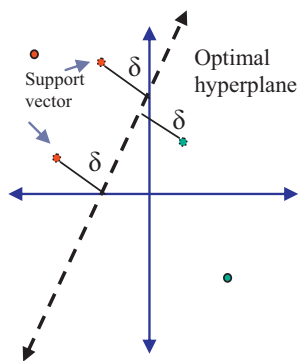


Fig. 10. SVM conceptual classification of users versus non-users.

SVM application, classification of linearly separable classes; that is, a citizen belongs to the user category or not.

SVMs are based on the structure risk minimization (SRM) principle, which has been shown to be superior to the traditional risk minimization (ERM) principle employed by neural networks (Kecman, 2005). SRM minimizes an upper bound of the generalization error on the Vapnik–Chernoverkis (VC) dimension, as opposed to ERM, which minimizes the training error. Recently, Li, Lord, Zhang, and Xie (2008) found that SVMs have better modeling performance than the MLP in short-term freeway traffic volume forecasting. Compared to neural networks, other SVMs advantages include their strong theoretical basis which provides them with high generalization capability. SVMs always have a solution, which can be quickly obtained by a standard quadratic programming algorithm.

SVMs have been used in a range of areas like financial applications (e.g., Ravi, Kurniawan, Thai, & Kumar, 2008), classification of fragrance properties (Luan, Liu, Wen, & Zhang, 2008), dynamic classification for video stream (Awad & Motai, 2008), classification of forest fire types (Koetz, Morsdorf, Linden, Curt, & Allgower, 2008), consumer churn prediction (Coussement & Van den Poel, 2008), text categorization (Hmeidi, Hawashin, & El-Qawasmeh, 2008), spam classification (Yu & Xu, 2008) and estimating production levels (Chen & Wang, 2007). To our knowledge no previous implementations of SVMs in e-government services usage are published.

In this study we used the SVM function in R software (Dimitradou et al., 2005) to conduct the analysis. This function provides a user-friendly interface to the LIBSVM software developed by Chang et al. (2001) along with visualization and parameter tuning methods. This function is currently one of the most widely used implementations of SVM algorithms as it provides a robust and fast SVM implementation and produces state of the art results on most classification and regression problems (Karatzoglou et al., 2005). Appendix A provides the R code used to conduct the SVM analysis. As seen in the appendix, the correct classification rate for both training and test samples was 100%.

5.8. Hypotheses testing

Group means for user and non-user groups on each of the independent variables used in the LDA are presented in Table 1. Given the unequal group sizes of user versus non-user groups, group specific covariance matrices were used as suggested by Hair, Andersen, Tatham, and Black (1998). Review of the significance levels of the individual attributes revealed that all the attributes except demographic variables displayed significant differences between the group means. Our results confirm previous studies which found e-government usage behavior to be correlated with perceived usefulness, ease of use, compatibility, trust, subjective norms and favorable attitudes to use the system (e.g., Helbig et al., 2009). For example Gilbert, Balestrini, and Littleboy (2004) found that trust is one of the strongest predictors of willingness to use e-government services. The finding that subjective norm is significant in predicting e-government services usage is consistent with Hofstede's (1991) cultural dimensions. In a high power distance collectivist culture such as Egypt one would expect significant others' opinions to have more impact on the individual because of face saving and group conformity, also a higher power distance would invoke a more influential role of peers.

It should be noted that we tested the research hypotheses using LDA as data mining techniques are of limited ability to statistically test and interpret hypotheses concerning the roles of specific variables that are included in the models as predictors. However, this limitation "should not be a serious drawback if one simply desires classification from the model" (Swicegood & Clark, 2001, p. 176).

6. Implications

The results of this study have several important implications for both theory and practice. From a theoretical perspective, the superior performance of data mining techniques found in this study confirms the theoretical work by Hecht-Nielson (1989) who has shown that machine learning techniques, such as neural network models, can learn input-output relationships to the point of making perfect forecasts with the data on which the model is trained. However, perfect forecasts with the training data do not

guarantee optimal forecasts with the testing data due to differences in the two data sets. Our results also corroborate the findings of other researchers who have investigated the performance of machine learning techniques compared to other traditional statistical techniques, such as regression analysis, discriminant analysis, and logistic regression. For example, in a study of clinical diagnosis of cancers, Shan, Zhao, Xu, and Liebich Zhang (2002) found a hit ratio of 85% for the PNN model compared to 80% for the LDA model. In a study of credit-scoring models used in commercial and consumer lending decisions, Bencic, Sarlija, and Zekic-Susac (2005) compared the performance of logistic regression, neural networks and decision trees. The PNN model produced the highest hit rate and the lowest type I error. In a study profiling Internet banking users in India, Ravi, Carr, and Sagar (2007) compared statistical and intelligent techniques on a data set of 165 users. The results revealed that neural networks and logistic regression achieved 100% overall accuracies for the test data, while CART and SVM gave 70% and 78%, respectively. In a study predicting the going concern using data mining techniques, Koh (2004) found a hit ratio of 95.22% for the logistic regression model compared to 97.39% for CART. Finally, Kiang and Kumar (2001) used simulated data where true cluster memberships are known and found that data mining techniques provide more accurate recovery of underlying clusters when the input data are skewed.

From a practical perspective, understanding the factors influencing user acceptance of e-government services allows governments to develop strategies for e-government systems implementation in ways that will improve the performance of government departments and agencies. Knowledge of these factors, how they can be measured, and how they relate to each other, is crucial in the development, implementation, and management of successful e-government systems (Hamner & Qazi, 2009). This is because the decision to accept or reject a new technology is ultimately determined by the individual user. It is therefore imperative to know which factors affect a user's decision to use the e-government system. This knowledge can then be used to enhance e-government services acceptance and correspondingly increase utilization. Moreover, government can also use knowledge of these factors to facilitate appropriate investment in e-government systems.

A key finding in our study is the positive relationship between perceived usefulness and ease of use and e-government adoption. Choosing to adopt e-government services such as filing taxes online is, then, a function of perceived usefulness and ease of use of the government Web site. Greater publicity regarding the usefulness of e-government services and their resulting savings would also introduce greater awareness and improve their perceived benefits in the eyes of the public. The portrayal of an up-to-date and effective e-government system may encourage more customers to make queries, download forms, and file taxes, leading to significant cost savings and efficiency gains for both the government and the public.

Trust was found to be one of the most important factors in determining e-government services usage. Because governmental agencies may be required by law to share information with other agencies, the need for trust in the maintenance of accurate citizen information will increase. Thus, a strategic aim could be to develop a trustworthy relationship with the public, giving assurances that their data will be secure, and that the information contained on the Web would be both current and accurate. This can be done through tools and techniques that Web developers can use to increase and promote the security of e-government Web sites, such as firewalls and encryption technology. Therefore, e-government services need to be user-friendly, and citizens need to have confidence in the

Appendix A. R software code used to implement the SVM.

```

> library(e1071)
Loading required package: class
> egov<-read.table("c:\\egov.txt", header= TRUE)
> x<-egov[, 1:10]
> y<-egov[, 11]
> model<-svm(x, y)
> print(model)
> summary(model)
Call:
svm.default(x = x, y = y)

Parameters:
  SVM-Type:  C-classification
  SVM-Kernel:  radial
           cost:  1
           gamma:  0.1

Number of Support Vectors:  40
(28 12)

Number of Classes:  2
Levels:
no yes
> pred<-predict(model, x)
> table(pred, y)

pred   no  yes
no     72   0
yes    0  704

```

system. In this process, the government need to be careful to protect its brand and credibility.

7. Limitations and future research

The study suffers from a number of limitations. First, this study has used a cross-sectional rather than a longitudinal approach. This implies that much more emphasis has been placed on observing respondents' behaviors than in observing changes in behavior. There would seem to be hence a need for much more longitudinal research to focus on observing changes in respondents' behavior over time. Second, the measures used in the study are based on self-reports of past behaviors or predictions about future actions. Though such self-reports often represent fairly good approximations of actual behaviors (Ajzen & Fishbein, 1980), they clearly have limitations. In particular, socially desirable past behaviors and intentions are usually over-reported and less desirable past behaviors are under-reported. Future research should examine the potential impact of social desirability bias on consumers' responses to questions about e-government services usage behavior. Finally, for the purpose of this research, a data mining approach was adopted to identify respondents' behavior regarding e-government services. The use of quantitative methods alone is valuable in establishing relationships between variables, but is considered weak when attempting to identify the reasons for those relationships (Chisnall, 1997). Using qualitative research along quantitative methods in future studies may enable us to further explore relationships amongst variables.

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