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ABSTRACT

Objectives: To develop and explore the predictability of patient perceptions of satisfaction through the hospital adoption of health information technology (HIT) in order to help understand the benefits of increased HIT investment.

Data and Methods: The solution proposed is based on an adaptive neuro-fuzzy inference system (ANFIS), which integrates artificial neural networks and fuzzy logic and can handle certain complex problems that include fuzziness in human perception, and non-normal and non-linear data. Two surveys were combined to develop the model. Hospital HIT adoption capability and use indicators in the Canadian province of Ontario were used as inputs, while patient satisfaction indicators of healthcare services in hospitals were used as outputs.

Results: Seven different types of models were trained and tested for each of four patient satisfaction dimensions. The accuracy of each predictive model was evaluated through statistical performance measures, including root mean square error (RMSE), and adjusted coefficient of determination $R^2{}_{Adjusted}$. The impact of HIT adoption on patient satisfaction was obtained for different HIT adoption scenarios using ANFIS simulations.

Conclusions: The results revealed that ANFIS simulations provide good accuracy and reliability for predicting the impact of health information technology adoption on patient satisfaction in hospitals. These simulations can therefore be helpful as decision support mechanisms to assist government and policy makers in understanding and predicting the effects of successful implementation and use of HIT in hospitals.

Keywords: Health Information Technology (HIT), Electronic Health Records (EHRs), Technology Adoption, eHealth, Patient Satisfaction, Neuro-fuzzy model, ANFIS

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INTRODUCTION

Healthcare is a complex environment in which there are multiple problems, including increasing expenditures, inconsistent quality, human resource shortages, and gaps in care and access. Investments in health information technology (HIT) applications, such as electronic health records (EHRs), computerized physician order entry (CPOE) systems, wireless mobile technology, and clinical decision support systems (CDSS) are often based on an expectation that they will result in a significant reduction in some of these problems[1,2].

Recent literature suggests that the adoption of HIT in hospitals can improve information and service integration, communication, and coordination among clinicians[3-6], health care quality and safety[7-10], reduce costs[11,12], control resource allocation, increase service efficiency and productivity, and enhance service availability, quality, and satisfaction for patients and health care providers[1, 13-16]. HIT may result in an improvement in health care quality through the use of standardized clinical pathways; e-prescribing systems, which would detect drug interactions; and better and more complete documentation of care[4, 17]. These improved processes are expected to lead to significant reductions in medical errors[18-21]. The automated access of physicians to patient laboratory and other diagnostic results[4, 22] may reduce lost orders and errors due to illegible handwriting, and minimize duplicate orders[23], thus improving health care quality outcomes and efficiency[24].

Patient satisfaction as an outcome indicator of health care delivery has been widely accepted as a significant indicator for measuring quality of health care and as a critical component in performance improvement and clinical effectiveness[25-29]. Although studies of the impact of HIT adoption on patient satisfaction and clinical performance have been found to have neutral or positive effects on patient satisfaction, most related studies concluded that further research and new development methods are required to understand the effects that may be achieved through the successful implementation and use of HIT[30-37].

Predicting and measuring patient satisfaction as a result of HIT adoption is a complicated and difficult task, as there are many factors involved[38-53]. First, uncertainty is inherent in clinical medicine and this may contribute to variability in physician practice patterns, patient satisfaction, and exchange of information[38]. Second, there is no consensus in recent patient satisfaction literature about which dimensions of health care should be evaluated in order to measure patient satisfaction[39, 40]. Most researchers agree that patient satisfaction is a multidimensional concept including: patient expectations as customers; patient views about the amount and quality of the information and communications they received about their conditions and treatments; patient perceptions of their providers' competence and caring, and how coordinated and integrated care was when it was delivered[41-45]. Lastly, patient satisfaction is a human perception which is subjective and vague[46]. It is affected by several individual factors such as personality characteristics and health status, and socio-demographic variables, such as education, age, and gender[26, 27, 47, 48]. Traditional evaluations of patient satisfaction that use a Likert scale to represent patient or customer perceptions based on linguistic assessments (e.g., Very satisfied = 5, satisfied = 4, fair = 3, unsatisfied = 2, very unsatisfied = 1) are often impractical[46, 49-52]. In addition, differences in individual perceptions and personalities mean that the same words can mean very different perceptions in the viewpoints of different individuals[53].

During the last decades "soft" computing methodologies such as fuzzy logic, neural and genetic computing have provided alternative methods that can tackle the non-linearity, imprecision, uncertainty, and partial truths found in the real world when modeling complex systems[54-70]. Recent reviews of the application of soft computing show that these approaches have been widely applied for financial stock market prediction[57], agricultural and biological engineering[58], medical diagnosis prediction[59-71] and many other complex fields. However, there have been few or no studies of the use of soft computing techniques to analyze and predict the impact of HIT adoption on patient satisfaction. In fact, there are very few studies of the utilization of soft computing in customer satisfaction prediction and performance[46, 49, 72-76].

To fill this gap, we developed an adaptive network based fuzzy inference system (ANFIS) to study the combined results from two surveys in the Canadian province of Ontario that measured: 1) patient satisfaction with healthcare services in hospitals and 2) HIT adoption in hospitals. Using this approach, we were able to predict and find a preliminary understanding of the impact of HIT on hospital patient satisfaction through ANFIS modeling and simulation.

The paper is organized as follows. Section 2 describes the survey data used for the study. In Section 3 the methodology for system modeling with the help of ANFIS is discussed. Implementation and model validation details are given in Section 4. Results are presented in Section 5, followed by conclusions in Section 6.

DATA

Health Canada is the national agency for health in Canada. Some of its priorities and efforts have focused on addressing policy issues and challenges in mainstreaming eHealth services within Canada's health care system and in measuring progress in the deployment and investment in these services[77]. One of their projects was a joint study with the Ontario Hospital Association (OHA) to measure progress in HIT adoption capability and use through the 2007 e-Health Adoption Survey Top Line Report[78]. This study evaluated hospital capability throughout the province of Ontario for registering patients electronically, capturing patient-reported information, and managing clinical records. Additionally, the study measured how these features were integrated into hospital EHRs (Electronic Health Records), in order to electronically capture, present, and interpret clinical and laboratory results and reports, provide notifications/alerts of abnormal laboratory results, and share health information through information and communication technologies. The OHA created a scoring system for hospital responses to each of the questions, which applied to all the indicators studied (Table 1) and created a normalized overall score for each indicator on the range 0 to 100[78]. Of the 211 Ontario hospitals that were invited to participate in this survey, 138 responded.

Health outcomes data for Ontario hospitals, such as the patient satisfaction indicators used in this research are contained within the Hospital Report Series, produced by the Hospital Report Research Collaborative (HRRC)[79]. The HRRC is an independent research collaborative dedicated to performing research related to performance measurement within Ontario hospitals, and reports are available from http://www.hospitalreport.ca/downloads/annual.html.

Table 1. HIT Adoption Indicators

Indicator	Description
Patient Registration, Records Management, and Registry Services (x1)	Hospital capability to register patients electronically, capture patient-reported information and manage records, as well as maintain a functional directory of care provider information.
Point-of-Care Order Entry (x2)	Hospital capability to electronically order tests and medications at the bedside or nursing station. Ordering may be done by any care provider, but must be electronically signed by a qualified practitioner. Includes availability of electronic decision support information at the time of ordering.
Clinical Documentation (x3)	Hospital capability to capture clinical patient information, reports, and structured data, as well as hospital capability to integrate these features into an electronic patient record (EPR).
Results Reporting (x4)	Hospital capability to electronically capture, present and interpret clinical, laboratory results and reports, and provide notifications/alerts of abnormal laboratory results.
Information Infrastructure (x5)	Hospital adoption of technical capabilities essential to the smooth, safe and effective use of e-Health applications.

For this research the hospital report data for Acute Care was downloaded for 2007 in order to link health outcomes data with HIT adoption data for that year. For patient satisfaction indicators, full data were available for 82 of the 123 participating hospitals. These indicators help to describe a patient's perception of quality of services provided by hospitals. Indicators including reports on patient experiences, evaluation of services, and their interaction with hospital staff are presented in Table 2. For all of these indicators a higher score is desirable, with a maximum of 100 in each case.

All the Ontario hospitals that could be matched by name between the e-Health adoption data and the patient satisfaction data were included in this study. 82 hospitals were included in the analysis, representing three hospital types or peer-groups (Teaching, Small and Community) and LHINs (Local Health Integration Networks) which represent the 14 health regions in Ontario.

Table 2. Patient Satisfaction Indicators

Overall Impressions	Patient views of their overall hospital experience, including the overall quality of care and services they received at the hospital, and their confidence in the doctors and nurses who cared for them. *A higher score means they were more likely to trust their health care team, and they were more likely to recommend the hospital*
Communications	Patient views about the amount and quality of the information and communications they received about their condition, treatment, and preparation for discharge and care at home, and whether they felt family and friends were given sufficient information. *A higher score means patients felt they understood what was happening*

	to them and they knew how to care for themselves after leaving the hospital.
Consideration	Patient views about whether they were treated with respect, dignity and courtesy. *A higher score means patients felt they were treated with respect concerning their preferences, whether they were involved in decisions about their care, and any communication or sharing of information about themselves and their care, when they desired it.*
Responsiveness	Patient assessments of the extent to which they got the care they needed in hospital, and how coordinated and integrated that care was when it was delivered. *A higher score means patients felt they did not have to wait long to see a doctor or get tests. It also means they felt staff helped control pain, and the nurses and doctors worked well together.*

ARCHITECTURE AND LEARNING ALGORITHM OF ADAPTIVE NEURO-FUZZY INFERENCE SYSTEM

The neuro-fuzzy technique is a soft computing method with a hybrid combination of artificial neural networks (ANN) and fuzzy inference systems (FIS). An adaptive neuro-fuzzy inference system (ANFIS) developed by Jang[80] is a system which incorporates the generic advantages of artificial neural networks (such as robustness and learning) and fuzzy logic (modeling imprecise and qualitative knowledge, handling uncertainty) and can solve certain complex problems (such as forecasting, prediction, and approximation) with a high degree of accuracy[81].

Architecture of ANFIS

The adaptive neuro-fuzzy inference system (ANFIS) is a multi-layer realization of the functionality of fuzzy systems, using neural networks with supervised learning and adaptation capability, the functional equivalent of a Sugeno-type fuzzy inference system[82, 83]. In such inference systems, the output of each rule is a linear combination of input variables plus a constant, and the final output is the weighted average of each rule's output. For a Sugeno fuzzy model with five inputs $(x_1, x_2, x_3, x_4, x_5)$ and one output y a typical rule set based on if-then rules can be expressed as:

$$\text{IF } x_1 = A_i \text{ and } x_2 = B_i \text{ and } x_3 = C_i \text{ and } x_4 = D_i \text{ and } x_5 = E_i$$
$$\text{THEN } y = \alpha_i x_1 + \beta_i x_2 + \chi_i x_3 + \phi_i x_4 + \gamma_i x_5 + \varepsilon_i , \qquad (1)$$

where i=1, 2,… k and $\{\alpha_i, \beta_i, \chi_i, \phi_i, \gamma_i\}$ are coefficients in Eq. (1) and ε_i is the residual (error). $\alpha_i, \beta_i, \chi_i, \phi_i, \gamma_i, \varepsilon_i$ are design parameters to be determined during the training stage, and A_i, B_i, C_i, D_i, E_i are the linguistic labels associated with the inputs x_1, x_2, x_3, x_4, x_5 respectively. The basis of ANFIS is to provide a method whereby the fuzzy modeling procedure can learn about a data set, in order to compute the membership function parameters that best allow the associated fuzzy inference system (FIS) to map the given input/output data. This learning method is similar to those used with neural networks. A more detailed description of the ANFIS model can be found in[80, 82, 83].

Figure 1 shows the architecture of the ANFIS structure with five inputs and one output. This architecture is formed by using five layers and thirty two if-then rules. The output of the *i*-th node is denoted in layer *l* as $O_{l,i}$ as specified in Equation 2.

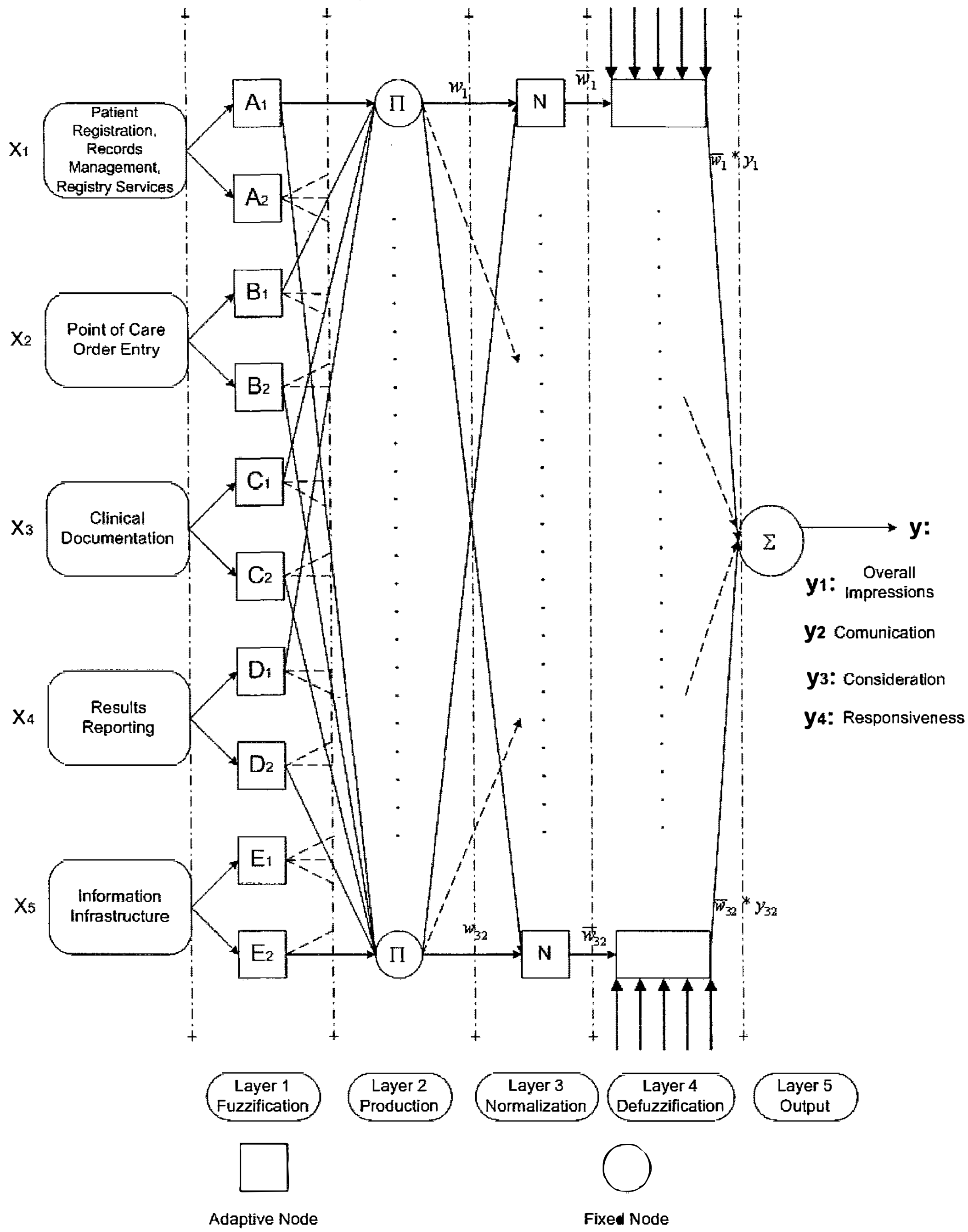

Figure 1. The ANFIS Architecture for a Five Input and Single Output Sugeno Fuzzy Model

In Figure 1, **Layer 1** is a fuzzification layer, where every node has a function described by

$$O_{1i} = \mu_{Ai}(x_1), i = 1,2\,; O_{1i} = \mu_{Bi}(x_2), i = 3,4\,; O_{1i} = \mu_{Ci}(x_3), i = 5,6;\; O_{1i} = \mu_{Di}(x_4), i = 7,8\,;$$
$$O_{1i} = \mu_{Ei}(x_5), i = 9,10\,. \tag{2}$$

The outputs $O_{l,i}$ identify the degree to which the input $x_{j,} j = 1,2...,5$ relates to the linguistic label associated with the *i*th node A_i, B_i, C_i, D_i, E_i respectively. The node function is determined by its membership function.

Different mathematical functions can be adopted to represent the membership function, which must be bounded from below by 0 and from above by 1. Typical membership functions are triangular, trapezoidal, and Gaussian. Since the Gaussian membership function is widely employed in fuzzy logic, it was selected for our study. It is expressed as follows:

$$\mu_{Ai}(x_1) = e^{-\frac{(x_1-a_i)^2}{2\delta_i^2}},\; \mu_{Bi}(x_2) = e^{-\frac{(x_2-a_i)^2}{2\delta_i^2}},...,\; \mu_{Ei}(x_5) = e^{-\frac{(x_5-a_i)^2}{2\delta_i^2}}, \tag{3}$$

where a_i and δ_i denote the center and width of the Gaussian function, respectively. The set $\{a_i, \delta_i\}$ are the parameter set which are referred to as premise parameters. The values of these parameters are tuned (adjusted) during the learning process. As a result, the shape of the Gaussian function will change according to the parameter values and could represent different forms of membership functions in the linguistic labels A_i, B_i, C_i, D_i, E_i.

Layer 2 is the production layer, which multiplies the outputs from Layer 1 and estimates the firing strength of a rule w_i. The output is a product of the five membership values:

$$O_{2i} = w_i = \mu_{Ai}(x_1) \times \mu_{Bi}(x_2) \times \mu_{Ci}(x_3) \times \mu_{Di}(x_4) \times \mu_{Ei}(x_5), i = 1,2,...32 \tag{4}$$

Layer 3 is the normalization layer, where each node estimates the ratio of the *i*th rule's firing strength (w_i) to the sum of the firing strength of all rules.

$$O_{3i} = \overline{w}_i = \frac{w_i}{\sum_{j=1}^{i} w_i}, i = 1,2,...32 \tag{5}$$

Layer 4 is the defuzzification layer, where the output from Layer 3 is multiplied by a linear function as:

$$O_{4i} = \overline{w_i} y_i = \overline{w_i}(\alpha_i x_1 + \beta_i x_2 + \chi_i x_3 + \phi_i x_4 + \gamma_i x_5 + \varepsilon_i), i = 1,2,...32; \tag{6}$$

where $\{\alpha_i, \beta_i, \chi_i, \phi_i, \gamma_i, \varepsilon_i\}$ are design parameters, referred to as consequent parameters.

Layer 5 is the total output layer with a single node, where all of the incoming signals are summed.

$$O_{5i} = \sum_i \overline{w}_i y_i = \frac{\sum_i w_i y_i}{\sum_i w_i}, i = 1,2,...32 \quad (7)$$

Learning algorithm

The overall output can be expressed as a linear combination of the consequent parameters; more precisely the output y can be rewritten as:

$$\begin{aligned} y &= \frac{w_1}{w_1 + w_2 + ... + w_{32}} y_1 + ... + \frac{w_{32}}{w_1 + w_2 + ... + w_{32}} y_{32} = \\ &= \overline{w}_1 y_1 + ... + \overline{w}_{32} y_{32} = \\ &= (\overline{w_1 x_1})\alpha_1 + (\overline{w_1 x_2})\beta_1 + (\overline{w_1 x_3})\chi_1 + (\overline{w_1 x_4})\phi_1 + (\overline{w_1 x_5})\gamma_1 + (\overline{w_1})\varepsilon_1 + ... \\ &+ (\overline{w_{32} x_1})\alpha_{32} + (\overline{w_{32} x_2})\beta_{32} + (\overline{w_{32} x_3})\chi_{32} + (\overline{w_{32} x_4})\phi_{32} + (\overline{w_{32} x_5})\gamma_{32} + (\overline{w_{32}})\varepsilon_{32} \end{aligned} \quad (8)$$

ANFIS uses the hybrid learning algorithm (HLA) which combines the back-propagation gradient descent method and least squares error estimation. The premise parameters defining the optimum value for the parameters of the membership functions are identified by the back-propagation learning algorithm, whereas the consequent parameters for each rule are identified by the least-squares error estimation to update the linear parameters in the adaptive network so as to minimize the error[80,82].

Lets p- is the number of fuzzy partitions of each variable and n- is the number of input variables. ANFIS uses parameter set S which can be decomposed into two sets:

$$S = S_1 \oplus S_2, \quad (9)$$

$S_1 =$ set of premise (nonlinear) parameters which represents the fuzzy partitions used in the rules:

$$S_1 = \{\{a_{11}, \partial_{11}\}, \{a_{12}, \partial_{12}\}, ..., \{a_{1p}, \partial_{1p}\}, ..., \{a_{np}, \partial_{np}\}\} \quad (10)$$

$S_2 =$ set of consequent (linear) parameters which represents the coefficients of linear functions in the rules:

$$S_2 = \{\{c_{10}, c_{11}, ..., c_{1n}\}, ..., \{c_{p^n 0}, c_{p^n 1}, ..., c_{p^n n}\}\} \quad (11)$$

ANFIS uses a two pass learning algorithm:

- *Forward Pass*: Here S_1 is unmodified and S_2 is computed using a Least Squared Error (LSE) algorithm.

- *Backward Pass*. Here S_2 is unmodified and S_1 is computed using a gradient descent algorithm such as back-propagation.

Output can be presented as:

$$Y = F(\overline{I}, S), \tag{12}$$

where $\overline{I}$ is the set of input variables, and F is a function of the fuzzy inference system. If there exists an identity function H such that the composite function $H \circ F(\overline{I}, S)$ is linear in some elements of S, then these elements can be identified by the LSE algorithm. Applying H to (12):

$$H(Y) = H \circ F(\overline{I}, S), \text{ where } H \circ F \text{ is linear in } S_2 . \tag{13}$$

For given values of S1, using K training data, we can transform the above equation into

$$B = AX, \tag{14}$$

where X is an unknown vector which contains the elements in S_2.
This is usually solved by

$$X^* = (A^T A)^{-1} A^T B, \tag{15}$$

where A^T is the transpose of A; $(A^T A)^{-1} A^T$ is the pseudo-inverse of A if $A^T A$ is nonsingular. The LSE minimizes the error $\|AX - B\|^2$ by approximating X with X^*. Rather than solving directly through $X^* = (A^T A)^{-1} A^T B$, in ANFIS it is solved iteratively:

$$\left.\begin{aligned} S_{i+1} &= S_i - \frac{S_i a_{(i+1)} a_{(i+1)}^T S_i}{1 + a_{(i+1)}^T S_i a_{(i+1)}} \\ X_{i+1} &= X_i + S_{(i+1)} a_{(i+1)} (b_{(i+1)}^T - a_{(i+1)}^T X_i) \end{aligned}\right\} for \quad i = 0, 1, \ldots, K-1, \tag{16}$$

where S_i is often called the covariance matrix; $X^* = X_K$; a_i^T - ith row vector in matrix A; b_i^T - ith element of vector B. The initial conditions to Eq. (16) are $X_0 = 0$ and $S_0 = \gamma I$, where γ is a positive large number, I is an identity matrix of dimension M, and $M = |S_2|$. The output of layer 5 is compared with the actual output and the error measure E_k for the $k^{th} (1 \le k \le K)$ entry of the training data is calculated as:

$$E_k = \sum_{m=1}^{N(L)} (D_{m,k} - O_{m,k}^L)^2, \tag{17}$$

where $N(L)$- is number of nodes in Layer L; $D_{m,k}$- mth component of k*th* desired output vector; $O^L_{m,i}$-mth component of actual output vector produced by kth input vector. The sum of squared errors for the entire training set is:

$$E = \sum_{k=1}^{K} E_k \,. \tag{18}$$

In order to develop a learning procedure that implements gradient descent in E over the parameter space, the error rate $\delta = \partial E_k / \partial O$ for kth training data and for each node output x is calculated. The error rate for output node at layer (L, i) is calculated from Equation 17.

$$\delta = \frac{\partial E_k}{\partial O^L_{i,k}} = -2(D_{i,k} - O^L_{i,k}) \tag{19}$$

This delta value gives the rate at which the output should be changed in order to minimize the error function. As the output of adaptive nodes depends on design parameters, design parameters must be updated accordingly. This delta value of output must be propagated backward to inner layers in order to distribute the output error to all layers connected to it and to adjust the corresponding parameters. For any lth layer the delta value may be calculated using the following formula:

$$\frac{\partial E_k}{\partial O^l_{i,k}} = \sum_{m=1}^{l+1} \frac{\partial E_k}{\partial O^{l+1}_{m,k}} \frac{\partial O^{l+1}_{m,k}}{\partial O^l_{i,k}} \tag{20}$$

where $1 \le l \le L-1$. So the error rate of an internal node can be expressed as a linear combination of the error rates of the nodes in the next layer.

If α is a set of design parameters of a given adaptive network, then

$$\frac{\partial E_k}{\partial \alpha} = \sum_{O' \in S} \frac{\partial E_k}{\partial O'} \frac{\partial O'}{\partial \alpha}, \tag{21}$$

where S is the set of adaptive nodes whose outputs depends on α. The derivative of overall error measure E with respect to α will be:

$$\frac{\partial E}{\partial \alpha} = \sum_{k=1}^{K} \frac{\partial E_k}{\partial \alpha} \tag{22}$$

The updated formula generic parameter α is

$$\Delta\alpha = -\eta \frac{\partial E}{\partial \alpha} \tag{23}$$

where η is the learning rate, expressed as

$$\eta = \frac{s}{\sqrt{\sum_{\alpha}\left(\frac{\partial E}{\partial \alpha}\right)^2}} \tag{24}$$

Here, s - is the step size, the length of each gradient transition in the parameter space.

Each epoch of the HLA is composed of a forward pass and a backward pass. In the forward pass after training data is provided, the functional signals go forward to calculate each node output (matrices A, B from Equation 14 and parameters in S_2 from Equation 16). The overall output in Layer 5 is calculated using LSE. Then this output is compared with actual outputs. The error measure can be calculated from Equation 17 and 18. In a backward pass, error rates propagate backward from the output end towards the input end and nonlinear parameters S_1 in Layer 1 are updated using the gradient descent method (Equations 19-24)[80, 82].

IMPLEMENTATION

Since our study involves four output indicators which represent patient satisfaction with their hospital experience, the training process is carried out independently for each output satisfaction indicator. As shown in Figure 2, each ANFIS modeling process generates a fuzzy inference system between each output indicator and five input indicators which represent the level of HIT adoption in Ontario hospitals. Table 3 represents the description of each input and output indicator, its range, and the number and type of membership function used. Each fuzzy inference system contains different membership rules, which can be used for interpreting the relationships between input and output indicators.

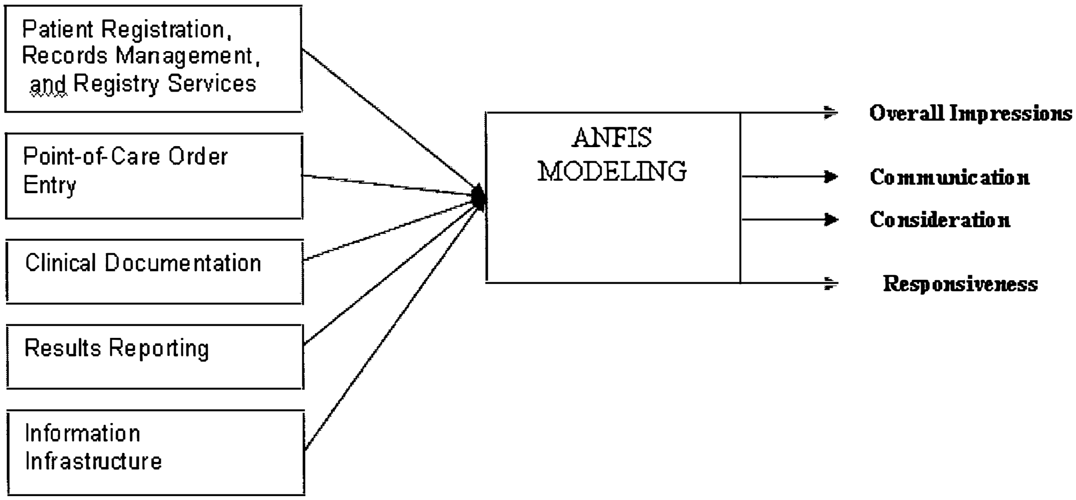

Figure 2. The ANFIS Modeling System for Hospital Patient Satisfaction

Numerical data in ANFIS modeling can be partitioned by grid partition (when the number of the fuzzy partition for each input indicator is known) or subtractive clustering (requires an estimate of the number of clusters) [84].

Table 3. Description of Input and Output Indicators
Number of Hospitals N = 82

Parameter name	Range	Mean	Number of MF	Type of MF
Inputs				
Patient Registration, Records Management & Registry Services (PR_RM_RS)	[56,100]	86.50	2	*Gaussian*
Point-of-Care Order Entry (PCOE)	[0,100]	55.61	2	*Gaussian*
Clinical Documentation (CD)	[21,99]	59.90	2	*Gaussian*
Results Reporting (RP)	[6,94]	76.40	2	*Gaussian*
Information Infrastructure	[11,94]	66.68	2	*Gaussian*
Outputs				
Overall Impressions	[74.6,94.4]	85.43		Linear
Communication	[69.9, 88.9]	78.78		Linear
Consideration	[71.7,91.5]	82.15		Linear
Responsiveness	[72.9,92.3]	83.23		Linear

The number of rules in an ANFIS model is equal to the number of clusters estimated through subtractive clustering. For subtractive clustering the important parameter is the radius, which presents a vector of entries between 0 and 1 that specifies a cluster center's range of influence in each of the data dimensions, assuming that the data falls within a unit hyper box[84]. The centers of the membership functions are obtained by projecting the center of each cluster on the corresponding axis, and the widths of membership functions are obtained on the basis of the cluster radius[85]. Small radius values generally result in finding a few large clusters, which will lead to very a large number of rules. We implemented our models for radii from 0.40 to 0.65 with step size 0.05 (i.e. the cluster radius was varied from 0.4 to 0.65 times the width of the data hypercube). This produced models of varying size, obtaining from 47 to 4 rules correspondingly.

The number of rules in ANFIS where the data are partitioned by grid partition is equal to p^n, where p is the number of fuzzy partitions and n is the number of inputs. The input response range was divided into two regions according to the input data {Pilot/Implemented, Fully Implemented}. Since the number of membership functions associated with five input indicators is two, our five-dimensional input space can be partitioned into 2^5 subspaces, meaning that each fuzzy inference set contains 32 rules.

The Gaussian function was selected for the membership function, and the center and width of each membership function adjusted during ANFIS training. For the Sugeno-type fuzzy inference system, the membership function of the output indicator can be either linear or constant. For this application, the linear type of output was selected, as our outputs are not constant and cover a range of values (Table 3). The ANFIS architecture with training parameters is presented in Table 4.

Table 4. ANFIS Architecture and Training Parameters

Architecture:	
Layers	5
Inputs	5
Rules	Subtractive - 4,5,8,16,32,47 Grid - 32
Model outputs	Grid - 1; Subtractive - 4.
Membership function	*Gaussian*
Training parameters	
Partition	Grid, Subtractive
Optimization method	Hybrid Learning Algorithm: back-propagation for parameters associated with the input membership functions and least squares errors estimation for parameters associated with the output membership functions

In order to determine the best number of membership functions for each indicator, which is directly related to the required number of parameters in the rule base, an analysis was carried out to validate empirically the predictive ability of each model while varying the number of modeling parameters. The statistical performance measures for evaluating the accuracy of each predictive model considered are: root mean square error (RMSE) and adjusted coefficient of determination $R^2{}_{Adjusted}$, which are defined in Equations 25 and 26, respectively:

$$RMSE = \sqrt{\frac{\sum_{K=1}^{N}(P_K - A_K)^2}{N}}; \qquad (25)$$

$$R_{Adjusted}^{\ 2} = 1 - \left(1 - \frac{\sum_{K=1}^{N}(A_K - \overline{A}_m)(P_K - \overline{P}_m)}{\sqrt{\sum_{K=1}^{N}(A_K - \overline{A}_m)^2} \times \sqrt{\sum_{K=1}^{N}(P_K - \overline{P}_m)^2}}\right)\left(\frac{N-1}{N-m-1}\right) = \qquad (26)$$

$$= 1 - (1 - R^2)\left(\frac{N-1}{N-m-1}\right)$$

where A_k - k[th] actual value, $\overline{A}_m$ -actual mean value; P_k - k[th] predicted value, $\overline{P}_m$ -predicted mean value, N- number of observations, m- number of independent variables.

RESULTS AND DISCUSSION

Of the 82 data pairs, 61 (74.4%) were used for training the model. We implemented 7 models for each 4 outputs to find the best prediction of patient satisfaction indicators based on HIT adoption. The membership functions for the first input indicator and the "Overall Impressions" output are shown in Figure 3.

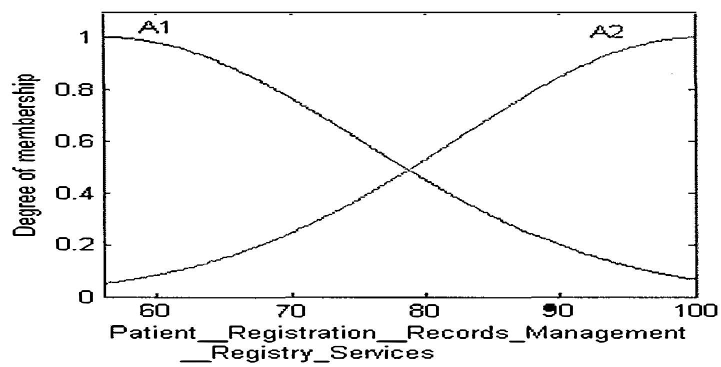

Figure 3. Gaussian Membership Functions for "Patient Registration, Records Management and Registry Services" Variable after Training for "Overall Impressions" Output.

Table 5 shows ANFIS model specific clustering algorithm parameters (radius value, number of generated rules) for every calculated ANFIS model for each patient satisfaction indicator. It also presents the values of the performance measures RMSE and adjusted coefficient of determination $R^2_{Adjusted}$ between the actual and the predicted output values for each model trained. As can be seen from this table, the grid partition model with 32 rules and subtractive clustering with radius 0.4, 0.45 and 0.5 (with 47, 32 and 16 rules correspondingly) seemed to perform best overall in terms of RMSE and $R^2_{Adjusted}$. Since the grid model has better interpretative power, and as the number of fuzzy partitions for every input indicator is 2 and can be identified linguistically, we have chosen this model for explaining and interpreting the results.

Table 5 Prediction Accuracy Results

Model	Subtr. Radii/ Model	Number of Rules	Accuracy Measures	
			RMSE	Adjusted R^2
Overall Impressions				
1	0.40	47	0.0625	0.9999
2	0.45	32	0.0625	0.9999
3	0.50	16	0.0625	0.9999
4	0.55	8	2.4218	0.7482
5	0.60	5	2.7087	0.6689
6	0.65	4	2.7989	0.6426
7	Grid	32	0.0724	0.9998
Communication				
1	0.40	47	0.3592	0.9947
2	0.45	32	0.3592	0.9947
3	0.50	16	0.3592	0.9947
4	0.55	8	2.2176	0.7726
5	0.60	5	2.5082	0.6969
6	0.65	4	2.5887	0.6730
7	Grid	32	0.4165	0.9928
Consideration				
1	0.40	47	0.1093	0.9996
2	0.45	32	0.1093	0.9996
3	0.50	16	0.1093	0.9996
4	0.55	8	2.4950	0.7369
5	0.60	5	2.7903	0.6535
6	0.65	4	2.8070	0.6501
7	Grid	32	0.1268	0.9994
Responsiveness				
1	0.40	47	0.2343	0.9980
2	0.45	32	0.2343	0.9980
3	0.50	16	0.2343	0.9980
4	0.55	8	2.5142	0.7429
5	0.60	5	2.9444	0.6201
6	0.65	4	2.8867	0.6406
7	Grid	32	0.2716	0.9975

The results, which can be obtained either in 3-D or 2-D plots, are fairly simple to read and give information about the associations between the input(s) and the output from the modeling system. The examples of 3-D plots (surface or sensitivity plots), shown on Figures 4 and 5, present the relationships between the inputs and output parameters found by the ANFIS model.

Since these relationships exist in the fuzzy domain their associations can be represented by smooth surfaces (McNamee et al., 2005).

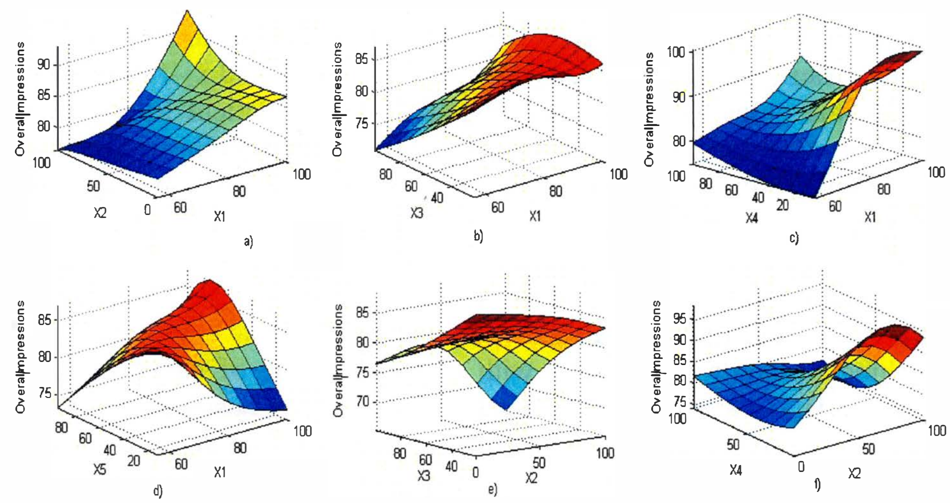

Figure 4. 3-D Surface Simulation for Patient Satisfaction Indicator "Overall Impression" by HIT Adoption Indictors: x_1- "Patient Registration, Records Management & Registry Services"; x_2- "Point-of-Care Order Entry"; x_3- "Clinical Documentation"; x_4- "Results Reporting"; x_5- "Information Infrastructure" for Hamilton Health Sciences Corporation.

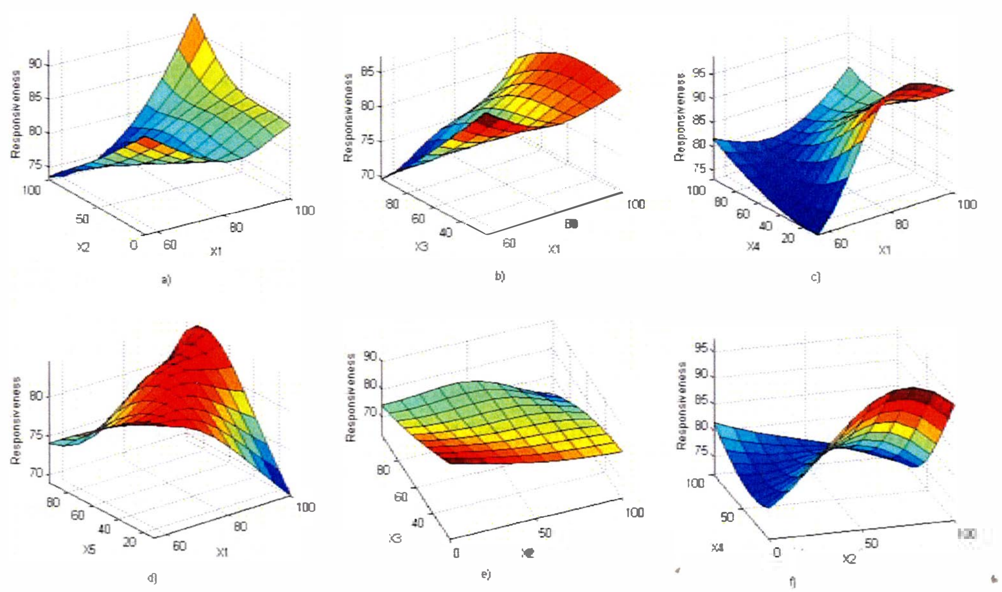

Figure 5. 3-D Surface Simulation for Patient Satisfaction Indicator "Responsiveness" by HIT Adoption Indictors: x_1- "Patient Registration, Records Management & Registry Services"; x_2- "Point-of-Care Order Entry"; x_3- "Clinical Documentation"; x_4- "Results Reporting"; x_5- "Information Infrastructure" for Hamilton Health Sciences Corporation.

Interpretations of these plots can be carried out in terms of input-output relationships by locating the point of each input indicator along its respective axis and locating the output point along the surface of the plot. For example, Figure 4a presents the input indicators of x_1- "Patient Registration, Records Management & Registry Services" adoption and x_2- "Point-of-Care Order Entry" adoption with the output "Overall Impressions". When "Patient Registration, Records Management & Registry Services" is fully implemented (high) and "Point-of-Care Order Entry" adoption has increased to full implementation, the patient satisfaction indicator "Overall Impressions" increases.

Figure 6 (a-d) represents a two-dimensional view of the impact of the "Patient Registration, Records Management & Registry Services" adoption indicator on average patient satisfaction indicators for teaching hospitals in Ontario, with different levels of adoption for other HIT indicators. The average HIT adoption indicator values for teaching hospitals can be represented as $[x_1, x_2, x_3, x_4, x_5]$ or [84 59 63 88 72] which basically show 'pilot implementations' of all HIT, especially for "Point-of-Care Order Entry (x_1)" and "Clinical Documentation (x_2)" systems. The average patient satisfaction scores ("Overall Impressions (y_1)", "Communication (y_2) ", "Consideration (y_3)" and " Responsiveness (y_4)") for teaching hospitals are [85.9 78.7 81.6 81.3] respectively.

Several simulation scenarios were considered:

1) Varying (until 'full implementation') "Patient Registration, Records Management & Registry Services (x_1)" when all other systems implementation scores remain the same can be presented as [Nan 59 63 88 72], where Nan is the indicator which is being varied;
2) Varying (until 'full implementation') "Patient Registration, Records Management & Registry Services (x_1)" with continuous implementation "Point-of-Care Order Entry (x_2) " systems when all other systems implementation scores remain the same can be presented as [Nan 80 63 88 72];
3) Varying (until 'full implementation') "Patient Registration, Records Management & Registry Services (x_1)" with continuous implementation "Clinical Documentation (x_3)" systems when all other systems implementation scores remain the same can be presented as [Nan 59 80 88 72];
4) Varying (until 'full implementation') "Patient Registration, Records Management & Registry Services (x_1)" with continuous implementation "Point-of-Care Order Entry (x_2) " and "Clinical Documentation (x_3)" systems when all other systems implementation scores remain the same can be presented as [Nan 80 80 88 72];
5) Varying (until 'full implementation') "Patient Registration, Records Management & Registry Services (x_1)" with continuous implementation "Information Infrastructure (x_5) " systems when all other systems implementation scores remain the same can be presented as [Nan 59 63 88 80].

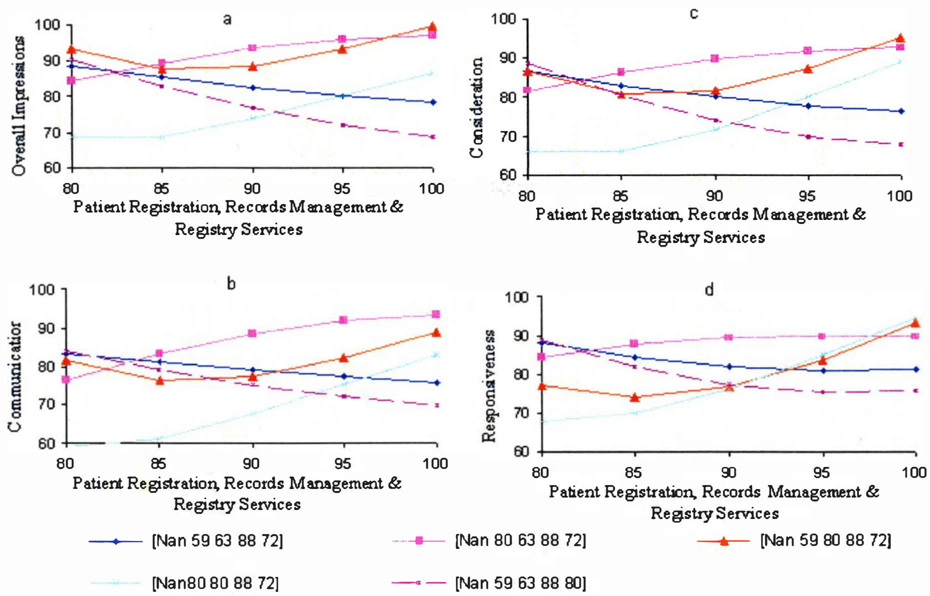

Figure 6. Impact of "Patient Registration, Records Management & Registry Services" by Different Scenario Simulations on Patient Satisfaction: a) Overall Impression; b) Communication; c) Consideration; d) Responsiveness, for Average Ontario Teaching Hospital Simulation. (Nan is indicator being varied.)

'Full implementation' of only "Patient Registration, Records Management & Registry Services" systems, as well as "Information Infrastructure" systems, without stable implementation of other systems, has a negative impact on all indicators of patient satisfaction (Scenario 1 and Scenario 5).

An increase of "Point-of-Care Order Entry" systems implementations from 59 to 80% (Scenario 2), with 'fully implemented' "Patient Registration, Records Management & Registry Services" improves "Overall Impressions" from 85.9 to about 97% (Figure 6a), patient perceptions about "Communication" from 79 to about 93% (Figure 6b), and patient perceptions about "Consideration" and "Responsiveness" from 81 to 92% (Figure 6c) and 81 to 89% (Figure 6d) respectively.

An increase of "Clinical Documentation" systems implementations from 63 to 80% (Scenario 3), with 'fully implemented' "Patient Registration, Records Management & Registry Services" improves "Overall Impressions" from 85.9 to about 100% (Figure 6a), patient perceptions about "Communication" from 79 to about 89% (Figure 6b), and patient perceptions about "Consideration" and "Responsiveness" from 81 to 95% (Figure 6c) and 81 to 93% (Figure 6d) respectively.

An increase of "Point-of-Care Order Entry" and "Clinical Documentation" systems implementations from 59 to 80% and 63 to 80% respectively (Scenario 4), with 'fully implemented' "Patient Registration, Records Management & Registry Services" slightly enhances "Overall Impressions" from 85.9 to about 86% (Figure 6a), patient perceptions about "Communication" from 79 to about 83% (Figure 6b), and patient perceptions about

"Consideration" and "Responsiveness" from 81 to 89% (Figure 6c) and 81 to 95% (Figure 6d) respectively

An alternative representation of Figure 6 (a-d) is shown in Figure 7 (a-e), where the patient satisfaction indicators with different levels of HIT adoption on the "Patient Registration, Records Management & Registry Services" adoption indicator for different scenarios are presented. The patient satisfaction scores for each of four average indicators for teaching hospitals in Ontario can be observed in Figure 7a where the initial "Patient Registration, Records Management & Registry Services" adoption indicator is 84%.

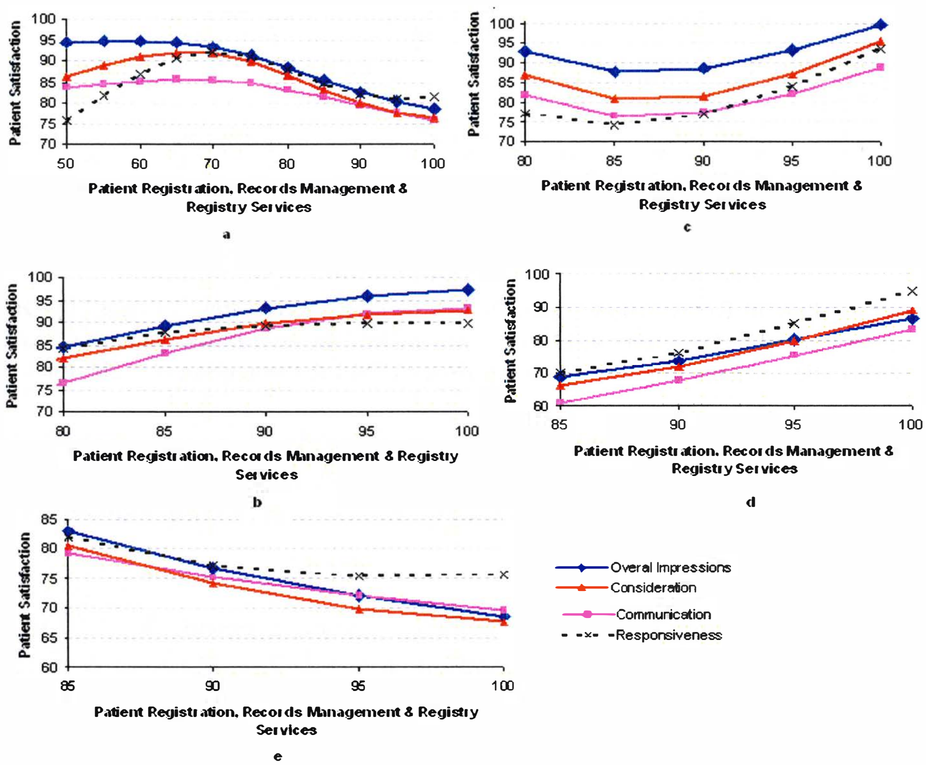

Figure 7. Patient Satisfaction as a Function of "Patient Registration, Records Management & Registry Services" Adoption Level and by Constant Values for Other Input Indicators: a) [Nan 59 63 88 72]; b) [Nan 80 63 88 72]; c) [Nan 59 80 88 72]; d) [Nan 80 80 88 72]; e) [Nan 59 63 88 80] for Average Ontario Teaching Hospital Simulation. (Nan is the indicator being varied).

CONCLUSIONS

Patient satisfaction as an outcome indicator of health care delivery has been mainly accepted as a significant indicator for measuring quality of health care, and is a critical component of performance improvement and clinical effectiveness. Predicting patient satisfaction through hospital adoption of health information technology could provide a better understanding of the benefits of increased investment in HIT. This is a highly complicated and difficult task as there are many factors that influence patient perceptions of hospital service, and patient satisfaction is a human perception which is subjective and vague. Soft computing methodologies which integrate the modeling of imprecise and qualitative knowledge with adaptive learning ability through an adaptive neural fuzzy inference system (ANFIS) have been successfully applied for solving such complex problems.

In this study ANFIS was adopted to explore and predict non-linear and uncertain patient satisfaction measures as functions of HIT adoption in Ontario hospitals. Some conclusions concerning the impact of HIT implementation for average teaching hospitals were obtained through the ANFIS analysis. We found that full implementation of only "Patient Registration, Records Management & Registry Services" systems, as well as "Information Infrastructure" systems, without continuous implementation of other systems, has a negative impact on all indicators of patient satisfaction.

The accuracy of each predictive model was evaluated by calculating statistical performance measures which show very promising predictive power for patient satisfaction dimensions, such as "Overall Impressions", "Communication", "Consideration" and "Responsiveness". We therefore conclude that the proposed ANFIS modeling technique can be used as a decision support mechanism to assist government and policy makers in predicting patient satisfaction through the implementation of HIT in hospitals.

Some limitations of this study should be acknowledged, which can also be considered opportunities for future research. This study is an initial step toward identifying the potential contribution of HIT adoption in hospitals as predictors of patient satisfaction. The major limitation of this study is that an assumption has been made that HIT adoption indicators are the only indicators that impact patient satisfaction, and that other indicators can be held constant while HIT adoption indicators change. Other indicators affecting hospital capacity and performance, including the number of general and intensive care beds, imaging devices, and procedure suites like operating rooms and cardiac catheterization labs, length of stay, waiting time, socio-demographic variables, etc., might be included in future studies. Our findings are also subject to geographic restrictions and may not generalize to patients in non- acute hospitals. Future studies are needed to evaluate the moderating effects of various hospital indicators on patient satisfaction.

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