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Predicting the impact of hospital health information technology adoption on patient satisfaction

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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), leading to a better understanding of the benefits of increased HIT investment.

Data and methods: The solution proposed is based on comparing the predictive capability of artificial neural networks (ANNs) with the adaptive neuro-fuzzy inference system (ANFIS). The latter 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. Secondary data from 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 acute hospitals were used as outputs.

Results: Eight 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 $R^2{}_{Adjusted}$. For all four patient satisfaction indicators, the performance of ANFIS was found to be more effective ($R^2_{Adjusted} = 0.99$) when compared with the results of ANN modeling in predicting the impact of HIT adoption on patient satisfaction ($R^2_{Adjusted} = 0.86$–0.88).

Conclusions: The impact of HIT adoption on patient satisfaction was obtained for different HIT adoption scenarios using ANFIS simulations. The results through simulation scenarios revealed that full implementation of HIT in hospitals can lead to significant improvement in patient satisfaction. We 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 resulting from the implementation of HIT in hospitals

1. 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 [1,13,14]. HIT may also improve 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 [4,15]. These improved processes are expected to lead to significant reductions in medical errors [16–18]. The automated access of physicians to patient laboratory and other diagnostic results may reduce lost orders and errors due to illegible handwriting, and minimize duplicate orders [19,20], thus improving health care quality outcomes and efficiency [21]. 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 [22,23].

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Although research examining the impact of HIT adoption on patient satisfaction has shown increased patient satisfaction, most research has concentrated primarily on HIT adoption in physician offices [24], adoption of only one system, such as a computer-based patient record system [25,26] or special patient treatment [27]. Most related studies have 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 [25–28].

Predicting and measuring patient satisfaction as a result of HIT adoption is a complicated and difficult task, as there are many factors involved. First, uncertainty is inherent in clinical medicine and this may contribute to variability in physician practice patterns, patient satisfaction, and exchange of information [29]. 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 [30]. 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 receive about their conditions and treatments; patient perceptions of their providers' competence and caring, and how coordinated and integrated care was when it was delivered [31,32]. Lastly, patient satisfaction is a human perception which is subjective and vague [33]. It is affected by several individual factors such as personality characteristics and health status, and socio-demographic variables, such as education, age, and gender [22,23,34,47,48]. 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 [33,35,36]. In addition, differences in individual perceptions and personalities mean that the same words can mean very different perceptions in the viewpoints of different individuals [37].

Artificial intelligence (AI) algorithms, such as fuzzy logic, artificial neural networks (ANNs) and adaptive neuro-fuzzy inference systems (ANFIS), have provided alternative methods that can tackle the non-linearity, imprecision, uncertainty, and partial truths found in the real world when modeling complex systems [38–45]. Because AI is adaptive and relies on observed data rather than on an analytical model of the system, the resulting scheme is robust. Recent reviews of the application of AI computing show that these approaches have been widely applied for financial stock market prediction [41], agricultural and biological engineering [42], medical diagnosis prediction [43–52] and many other complex fields. However, there have been few or no studies of the use of AI techniques to analyze and predict the impact of HIT adoption on patient satisfaction. In fact, there have been few studies of the utilization of AI on customer satisfaction prediction and performance [33,35,53–57]. To the best of our knowledge (based on the open literature) the use of ANN and ANFIS models for predicting patient perceptions of satisfaction through hospital adoption of health information technology have not been reported.

To fill this gap, we have studied the predictive capability of the hospital adoption of health information technology on patient satisfaction by using both ANN and ANFIS approaches. We combined data 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. By comparing the results of these methods with one another, their advantages and disadvantages became evident. ANFIS modeling and simulation proved to be the best of these two predictive approaches to enable a preliminary understanding of the impact of HIT on hospital patient satisfaction.

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 ANNs and ANFIS is discussed. Implementation, input selection and model validation details are given in Section 4. Results are presented in Section 5, followed by conclusions in Section 6.

2. 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 [58]. One of their projects was a joint study with the Ontario Hospital Association (OHA) to measure progress in HIT adoption capability and use in the province of Ontario through the 2007 e-Health Adoption Survey Top Line Report [59]. The report portrays the extent to which various clinical practices are capturing, using, and sharing health information through information and communication technologies. This study evaluated hospital capability throughout 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, 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 developed a normalized overall score for each indicator on the range 0–100 [59]. We used practical applications of information and communications technologies (e-Health) in Ontario hospitals, such as computer-based patient records, electronic health records, electronic medical records, telemedicine, and decision support systems, in the delivery of health care to predict patient satisfaction. We selected five indicators of the level of e-Health capability and use: "Patient registration, records management & registry services" (x_1), "Point-of-care order entry" (x_2), "Clinical documentation" (x_3), "Results reporting" (x_4), "Information infrastructure" (x_5).

Table 1
HIT adoption indicators.

Indicator	Description
Patient registration, records management, and registry services (x_1)	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 (x_2)	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 (x_3)	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 (EHR)
Results reporting (x_4)	Hospital capability to electronically capture, present and interpret clinical, laboratory results and reports, and provide notifications/alerts of abnormal laboratory results
Information infrastructure (x_5)	Hospital adoption of technical capabilities essential to the smooth, safe and effective use of eHealth applications. Hospital capability to secure personal health information (PHI), authenticate authorized users when they attempt to access the EHR/EMR, and electronically provide a data audit

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 patients 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*

Of the 211 Ontario hospitals that were invited to participate in the survey that we used, 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) [60]. The HRRC is an independent research collaborative dedicated to performing research related to performance measurement within Ontario hospitals, and its reports are available from http://www.hospitalreport.ca/downloads/annual.html. For this research the hospital report data for acute care were 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 acute care hospitals in Ontario. These indicators help to describe a patient's perception of quality of services provided by hospitals, and included reports on patient experiences, evaluation of services, and their interaction with hospital staff (see Table 2). For all of these indicators a higher score is desirable, with a maximum of 100 in each case.

The HIT adoption survey included the responses of acute hospitals as well as responses for complex continuing care (CCC), rehabilitation, and mental health hospitals. As we are interested only in acute care hospitals, since these correspond with the satisfaction survey data, the CCC, rehabilitation and mental health hospitals were excluded from the analysis (20 hospitals of the total of 138). There remained 118 acute care hospitals with HIT adoption data (from the 123 acute care hospitals in 2007 in Ontario) versus 82 acute care hospitals that had reported patient satisfaction data.

All Ontario acute care hospitals that could be matched between the e-Health adoption data (138 hospitals), and the health satisfaction data (82 hospitals) were included in this study. From the 123 acute care hospitals with patient satisfaction data, only 82 could be matched between the two secondary data surveys. Matching was done by hospital name. Table 3 provides the characteristics of the 82 acute care hospitals that were included in the final analysis, by indicator. There is a significant difference between the number of beds for teaching, community and small hospitals included; $F(2,78) = 46.93$, $p < 0.05$. All four indicators of patient satisfaction in small hospitals were significantly different from teaching and community hospitals ($p < 0.05$), but there were no significant differences between teaching and community hospitals.

A technique to address problems of nonresponse bias was used to weight survey respondents based on all acute hospitals in Ontario in 2007 and to compare the weighted and unweighted means of the resulting indicators [61]. If they differed, we might conclude that these differences indicate that there is non-response bias in the data, assuming that the indicators have an association with the response rate. To address this problem we weighted survey respondents based on hospital type for all acute hospitals in Ontario. Table 3 shows both the unweighted and weighted means and standard errors of means for all indicators. There is no significant difference between means, so we concluded that there is no nonresponse bias in our data. Our results confirm the published findings of a meta-analysis of 59 surveys, that there is a very weak relationship between the nonresponse rate and nonresponse bias [62].

3. Architectures and learning algorithms for ANN and ANFIS

3.1. Artificial neural networks

A multilayer perceptron (MLP) is a feedforward ANN model that maps sets of input data onto an appropriate output set. An MLP consists of multiple layers of nodes in a directed graph, with each layer fully connected to the next one. Except for the input nodes,

Table 3
Characteristics of acute care hospitals by type.

Variable	Means (st. error of means) by hospital type							
	Unweighted				Weighted**			
	Teaching	Small	Community	Total	Teaching	Small	Community	Total
Number of hospitals (percentage)	14 (17.1%)	21 (25.6%)	47 (51.3%)	82 (100%)	10 (12.2%)	29 (35.8%)	43 (52.0%)	82 (100%)
Number of hospital beds staffed*	601 (72.7)	50 (5.3)	283 (26.0)	278 (27.4)	601 (87.3)	50 (4.5)	283 (27.3)	239 (25.9)
Overall impressions	85.9 (0.5)	88.7 (0.7)	83.8 (0.5)	85.4 (0.4)	85.9 (0.6)	88.7 (0.6)	83.8 (0.5)	85.8 (0.4)
Communication	78.7 (0.6)	82.1 (0.7)	77.3 (0.5)	78.8 (0.4)	78.7 (0.7)	82.1 (0.6)	77.3 (0.5)	79.2 (0.4)
Consideration	81.6 (0.4)	86 (0.6)	80.6 (0.5)	82.2 (0.4)	81.6 (0.5)	86 (0.5)	80.6 (0.5)	82.6 (0.4)
Responsiveness	81.3 (0.6)	87.2 (0.6)	82.0 (0.5)	83.2 (0.4)	81.3 (0.8)	87.2 (0.5)	82.0 (0.5)	83.8 (0.4)
Patient registration, records management & registry services	84.4 (2.5)	80.4 (2.4)	89.9 (1.2)	86.5 (1.1)	84.4 (3.0)	80.4 (2.0)	89.9 (1.2)	85.8 (1.1)
Point-of-care order entry	58.6 (6.5)	47.8 (6.2)	58.2 (2.5)	55.6 (2.4)	58.6 (7.8)	47.8 (5.2)	58.2 (2.6)	54.5 (2.5)
Clinical documentation	63.4 (3.3)	50.5 (4.1)	63.1 (2.0)	59.9 (1.7)	63.4 (4)	50.5 (3.5)	63.1 (2.1)	58.6 (1.8)
Results reporting	88.2 (2.1)	62 (4.8)	79.3 (1.6)	76.4 (1.9)	88.2 (2.6)	62 (4.0)	79.3 (1.7)	74.2 (2.0)
Information infrastructure	71.9 (3.3)	55.6 (4.4)	70.1 (1.9)	66.7 (1.8)	71.9 (3.9)	55.6 (3.7)	70.1 (12.0)	65.1 (1.9)

* *Source*: Canadian MIS database (CMDB), CIHI, 2006–2007.
** Proportional weight based on number of acute care hospitals in Ontario in 2007 (calculated by authors).

each node is a neuron (or processing element) with a nonlinear activation function. MLP utilizes a supervised learning technique called backpropagation for training the network [63].

3.2. Adaptive neuro-fuzzy inference system

The fuzzy inference system (FIS) involves knowledge representation where each fuzzy rule describes a local behavior of the system. ANNs and FIS, as AI computational methods, offer advantages over conventional modeling, including the ability to handle large amounts of noisy data from dynamic and nonlinear systems, especially when the underlying physical relationships are not fully understood. Each of these techniques has proven to be effective when used on its own. However, when combined together, the individual strengths of each approach can be exploited in a synergistic manner for the construction of powerful intelligent systems. In recent years, the integration of ANNs and fuzzy logic has given birth to new research into neuro-fuzzy systems.

ANFIS is a system developed by Jang [64] which incorporates the generic advantages of ANNs (such as robustness and learning) and fuzzy logic (modeling imprecise and qualitative knowledge, and handling uncertainty) and can solve certain complex problems (such as forecasting, prediction, and approximation) with a good degree of accuracy [65].

3.2.1. Architecture of ANFIS

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 FIS [66,67]. 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:

$$\begin{aligned} &\text{IF}\, x_1 = A_i \,\text{and}\, x_2 = B_i \,\text{and}\, x_3 = C_i \,\text{and}\, x_4 = D_i \,\text{and}\, x_5 = E_i \\ &\text{THEN}\, y = \alpha_i x_1 + \beta_i x_2 + \chi_i x_3 + \phi_i x_4 + \gamma_i x_5 + \varepsilon_i, \end{aligned} \tag{1}$$

where $i = 1,2,\ldots, k$ is a node associated with every linguistic label of each five inputs; $\{\alpha_i, \beta_i, \chi_i, \phi_i, \gamma_i\}$ 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 FIS to map the given input/output data. This learning method is similar to those used with ANNs. A more detailed description of the ANFIS model can be found in [64,66,67].

Fig. 1 shows the architecture of an 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 ith node is denoted in layer l as $O_{l,i}$ as specified in Eq. (2).

In Fig. 1, Layer 1 is a fuzzification layer, where every node has a function described by

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

The outputs $O_{l,i}$ identify the degree to which the input $x_j, j = 1, 2\ldots, 5$ relates to the linguistic label associated with the ith 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:

$$\begin{aligned} &\mu_{Ai}(x_1) = e^{-((x_1-a_i)^2/2b_i^2)}, \mu_{Bi}(x_2) = e^{-((x_2-a_i)^2/2b_i^2)}, \ldots, \mu_{Ei}(x_5) \\ &\quad = e^{-((x_5-a_i)^2/2b_i^2)}, \end{aligned} \tag{3}$$

where a_i and b_i denote the center and width of Gaussian function i, respectively. The parameter set $\{a_i, b_i\}$ contains the so-called 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 for 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:

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

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

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

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

$$\begin{aligned} &O_{4i} = \bar{w}_i y_i = \bar{w}_i(\alpha_i x_1 + \beta_i x_2 + \chi_i x_3 + \phi_i x_4 + \gamma_i x_5 + \varepsilon_i), \\ &\qquad i = 1, 2, \ldots, 32; \end{aligned} \tag{6}$$

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.

$$O_{5i} = \sum_i \bar{w}_i y_i = \frac{\sum_i w_i y_i}{\sum_i w_i}, \quad i = 1, 2, \ldots, 32 \tag{7}$$

3.2.2. 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:

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

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 least-squares error estimation to update the linear parameters in the adaptive network so as to minimize the error [64,66].

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

$$S = S_1 \oplus S_2, \tag{9}$$

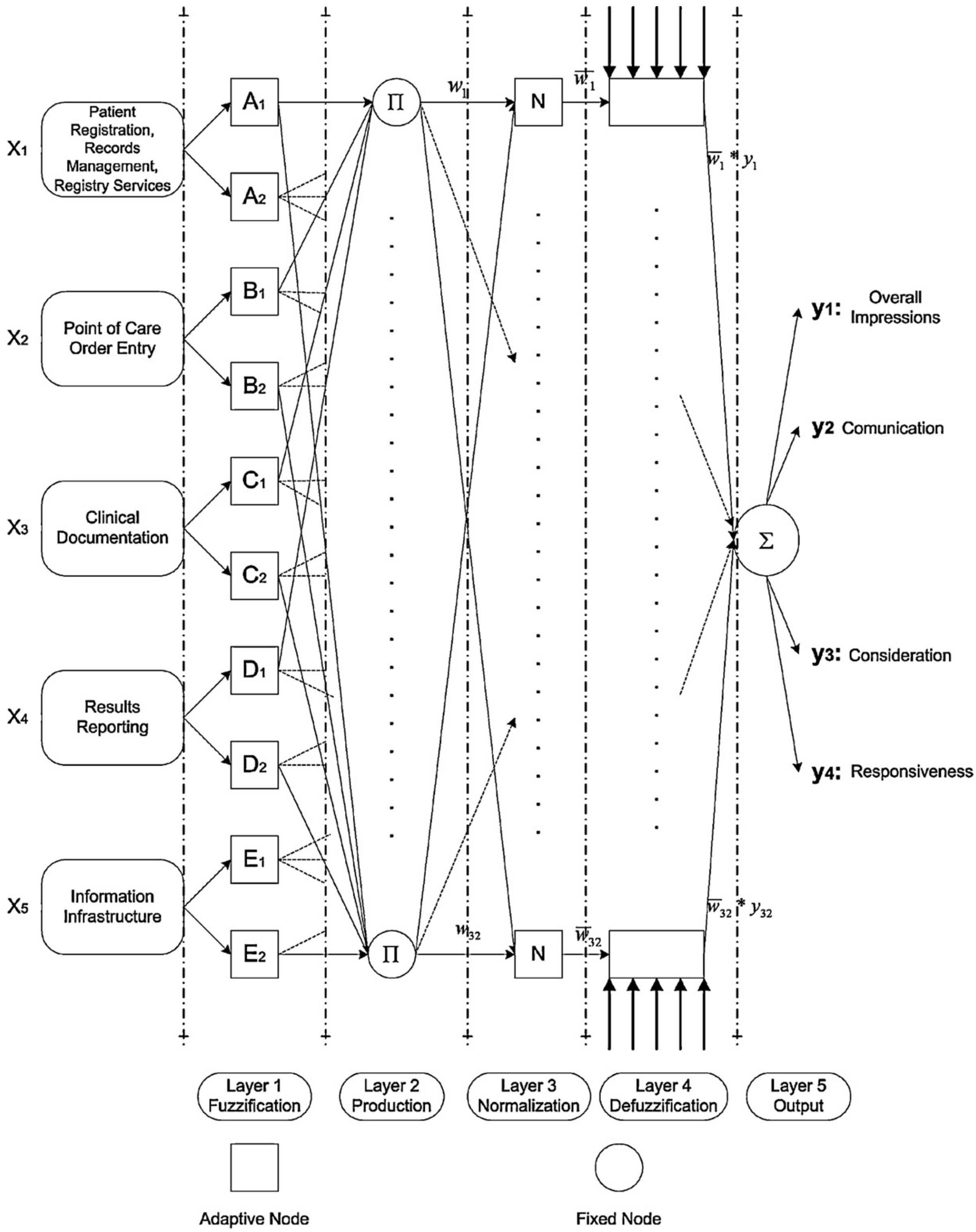

Fig. 1. The ANFIS architecture for a five input and single output Sugeno fuzzy model.

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

$$S_1 = \{\{a_{11}, \partial_{11}\}, \{a_{12}, \partial_{12}\}, \ldots, \{a_{1p}, \partial_{1p}\}, \ldots, \{a_{np}, \partial_{np}\}\} \tag{10}$$

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

$$S_2 = \{\{c_{10}, c_{11}, \ldots, c_{1n}\}, \ldots, \{c_{p^n0}, c_{p^n1}, \ldots, c_{p^nn}\}\} \tag{11}$$

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.

The output can be presented as:

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

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

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

For given values of S_1, using K training data values, we can transform the above equation into the form

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

where X is an unknown vector which contains the elements in S_2.

This can be 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 $\left\|AX - B\right\|^2$ by approximating X with X^*. Rather than solving directly through $X^* = (A^T A)^{-1} A^T B$, in ANFIS it is solved iteratively:

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

where S_i is often called the covariance matrix; $X^* = X_K$; a_i^T is the ith row vector in matrix A; b_i^T is the ith element of vector B. The initial conditions in 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 $M = \left|S_2\right|$. The output of layer 5 is compared with the actual output and the error measure E_k for the kth$(1 \le k \le K)$ entry of the training data is calculated as:

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

where $N(L)$ is the number of nodes in layer L; $D_{m,k}$ – mth component of kth 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 the kth training data and for each node output x is calculated. The error rate for output node at layer (L,i) is calculated from Eq. (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 the 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:

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

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

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

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

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

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 Eq. (14) and parameters in S_2 from Eq. (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 Eqs. (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 (Eqs. (19)–(24)) [64,66].

4. Implementation

For ANFIS and ANN implementations we examined all the relevant input indicators. For ANFIS inputs we constructed ANFIS models for various combinations of inputs, gave them initial training with a single application of least-squares, and then chose the model with the best performance for further training [68]. The input selection method is based on the assumption that the ANFIS model with the smallest RMSE (root mean squared error) after one epoch of training has a greater potential of achieving a lower RMSE when given additional training epochs. This modeling problem has 5 candidate inputs and 4 outputs. To find the most influential inputs to ANFIS, we constructed 26×4 ANFIS models (each with different combinations of 2–5 inputs), and trained them with a single pass of the least squares method. The ANFIS model with the smallest training error was then selected for further parameter adjustment, using the hybrid learning rule we suggested in order to tune the membership. Fig. 2 shows that ANFIS with all 5 HIT adoption input indicators had the smallest training error for all 4 outputs. It is therefore reasonable to choose all 5 HIT adoption indicators for ANFIS training for further parameter tuning.

The training process was carried out independently for each output satisfaction indicator. As shown in Fig. 3, each ANFIS modeling process generates a fuzzy inference system between the five input indicators of HIT adoption in Ontario hospitals and each output satisfaction indicator. Table 4 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.

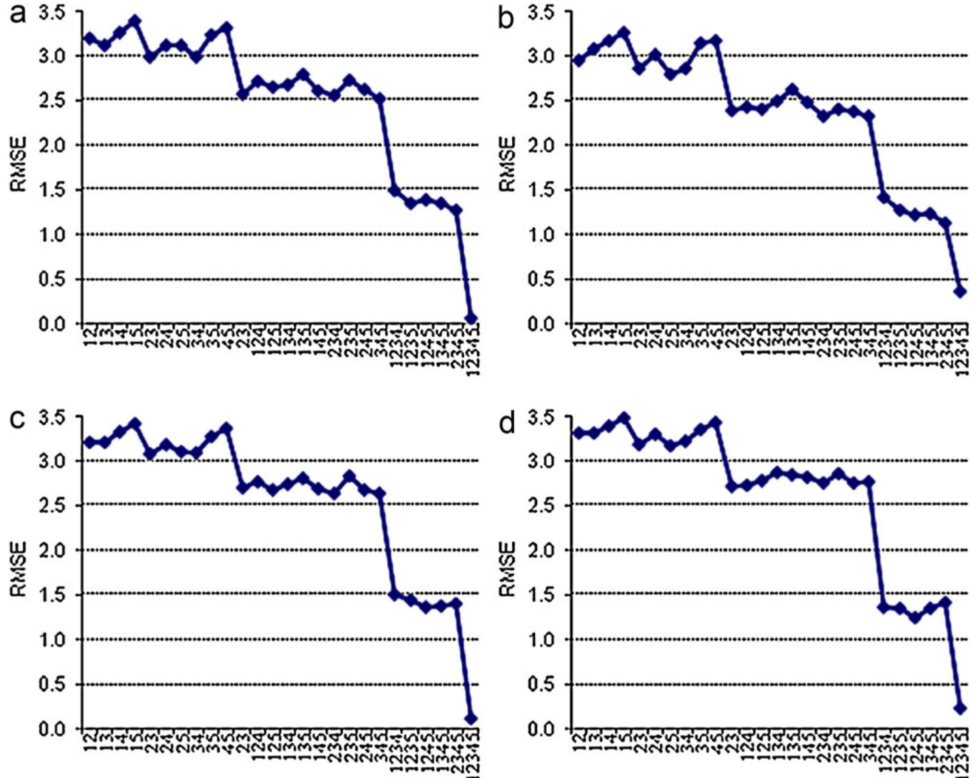

Fig. 2. RMSE as a function of combination of HIT adoption indicators for patient satisfaction prediction: (a) "Overall impressions"; (b) "Communication"; (c) "Consideration"; (d) "Responsiveness". See abscissa notation: 1. "Patient registration, records management & registry services"; 2. "Point-of-care order entry"; 3. "Clinical documentation"; 4. "Results reporting"; 5. "Information infrastructure".

Table 4
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

* *Note*: MF, membership function.

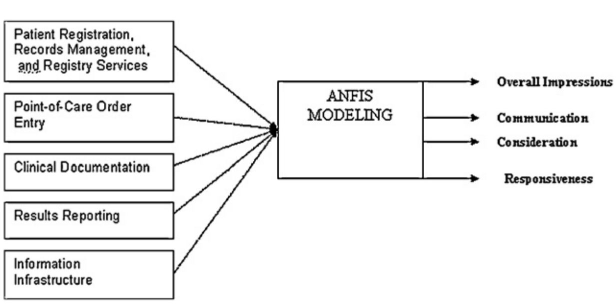

Fig. 3. The ANFIS modeling system for hospital patient satisfaction.

Numerical data in ANFIS modeling can be partitioned by grid partition (when the number of fuzzy partitions for each input indicator is known) or subtractive clustering (requires an estimate of the number of clusters) [67].

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 fall within a unit hyper box [69]. 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 [70]. Small radius values generally result in finding a few large clusters, which will lead to a very large number of rules. We implemented our models for

Table 5
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

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 respectively (see Table 5). 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 [66,67].

The input response range was divided into two regions according to the input data {partly implemented, fully implemented}. When functionality of the system is either in pilot or initial production (minimal progress has been made towards planning, procurement or implementation) and is used by a few intended users it is defined as "partly implemented"; when functionality of the system is fully implemented and is used by most or all intended users it is defined as "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 accordingly during ANFIS training. For the Sugeno-type FIS, 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 4). The ANFIS architecture with training parameters is presented in Table 5.

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: RMSE and adjusted coefficient of determination $R^2_{Adjusted}$, which are defined in Eqs. (25) and (26), respectively:

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

$$R^2_{Adjusted} = 1 - \left(1 - \frac{\sum_{K=1}^{N}(A_K - \bar{A}_m)(P_K - \bar{P}_m)}{\sqrt{\sum_{K=1}^{N}(A_K - \bar{A}_m)^2} \times \sqrt{\sum_{K=1}^{N}(P_K - \bar{P}_m)^2}}\right)\left(\frac{N-1}{N-m-1}\right) = 1 - (1 - R^2)\left(\frac{N-1}{N-m-1}\right) \tag{26}$$

where A_k is kth actual value, $\bar{A}_m$ is actual mean value; P_k is kth predicted value, $\bar{P}_m$ is predicted mean value, N is number of observations, m is number of independent variables.

Table 6
Independent variable importance.

Indicator	Importance	Normalized importance
1. Patient registration, records management & registry services	0.220	100.0%
2. Point-of-care order entry	0.215	97.5%
3. Clinical documentation	0.206	93.7%
4. Information infrastructure	0.188	85.2%
5. Results reporting	0.171	77.7%

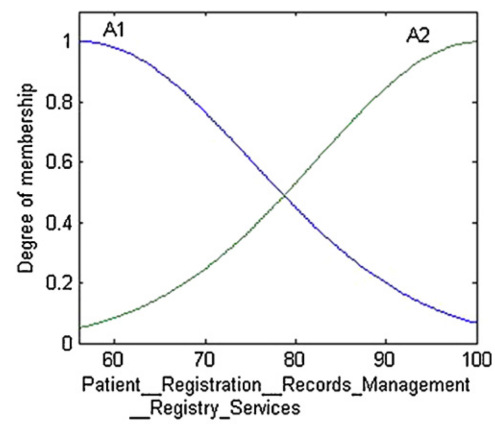

Fig. 4. Gaussian membership functions for "Patient registration, records management and registry services' variable after training for "Overall impressions" output. A1, A2 are labels associated with membership functions linguistically identified as "partly implemented", "fully implemented" respectively.

5. Results and discussion

Of the 82 acute care hospitals, 61 (74.4%) were selected randomly and the data were used for training the models, the remainder used for testing. We implemented 8 models for each 4 outputs to find the best prediction of patient satisfaction indicators, based on HIT adoption using both ANN and ANFIS methods.

The existence of relationships among HIT adoption indicators and patient satisfaction was demonstrated by the ANN training algorithm. The node weights in neural networks store information about the importance of each variable. Table 6 presents an analysis of the importance and normalized importance of each indicator in predicting patient satisfaction by using a neural network. The importance of an independent indicator is a measure of how much the network's model predicted value changes for different values of the independent variable. Normalized importance is simply the importance value divided by the largest importance value and expressed as a percentage. From Table 6, it is clear that the "Patient registration, records management & registry services" indicator contributes most to the neural network, followed by "Point-of-care order entry", "Clinical documentation","Information infrastructure" and "Results reporting" in that order.

The membership functions for the first input indicator and the "Overall impressions" output are shown in Fig. 4. A1 and A2 are labels associated with membership functions which are linguistically identified as "partly implemented", and "fully implemented" respectively.

Table 7
Prediction accuracy results.

Model	Subtr. radii/model	Number of rules	Accuracy measures	
			RMSE	Adjusted R^2
Overall impressions				
1	0.4	47	0.0625	0.9999
2	0.45	32	0.0625	0.9999
3	0.5	16	0.0625	0.9999
4	0.55	8	2.4218	0.7482
5	0.6	5	2.7087	0.6689
6	0.65	4	2.7989	0.6426
7	Grid	32	0.0724	0.9998
8	ANN	MLP	1.6948	0.8899
Communication				
1	0.4	47	0.3592	0.9947
2	0.45	32	0.3592	0.9947
3	0.5	16	0.3592	0.9947
4	0.55	8	2.2176	0.7726
5	0.6	5	2.5082	0.6969
6	0.65	4	2.5887	0.673
7	Grid	32	0.4165	0.9928
8	ANN	MLP	1.7130	0.8580
Consideration				
1	0.4	47	0.1093	0.9996
2	0.45	32	0.1093	0.9996
3	0.5	16	0.1093	0.9996
4	0.55	8	2.495	0.7369
5	0.6	5	2.7903	0.6535
6	0.65	4	2.807	0.6501
7	Grid	32	0.1268	0.9994
8	ANN	MLP	1.6377	0.8877
Responsiveness				
1	0.4	47	0.2343	0.9980
2	0.45	32	0.2343	0.9980
3	0.5	16	0.2343	0.9980
4	0.55	8	2.5142	0.7429
5	0.6	5	2.9444	0.6201
6	0.65	4	2.8867	0.6406
7	Grid	32	0.2716	0.9975
8	ANN	MLP	1.7246	0.8877

Table 7 shows MLP and ANFIS model specific clustering algorithm parameters (radius value, number of generated rules) for every calculated ANFIS model and 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) performed best overall in terms of RMSE and $R^2_{Adjusted}$. The results showed that ANN and ANFIS models were both potentially strong predictors of patient satisfaction through the hospital adoption of HIT. However, the ANFIS grid partition model showed better performance than the ANN model. 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.

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 in Figs. 5 and 6, present the relationships between the inputs and output parameters found by the ANFIS model for "Overall impression" and "Responsiveness" respectively. Since these relationships exist in the fuzzy domain their associations can be represented by smooth surfaces [71].

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, Fig. 5a 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" and "Point-of-care order entry" adoption have both increased to full implementation, the patient satisfaction indicator "Overall impressions" increases substantially in comparison to lower values of these input parameters.

Fig. 7(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 "partly implemented" HIT, especially for "Point-of-care order entry (x_2)" and "Clinical documentation (x_3)" 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 (S1–S5) were considered:

(S1) Varying (until "full implementation") "Patient registration, records management & registry services (x_1)" when all other systems implementation scores remain at their average values can be presented as [x_1 59 63 88 72], where x_1 is the indicator which is being varied;
(S2) 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 at their average values can be presented as [x_1 80 63 88 72];
(S3) 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 [x_1 59 80 88 72];
(S4) 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 [x_1 80 80 88 72];
(S5) 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 [x_1 59 63 88 80].

"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 (S1 and S5).

An increase of "Point-of-care order entry" systems implementations from 59% to 80% (S2), with "fully implemented" "Patient registration, records management & registry services" improves "Overall impressions" from 85.9% to about 97% (Fig. 7a), patient perceptions about "Communication" from 79% to about 93% (Fig. 7b), and patient perceptions about "Consideration" and "Responsiveness" from 81% to 92% (Fig. 7c) and 81 to 89% (Fig. 7d) respectively.

An increase of "Clinical documentation" systems implementations from 63% to 80% (S3), with "fully implemented" "Patient registration, records management & registry services" improves "Overall impressions" from 85.9% to about 100% (Fig. 7a), patient perceptions about "Communication" from 79% to about 89%

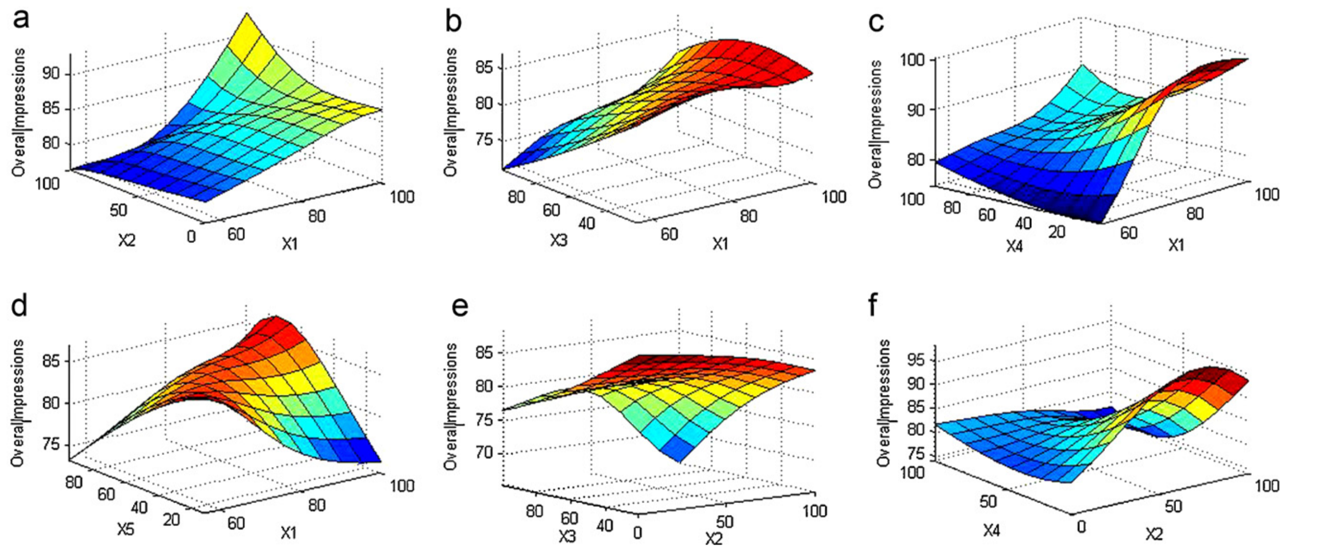

Fig. 5. 3-D surface simulation for patient satisfaction indicator "Overall impression" by HIT adoption indicators: x_1 – "Patient registration, records management & registry services"; x_2 – "Point-of-care order entry"; x_3 – "Clinical documentation"; x_4 – "Results reporting"; x_5 – "Information infrastructure" for Hamilton Health Sciences Corporation: (a) x_1, x_2; (b) x_1, x_3; (c) x_1, x_4; (d) x_1, x_5; (e) x_2, x_3; (f) x_2, x_4.

(Fig. 7b), and patient perceptions about "Consideration" and "Responsiveness" from 81% to 95% (Fig. 7c) and 81% to 93% (Fig. 7d) respectively.

An increase of "Point-of-care order entry" and "Clinical documentation" systems implementations from 59% to 80% and 63% to 80% respectively (S4), with "fully implemented" "Patient registration, records management & registry services" only slightly enhances "Overall impressions" from 85.9% to about 86% (Fig. 7a), patient perceptions about "Communication" from 79% to about 83% (Fig. 7b), and patient perceptions about "Consideration" and "Responsiveness" from 81% to 89% (Fig. 7c) and 81% to 95% (Fig. 7d) respectively.

An alternative representation of Fig. 7(a–d) is shown in Fig. 8(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 Fig. 8a where the initial "Patient registration, records management & registry services" adoption indicator is 84%.

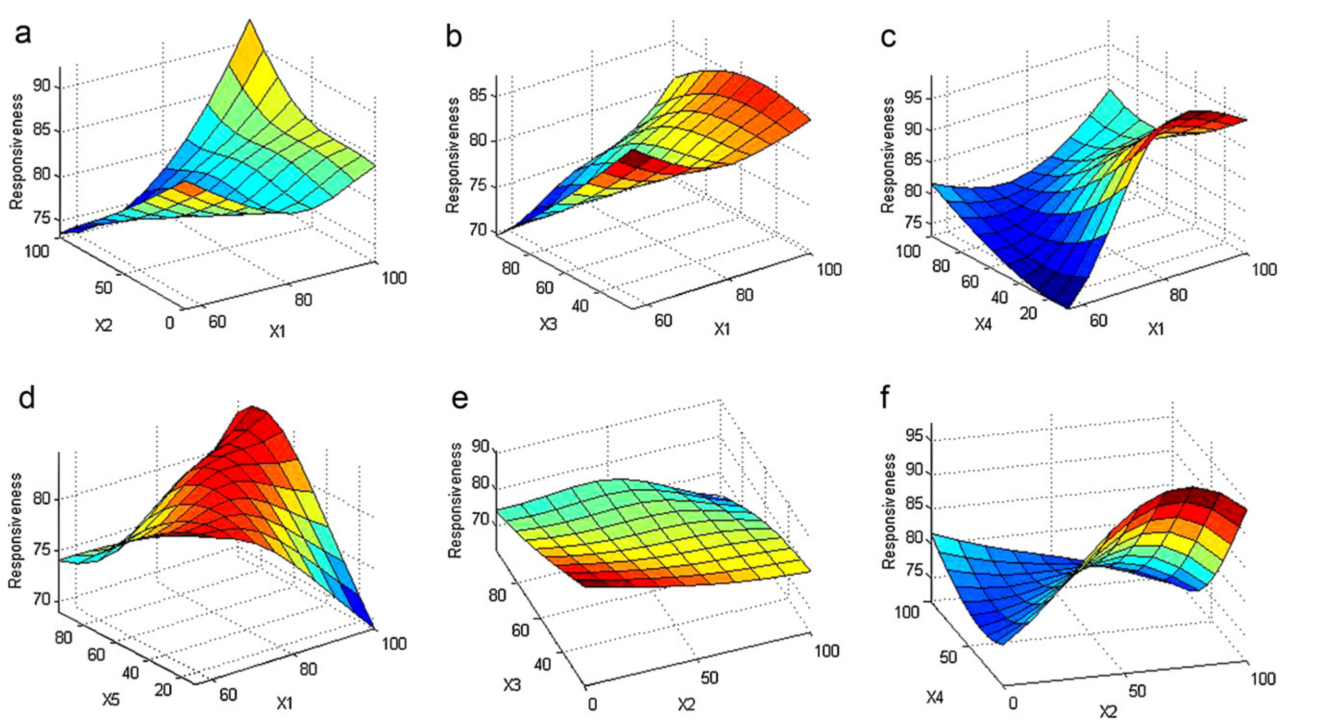

Fig. 6. 3-D surface simulation for patient satisfaction indicator "Responsiveness" by HIT adoption indictors: x_1 – "Patient registration, records management & registry services"; x_2 – "Point-of-care order entry"; x_3 – "Clinical documentation"; x_4 – "Results reporting"; x_5 – "Information infrastructure" for Hamilton Health Sciences Corporation: (a) x_1, x_2; (b) x_1, x_3; (c) x_1, x_4; (d) x_1, x_5; (e) x_2, x_3; (f) x_2, x_4.

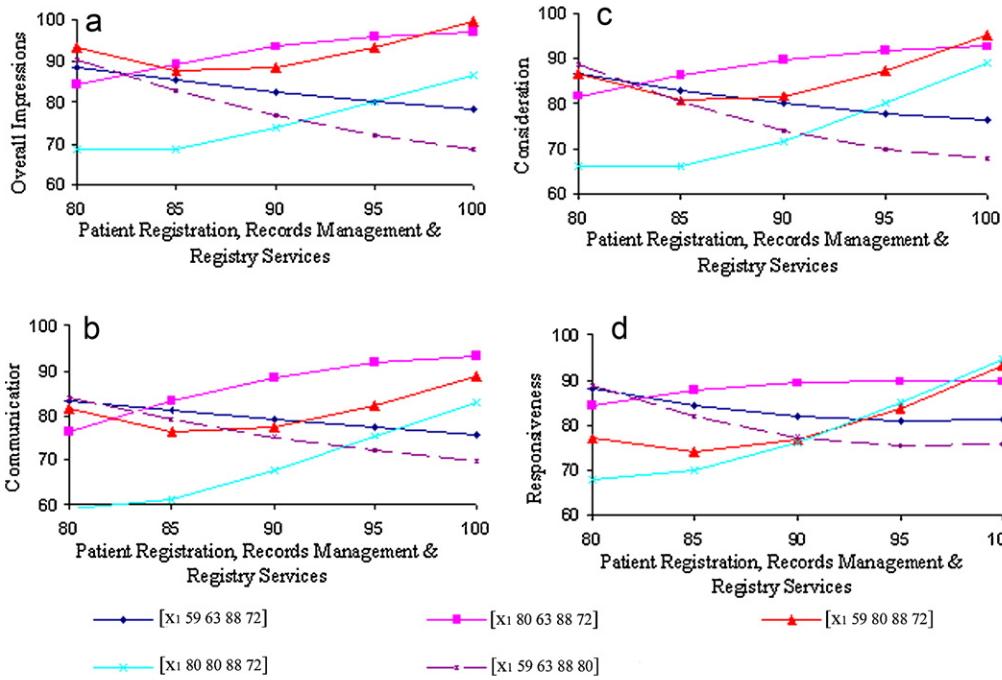

Fig. 7. Impact of varying x_1 (“Patient registration, records management & registry services”) in different scenario simulations on patient satisfaction: (a) “Overall impression”; (b) “Communication”; (c) “Consideration”; (d) “Responsiveness”, for an average Ontario teaching hospital simulation.

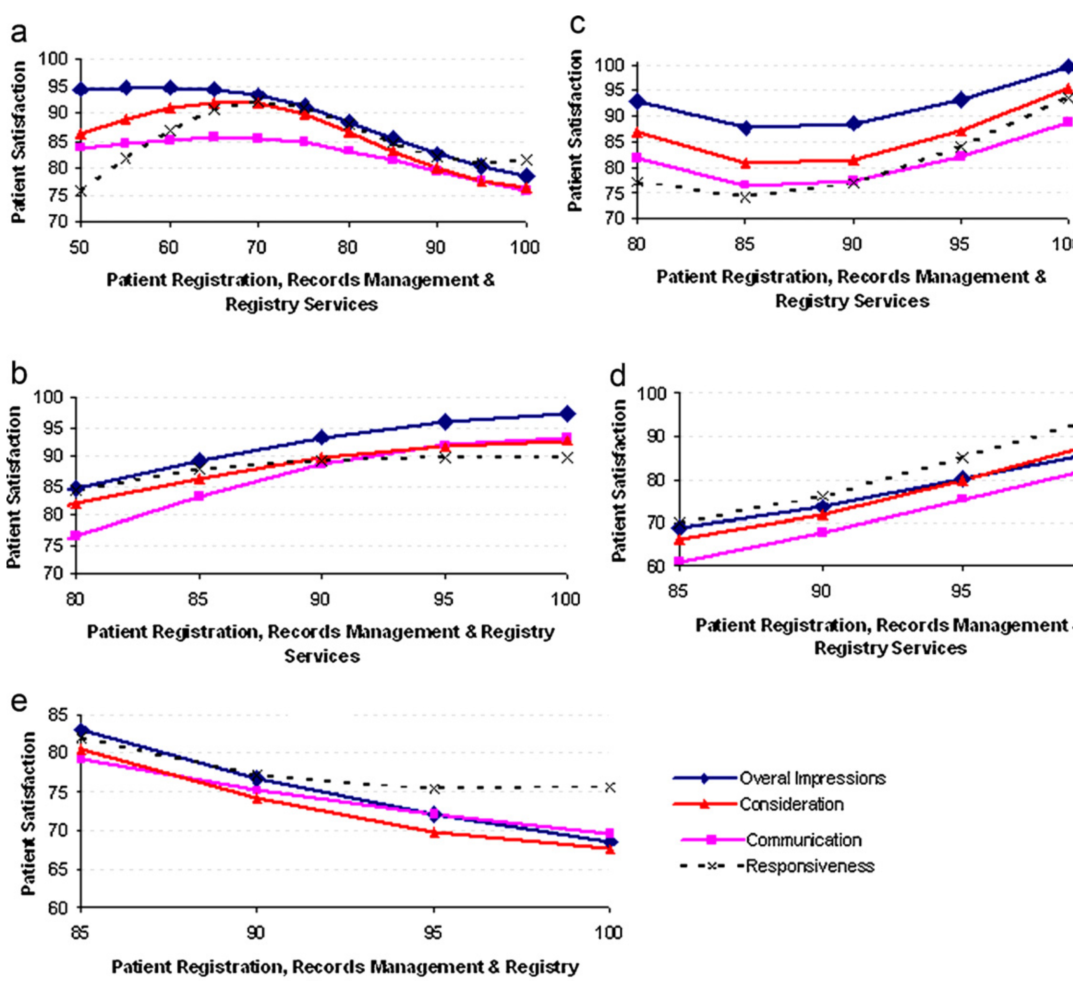

Fig. 8. Patient satisfaction as a function of x_1 (“Patient registration, records management & registry services”) adoption level and with constant values for other input indicators: (a) [x_1 59 63 88 72]; b) [x_1 80 63 88 72]; c) [x_1 59 80 88 72]; d) [x_1 80 80 88 72]; e) [x_1 59 63 88 80] for an average Ontario teaching hospital simulation.

6. Conclusions

Patient satisfaction as an outcome indicator of health care delivery has become 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 HIT could provide a better understanding of the benefits of increased investment in HIT. Although research examining the impact of HIT adoption on patient satisfaction showed mostly neutral or positive effects on patient satisfaction, most previous research has concentrated only on HIT adoption in physician offices, and involved the adoption of one system, such as a computer-based patient record or special treatment system. Our research is the first attempt to understand the impact of implementation of hospital adoption of information and communications technologies (such as computer-based patient records, electronic health records, electronic medical records, telemedicine, and decision support systems) on patient satisfaction.

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. AI methodologies which integrate the modeling of imprecise and qualitative knowledge with adaptive learning ability through ANN and ANFIS models were successfully applied in solving these complex problems.

In this study we compared the predictive availability of the ANFIS and ANN algorithms to explore and predict non-linear and uncertain patient satisfaction measures as functions of HIT adoption in Ontario hospitals. The accuracy of each predictive model was evaluated by calculating statistical performance measures. These showed very promising predictive power for patient satisfaction dimensions, such as “Overall impressions”, “Communication”, “Consideration” and “Responsiveness”. The results showed that ANNs and ANFIS were both potentially strong for prediction of patient satisfaction through hospital adoption of health information technology; however, ANFIS was found to be more effective when compared with the results of ANN modeling. 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 resulting from the implementation of HIT in hospitals.

Adoption of HIT technology in most hospitals is in a transitional and not fully implemented stage. This research examined all the steps in ANFIS modeling (input selection, comparison of models with different parameters) and provided simulation scenarios generated by the ANFIS models that provided the best fit to the data. This can clearly help in the understanding of patient satisfaction improvement by HIT adoption.

Some conclusions concerning the impact of HIT implementation for average teaching hospitals were obtained through the ANFIS analysis. We found through simulation scenarios that full implementation of HIT in hospitals can lead to significant improvement in patient satisfaction. Results showed 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. On the other hand, the “Point-of-care order entry” indicator, which represents the capability to electronically order tests and medications at the bedside and to support the availability of electronic decision support information at the time of ordering could *improve* patient satisfaction by 8-11%. Hospital capability for capturing clinical patient information, reports, and structured data, as well as hospital capability to integrate these features into an electronic patient record, when fully implemented, could improve patient satisfaction with care by 10-15%. Fully implemented HIT at hospitals may result in an improvement in health care quality. Thus patient satisfaction, through significant reductions in medical errors, reduced lost orders, and errors due to illegible handwriting, and minimized duplicate orders, could detect patient problems that might not be discovered during regular outpatient visits.

Some limitations of this study should be acknowledged, but these can also be considered opportunities for future research. 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 (due to data access restrictions). 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, sociodemographic variables, etc., should also be considered in future studies. Our findings are also subject to geographic restrictions and may not generalize to patients in non-acute hospitals. Future studies are also needed to evaluate the moderating effects of various other hospital indicators on patient satisfaction.

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