

Chapter 2

Artificial Neural Network Excellence to Facilitate Lean Thinking Adoption in Healthcare Contexts

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Abstract Over the years, healthcare organisations have improved their processes, services, and outcomes significantly. However, with the increasing importance placed on value making, healthcare organisations too often are struggling to demonstrate best performance and/or appropriate and sustained quality of care. Hence, in this chapter we explore the benefits of using artificial neural network (ANN) techniques to identify lost value for the healthcare organisations and to facilitate Lean thinking adoption.

Keywords Lean thinking • Artificial neural networks • Quality of care • Performance

2.1 Background

The key concept in Lean thinking is “value” (Joosten et al. 2009). Value has different connotations in each organisational context. However, Womack and Jones (2003) provide a comprehensive and general definition of value which is defined as “the capability to deliver exactly the (customised) product or service a customer wants with minimal time between the moment the customer asks for that product or service and the actual delivery at an appropriate price” (Womack and Jones 2003, p. 23).

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Although quality and safety are significant values of healthcare delivery, there are lots of hidden layers across them which should be discovered and developed to improve efficiency of care.

On the other hand, widespread use of medical information systems and the explosive growth of medical databases require traditional manual data analysis to be coupled with methods for efficient computer-assisted analysis (Lavrač 1999).

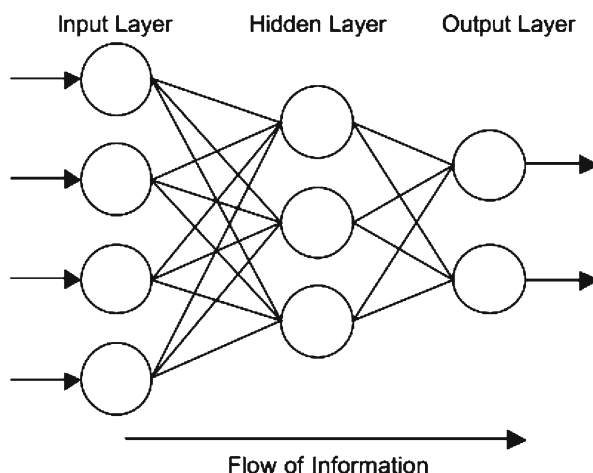
Therefore, taking these two issues into consideration, artificial intelligence techniques and intelligent systems have found many valuable applications to assist in this regard (Teodorrescu et al. 1998). Specifically, neural networks have been found to be very useful in many biomedical areas, to help with the diagnosis of diseases and studying the pathological conditions, and also for monitoring the progress of various treatment outcomes. Also, Shi et al. (2004) state that artificial neural networks (ANNs) are powerful tools to model the non-linear cause-and-effect relationships inherent in complex processes, usually for quality control (Shi et al. 2004).

ANNs are computational paradigms based on mathematical models that unlike traditional computing have a structure and operation that resembles that of the mammal brain (Margarita 2002). An artificial network performs in two different modes, learning (or training) and testing. During learning, a set of examples is presented to the network. At the beginning of the training process, the network “guesses” the output for each example. However, as training goes on, the network modifies internally until it reaches a stable stage at which time the provided outputs are satisfactory. Learning is simply an adaptive process during which the weights associated to all the interconnected neurons change in order to provide the best possible response to all the observed stimuli. Neural networks can learn in two ways, supervised or unsupervised (Beg et al. 2006):

- Supervised learning: The network is trained using a set of input–output pairs. The goal is to “teach” the network to identify the given input with the desired output. For each example in the training set, the network receives an input and produces an actual output. After each trial, the network compares the actual with the desired output and corrects any difference by slightly adjusting all the weights in the network until the output produced is similar enough to the desired output, or the network cannot improve its performance any further (Margarita 2002).
- Unsupervised learning: The network is trained using input signals only. In response, the network organises internally to produce outputs that are consistent with a particular stimulus or group of similar stimuli. Inputs form clusters in the input space, where each cluster represents a set of elements of the real world with some common features (Margarita 2002).

In both cases, once the network has reached the desired performance, the learning stage is over and the associated weights are frozen. The final state of the network is preserved and it can be used to classify new, previously unseen inputs. At the testing stage, the network receives an input signal and processes it to produce an output. If the network has correctly learnt, it should be able to generalise, and the actual output produced by the network should be almost as good as the ones produced in the learning stage for similar inputs.

Fig. 2.1 A multilayered feedforward network. Adapted from (Margarita 2002)



Neural networks are typically arranged in layers. Each layer in a layered network is an array of processing elements or neurons. A common example of such a network is the multilayer perceptron (MLP) (Fig. 2.1). MLP networks normally have three layers of processing elements with only one hidden layer, but there is no restriction on the number of hidden layers (Margarita 2002).

2.2 Neural Networks in Healthcare Contexts

Neural networks have been applied within the medical domain for clinical diagnosis (Baxt 1995), image analysis and interpretation (Miller et al. 1992; Miller, 1993), signal analysis and interpretation, and drug development (Weinstein et al. 1992a, b). The classification of the applications is presented below (Table 2.1).

2.3 The Case Study Analysis

This recent case presents an example of how ANNs can be applied in healthcare contexts. This case is presented from the research study conducted by Takehira et al. (2011). The aim of this study was to investigate the difference between the professional perspectives of pharmacists and nurses in Japan with regard to evaluation of the quality of life (QOL) of cancer patients. It is therefore a suitable case from which to develop an initial assessment of key concepts of ANNs and map them in order to present how ANNs can facilitate applying a Lean thinking approach to increase quality of care. Thus, the assessment criteria are set up based on Lean thinking key components.

Table 2.1 Some of ANN applications in healthcare contexts

Clinical issue	ANN application
<i>Clinical diagnosis</i>	<p>Papnet (Beg et al. 2006) is a commercial neural network-based computer programme for assisted screening of Pap (cervical) smears. A Pap smear test examines cells taken from the uterine cervix for signs of precancerous and cancerous changes. A properly taken and analysed Pap smear can detect very early precancerous changes. These precancerous cells can then be eliminated, usually in a relatively simple office or outpatient procedure. Detected early, cervical cancer has an almost 100 % chance of cure. Traditionally, Pap smear testing relies on the human eye to look for abnormal cells under a microscope. It is the only large-scale laboratory test that is not automated. Since a patient with a serious abnormality can have fewer than a dozen abnormal cells among the 30,000–50,000 normal cells on her Pap smear, it is very difficult to detect all cases of early cancer by this “needle-in-a-haystack” search. Imagine proofreading 80 books a day, each containing over 300,000 words, to look for a few books each with a dozen spelling errors! Relying on manual inspection alone makes it inevitable that some abnormal Pap smears will be missed, no matter how careful the laboratory is. In fact, even the best laboratories can miss from 10 to 30 % abnormal cases “Papnet-assisted reviews of [cervical] smears result in a more accurate screening process than the current practice leading to an earlier and more effective detection of pre-cancerous and cancerous cells in the cervix”</p> <p>The electrocardiography (ECG) signal is a representation of the bioelectrical activity of the heart’s pumping action. This signal is recorded via electrodes placed on the patient’s chest. The physician routinely uses ECG time-history plots and the associated characteristic features of P, QRS, and T wave-forms to study and diagnose the heart’s overall function. Deviations in these waveforms have been linked to many forms of heart diseases, and neural network has played a significant role in helping the ECG diagnosis process. For example, neural networks have been used to detect signs of acute myocardial infarction (AMI), cardiac arrhythmias, and other forms of cardiac abnormalities (Baxt 1991; Nazeran and Behbehani 2001). Neural networks have performed exceptionally well when applied to differentiate patients with and without a particular abnormality, for example, in the diagnosis of patients with AMI (97.2 % sensitivity and 96.2 % specificity; Baxt 1991)</p> <p>Electromyography (EMG) is the electrical activity of the contracting muscles. EMG signals can be used to monitor the activity of the muscles during a task or movement and can potentially lead to the diagnosis of muscular disorders. Both amplitude and timing of the EMG data are used to investigate muscle function. Neural networks have been shown to help in the modelling between mechanical muscle force generation and the corresponding recorded EMG signals (Wang and Buchanan 2002). Neuromuscular diseases can affect the activity of the muscles (e.g. motor neuron disease), and neural networks have been proven useful in identifying individuals with neuromuscular diseases from features extracted from the motor unit action potentials of their muscles (Pattichis et al. 1995)</p> <p>The EEG signal represents electrical activity of the neurons of the brain and is recorded using electrodes placed on the human scalp. The EEG signals and their characteristic plots are often used as a guide to diagnose neurological disorders, such as epilepsy, dementia, stroke, and brain injury or damage. The presence of these neurological disorders is reflected in the EEG waveforms. Like many other pattern recognition techniques, neural networks have been used to detect changes in the EEG waveforms as a result of various neurological and other forms of abnormalities that can affect the neuronal activity of the brain. A well-known application of neural networks in EEG signal analysis is the detection of epileptic seizures, which often result in a sudden and transient disturbance of the body movement due to excessive discharge of the brain cells. This seizure event results in spikes in the EEG waveforms, and neural networks and other artificial intelligence tools, such as fuzzy logic and support vector machines, have been employed for automated detection of these spikes in the EEG waveform. Neural networks-aided EEG analysis has also been undertaken for the diagnosis of much other related pathology, including Huntington’s and Alzheimer’s diseases (Jervis et al. 1992; Yagneswaran et al. 2002)</p>

Another important emerging application of neural networks is in the area of brain computer interface (BCI), in which neural networks use EEG activity to extract embedded features linked to mental status or cognitive tasks to interact with the external environment (Culpepper and Keller 2003)

An Entropy Maximization Network (EMN) has been applied to prediction of metastases in breast cancer patients (Choong and deSilva 1994). They used EMN to construct discrete models that predict the occurrence of axillary lymph node metastases in breast cancer patients, based on characteristics of the primary tumour alone. The clinical and physiological features used in the analysis are the age of the patient at the time of diagnosis of the primary tumour, mitotic count (the number of relative hyperchromatic nuclei per 10 hpf) in the primary invasive tumour, tubule formation of the primary tumour, assessment of the size of the tumour nuclei, assessment of the variability of the shape and size of the tumour nuclei, tumour grading, gross size of the primary tumour, and the presence/absence of carcinoma in peritumoural vessel. Results indicated that EMN is an effective way of constructing discrete models from small data sets

Serum electrophoresis is used as standard laboratory medical test for diagnosis of several pathological conditions such as liver cirrhosis or nephrotic syndrome. A multilayer perceptron trained using the backpropagation learning algorithm and a radial-based function network were used to implement an effective diagnostic aid system. Preliminary results confirm the suitability of such neural network architectures as aids for medical diagnosis (Costa et al. 1998)

Image analysis and interpretation

Aizenberg et al. (2001) present examples of filtering, segmentation, and edge detection techniques using cellular neural networks to improve resolution in brain tomographies and improve global frequency correction for the detection of microcalcifications in mammograms

Miller et al. 1992 trained different neural networks (NNs) to recognise regions of interest (ROIs) corresponding to specific organs within electrical impedance tomography images (EIT) of the thorax. The network allows automatic selection of optimal pixels based on the number of images, over a sample period, in which each pixel is classified as belonging to a particular organ. Initial results using simulated EIT data indicate the possible use of neural networks for characterisation of such images

Hall et al. (1992) compared neural networks (cascade correlation) and fuzzy clustering techniques for segmentation of magnetic resonance imaging (MRI) of the brain. Both approaches were applied to intelligent diagnosis. Results, validated by experienced radiologists, provided good insights as to the suitability of the applied techniques for automatic image segmentation in the context of intelligent medical diagnosis

Rajapakse and Acharya (1990) implemented a self-organising network multilayer adaptive resonance architecture (MARA) for the segmentation of CT images of the heart. Similarly, Däschlein et al. (1994) implemented a two-layer neural network for segmentation of CT images of the abdomen. The method required the discrimination of various tissues like kidney, liver, and bone and pathologic tissue like renal calculus and kidney tumour

An ANN was successfully applied to enhance low-level segmentation of eye images for diagnosis of Grave's ophthalmopathy (Ossen et al. 1994). The neural network segmentation system was integrated into an existing medical imaging system. The system provides a user interface to allow interactive selection of images, neural network architectures, training algorithms, and data

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Table 2.1 (continued)

Clinical issue	ANN application
	<p>In another study, Özkan et al. (1990) used neural networks trained with the backpropagation learning algorithm for segmentation and classification multispectral MRI images of normal and pathological human brain. Results indicate that sharp and compact segmentation of MRI images can be obtained with neural networks with a small architecture. Anthony et al. (1990) evaluated the performance of neural networks (NNs) in image compression of lung scintigrams. They discussed the suitability of NNs and presented limitations and recommendations with special reference to medical imaging</p> <p>A multi-module system was used to focus, segment, and classify lung-parenchyma lesions in standard chest radiographies. A Laplacian-of-Gaussian kernel filter is applied to the X-ray images to remove low-frequency components, while preserving detail contrast. An input mask of 19×19 units serves as input to the classification module, which consists of a feedforward network. The output of the network identifies ROIs in the image, which later are analysed by other modules in the system (DeDominicis 1994)</p> <p>Houston et al. (1994) compared an expert system rule induction and a neural network to determine the optimal diagnostic strategy for colorectal cancer using MRI and tumour markers. Data from 39 patients was used to assess the suitability of such methodologies. Inconclusive results indicated that both methods strongly rely on large number of samples</p> <p>ANNs have been used for automatic screening of blood cell classification from microscope images</p> <p>82 objects extracted from 133 digitised images were isolated using classical image enhancement algorithms. A single-layer perceptron was trained with the backpropagation learning algorithm. The output produced a binary output, indicating whether the input corresponded to a normal or a pathologic cell network correctly classified 65 out of 82 objects (Karakas et al. 1994)</p> <p>Xing and Feltham (1994) and Zheng et al. (1994) are two of multiple examples of neural networks applied to pattern recognition in mammograms. Xing and Feltham used 14 image features extracted from mammograms by experienced radiologists. A pyramidal neural network detects malignant tumours or clustered calcifications in preprocessed mammograms. Results indicate that abnormal patterns observed in mammograms can be mapped into a unique data set. Similarly, Zheng et al. used a multistage neural network (MNN) for locating and classification of microcalcifications in digital mammograms. The network is trained using backpropagation with Kalman filtering. Experimental results show 100 % detection with a false positive detection rate of less than 1 micro calcification cluster per image</p>

Sordo (1999) implemented a knowledge-based neural network (KBANN) for classification of phosphorus (31P) magnetic resonance spectra (MRS) from normal and cancerous breast tissues. Data from 26 cases was used as input to the network. A priori knowledge of metabolic features of normal and cancerous breast tissues was incorporated into the structure of the neural network to overcome the scarcity of available data. Classification rates of 62.4 % for “knowledge-free” neural networks and 87.36 % for KBANNs showed how KBANNs outperformed conventional neural networks in the classification of 31P MRS. This indicates that the combination of symbolic and connectionist techniques is more robust than a connectionist technique alone

Waltrus et al. (1993) reported results from the application of tools for synthesising, optimising, and analysing neural networks to an Electrocardiogram (ECG) Patient Monitoring task. A neural network was synthesised from a rule-based classifier and optimised over a set of normal and abnormal heartbeats. The classification error rate on a separate and larger test set was reduced by a factor of 2. Sensitivity analysis of the synthesised and optimised networks revealed informative differences. Analysis of the weights and unit activations of the optimised network enabled a reduction in size of the network by a factor of 40 % without loss of accuracy

Project Title: Artificial Neural Network Modelling of Quality of Life of Cancer Patients, Relationships Between Quality of Life Assessments, as Evaluated by Patients, Pharmacists, and Nurses (Takehira et al. 2011)¹

Methods: A group of cancer hospital inpatients ($n=15$) were asked to rate the condition of their health and their QOL by filling in a questionnaire. On the same day, a group of pharmacists ($n=8$) and nurses ($n=18$) also evaluated patient QOL. Three-layered ANN architecture was used to model the relationship between the different QOL evaluations made by patients, pharmacists, and nurses.

Results: Although there was no statistical difference between the QOL scores obtained from pharmacists and nurses, the correlation between these scores was weak (0.1188). These results suggest that pharmacists and nurses evaluate the QOL of their patients from different perspectives, based on their respective profession. QOL parameters were modelled with an ANN using the scores, given by patients in answer to questions regarding health-related QOL as input variables. Both the predictive performance of the ANN and the robustness of the optimised model were acceptable. The response surfaces calculated by ANN modelling showed that pharmacists and nurses evaluate patient's QOL using different information and reasoning, which is likely related to the nature of their contact with the patients.

Project Design and Outcomes

Patients: A group of cancer patients ($n=18$) hospitalised in Nippon Medical University Hospital (Sendagi, Tokyo, Japan) were initially included in this study. All patients took opioid analgesics for pain control, and a pain control team, organised by physicians, pharmacists, and nurses, provided appropriate in-hospital care. Patients were excluded if they began chemotherapy during the study period or if they did not complete the questionnaire, owing to the severity of their illness. Thus, 15 patients (eight females and seven males, age 64.7 ± 7.2 years, mean \pm SD) were enrolled in the study and gave written consent to answer the study questions. A questionnaire was designed to assess the HRQOL of patients referring SF36, Functional Living Index Cancer (FLIC), and Functional Assessment of Cancer Therapy, General (FACT-G); it consisted of four important domains, EWB, FWB, SWB, and PWB. The number of questions included was limited to 18 in order to avoid unnecessary burden on the patients, in accordance with the suggestion of a local research committee. Patient health-related status and subjective QOL were collected by pharmacists in the form of a bedside interview and data collection was conducted four times every week, using a questionnaire. Time required to fill the questionnaire by interviewing was about 5–10 min.

¹This case study & its results is extracted exactly from (Takehira et al. 2011) research study to present how exactly Artificial Neural Network can be apply in healthcare contexts.

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Pharmacists and nurses: Pharmacists ($n=8$) and nurses ($n=18$) providing patient care in a pain control team were involved in this study. Details regarding the amount of professional experience are possessed by the participating pharmacists and nurses. Pharmacists evaluated patient QOL when interviewing patients using the questionnaire. Nurses evaluated patient QOL on the same day as the patient answered the questionnaire. Patient QOL was evaluated on a simple scale ranging from 1 (very bad) to 5 (very good), rather than in a structured manner. The intended number of the answers in the research was 60 (each of 15 patients would answer 4 times). However, some patients, pharmacists, and nurses did not complete the questionnaires, so a number of paired (patient, pharmacist, and nurse) forms ($n=40$) were used in the analysis. Table 2.2 shows the items of the questionnaires which were selected to be used for the SEM and mean values of their score, as well as the mean QOL scores given by patients, pharmacists, and nurses. The study design and questionnaires were reviewed by a local research committee. The background of the patients and details of the questionnaires they were given are described in our previous study.

ANN

A three-layered ANN architecture was used and optimisation of the weights between neurons to match the evaluated QOLs with those that were predicted was carried out using a second-order, conjugate, gradient descent algorithm. In this algorithm, a search is performed along conjugated directions, which generally produce faster convergence compared with a backpropagation of the error algorithm. Scores obtained from patients are shown in Table 2.2 and were used for input data (independent parameters). These eight questions were from the initial 18 questions and sufficed to perform exploratory factor analysis. The subjective patient QOL scores and QOL evaluations made by pharmacists and nurses were used for output data (dependent parameters). The determination of the number of neurons in the hidden layer will be described subsequently. The optimised ANN model had initial value dependence, so at least ten runs were performed using reinitialised weights between neurons, after which the model with the best fit between observations and predictions from the training data was adopted as the optimised ANN model.

Statistica 06J, featuring a neural networks module, was used for ANN calculation. A sigmoid function was adopted for activation function of the hidden layer. Robustness of optimised ANN was investigated with leave-one-out cross-validation. The procedure is as follows: The data obtained from one patient was removed from the data set and the data from the remaining patient were used as the training data set. The ANN was optimised using the training data set, and then the outcome of the excluded patient was predicted by the optimised ANN model.

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Table 2.2 Prediction performance of QOL by ANN modelling

QOL score	QOL evaluated by patients		QOL by evaluated pharmacists		QOL evaluated by nurses	
	Answered	Predicted ¹⁾	Answered	Predicted ¹⁾	Answered	Predicted ^a
5	0	0	1	1	2	1
4	5	5	15	15	11	11
3	13	13	9	9	20	19
2	19	19	15	15	4	4
1	3	3	0	0	3	3
Performance ^b	100.0		100.0		95.0	

^aNumber of correct scores predicted
^bPerformance is the rate of correct scores predicted (%)

Table 2.3 Robustness of optimised ANN evaluated by leave-one-out cross-validation

	QOL evaluated by patients		QOL evaluated by pharmacists		QOL evaluated by nurses	
	Answered	Predicted ¹⁾	Answered	Predicted ¹⁾	Answered	Predicted ^a
5	0	0	1	0	2	0
4	5	4	15	8	11	8
3	13	8	9	3	20	12
2	19	13	15	13	4	1
1	3	1	0	0	3	1
Performance ^b	65.0		60.0		55.0	

^aNumber of correct scores predicted
^bPerformance is the rate of correct scores predicted (%)

Results

QOL was evaluated by patients, pharmacists, and nurses. As shown in Table 2.2, the subjective QOL scores given by patients were significantly lower than those given by both pharmacists and nurses, and the latter did not show statistical difference ($p=0.7649$ by Wilcoxon signed-rank test). At least to compare among QOL scores given by patients, pharmacists, and nurses, pharmacists and nurses may have a tendency to underestimate the condition of the patients. Table 2.3 shows the Spearman’s correlation coefficient between the QOL scores given by patients, pharmacists, and nurses. The correlation between patient and pharmacist scores was moderate ($r=0.4481$), and the correlation between the scores of patients and nurses was very weak to negligible($r=0.1187$). The correlation between those QOL scores given by pharmacists and those given by nurses was also very weak to negligible ($r=0.1188$). It has been suggested that doctors would underestimate the number of symptoms experienced by cancer patients. However, Sneeuw et al.

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reported that healthcare providers tend to assess patients as having more symptoms than did the patients themselves. Some other studies have reported that healthcare providers are likely to underestimate the physical symptoms of patients. Their results show that pharmacists and nurses seem to have the same tendency as doctors to underestimate the condition of health of patients. Furthermore, although there were no statistically differences in QOL as evaluated by pharmacists and nurses ($p=0.7649$), the correlation between them was very weak to negligible ($r=0.1188$). These results suggest that pharmacists and nurses evaluate the QOL of their patients from different perspectives, based on their respective profession.

ANN model for QOL of patients. They had previously reported that the QOL of cancer patients was modelled well with a score of eight answers (Table 2.2) in the questionnaire, using SEM. As described, pharmacists and nurses evaluate the QOL of their patients from different professional perspectives. We used an ANN to investigate the difference in perspectives between pharmacists and nurses with regard to evaluation of QOL using. As ANN architecture, we used a three-layer perceptron, an input layer comprises eight processing elements (the scores obtained from the answers to the questions), a hidden layer comprises processing elements with a sigmoid function as an activation function, and an output layer comprises the QOL scores obtained from patients, pharmacists, and nurses. The network diagram that was used in the present investigation is shown in Fig. 2.1. The neurons in the hidden and output layers work to calculate the sum of products of values of previous layers and the weight between connections. The neurons then transfer a value to neurons in the next layer according to an activation function. All weights among neurons were optimised to minimise differences between observed and modelled QOLs.

Figure 2.1 shows the effect on prediction performance of QOL of the number of neurons in the hidden layer, using the ANN model. The best fit was obtained when more than 11 neurons were arranged in the hidden layer. In order to avoid “over-fitting” a smaller number of neurons are preferable, so a three-layered architecture with 11 neurons in the hidden layer was used for modelling in this study.

Table 2.2 shows the prediction performance of QOL as evaluated by patients, pharmacists, and nurses using the ANN model. In the final model, subjective QOL, as assessed by patients, and the QOL scores given by pharmacists were all successfully predicted, and only a few of the data obtained from nurses were not predicted by the ANN model that was established. These results suggest that the necessary information to predict how pharmacists would evaluate QOL is contained in the input data.

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The robustness of the ANN model was evaluated with the leave-one-out cross-validation. Table 2.3 shows the prediction performance of QOL with leave-one-out cross-validation. The rate of correct prediction was approximately 60 % for the QOL scores obtained from patients, pharmacists, and nurses, which seems to indicate that the use of the ANN model to predict QOL is not robust. However, only 2/40 patients, 5/40 pharmacists, and 6/40 nurses had differences between evaluated and predicted QOL that were greater than 1 (results not shown). These results indicate that approximately 90 % of QOL data (from 107/120 individuals) could only be roughly, rather than precisely, predicted by the ANN model. QOL is a broad concept, including not only the condition of physical health, but also mental health, education, and social belonging. The patients evaluated their QOL subjectively, based not only on the condition of their own health, but also on their concept of values. We argue that pharmacists and nurses scored patients QOL primarily based on the condition of health of each patient, as assessed from their professional perspective. Therefore, it would be very difficult to make a precise prediction of patient QOL score using data from health professionals. Furthermore, each respective patient was not evaluated by a particular pharmacist and nurse every time. This may have led to individual differences in the evaluation of QOL. If these were considered, a roughly predictive performance of approximately 90 % by ANN would be acceptable.

The QOL of cancer patients was evaluated by the patients themselves and by pharmacists and nurses on the same day. When QOL was self-evaluated by the patients, the scores were different from the QOL scores obtained from pharmacists and nurses. The correlation between QOL scores given by patients and those given by pharmacists and nurses was low. Although the QOL scores given by pharmacists and nurses were not different statistically, the correlation coefficient between them was weak to negligible ($r=0.1188$). These results suggest that pharmacists and nurses evaluate the QOL of their patients from different perspectives, based on their respective profession. The QOL scores were modelled using the scores regarding the HRQOL of patients as input variables using an ANN with three-layer architecture. The predictive performance given by ANN and the robustness of the model were acceptable. Health professionals affect QOL scores as a result of the difference of the profession-based perspectives they hold.

2.4 Discussion and Conclusions

Due to the complexity of processes and the importance of quality improvement in the healthcare contexts, ANN techniques can play a significant role to discover hidden knowledge and values through huge data sets. Indeed Lean thinking key

concepts and models can facilitate value making in the healthcare contexts; however, ANN techniques can also be beneficial to facilitate value discovery. Therefore, taking this into consideration, we propose that ANN techniques should be incorporated to facilitate Lean thinking adoption especially for critical areas within the healthcare domain.

For example, the optimised ANN model in the case study above showed the “information flow” in the case of cancer patients by presenting the difference in perspectives between the pharmacists and nurses in their evaluations of QOL. “Flow” is a key concept in a Lean System (Black and Miller 2008) and “information flow” is one of the seven essential improvement targets to the healthy operation of a healthcare using Lean approach (Black and Miller 2008). Therefore, the presented case study could clearly demonstrate how the ANNs can facilitate Lean thinking adoption in healthcare contexts.

In conclusion, the power of ANNs is considerable in care performance improvement as well as Lean action plans. It is left to further studies to examine or even start to prototype the other numerous benefits of ANNs, and thereby provide a more in-depth analysis that will in turn serve to facilitate Lean thinking adoption in healthcare contexts.

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