ARTICLE ORIGINAL

Towards the Proposition of a New Approach Based on Artificial Neural Networks: Application to Quality of life Prediction through Illness Perception with Chronic Illness Patients

Vers la proposition d'une nouvelle approche basée sur les réseaux neuraux artificiels : application à la prédiction de la qualité de vie à travers la perception de la maladie chez les malades chroniques

Salah Aberkane

Department of Psychology, Faculty of Human and Social Sciences, University of Khenchela – Algeria

Correspondance to :
Salah ABERKANE
aberkanearris@yahoo.fr

ABSTRACT

Aim: Chronic illness affects many Algerians. It is possible to investigate the prediction ability of quality of life as a function to illness perception. In this study, we focus the assessment of the influence of patient's chronic health condition perception on the quality of life using an Artificial Neural Network (ANN) based approach (The Radial Basis Function). **Method**: Three hundred and sixteen participants (16-79 years old) from Arris and Batna regions in Algeria have completed the Revised Illness Questionnaire and Short Form 36 Health Survey Version 2.0 (SF-36V2) scale. **Results**: The correlations between the predicted and real values of quality of life dimensions were 0.34 to 0.43. The importance of the illness length is visible in the plots for perceived quality of life (Physical Functioning, Role Physical), whereas other quality of life dimensions (Vitality and Mental Health) are less visible. **Conclusion**: The artificial neural networks has proved the diagnosis results to be correct and could be useful for assessment of the influence of patients' chronic health condition perception on the quality of life.

Keywords: Illness perception ; Quality of life ; Artificial Neural Networks (ANN) ; The Radial Basis Function (RBF).

RÉSUMÉ

But : La maladie chronique affecte plusieurs algériens. Il est possible d'étudier la capacité prédictive de la qualité de vie comme fonction de la perception de la maladie. Dans cette étude, nous avons évalué l'influence de la perception du patient de la maladie chronique sur la qualité de vie appréciée en utilisant une approche de fonction à base radiale (RBF) du réseau neural artificiel (RNA). **Méthodes** : Trois-cent seize participants (16-79 ans) provenant des villes de Arris et de Batna avaient complété le questionnaire Revised Illness Questionnaire et le questionnaire Short Form 36 Health Survey Version 2.0 (SF-36V2). **Résultats** : Les corrélations entre les valeurs prédites et les valeurs réelles des dimensions de qualité de vie étaient de 0,34 à 0,43. L'importance de l'ancienneté de la maladie est visible dans les graphiques pour la perception de la qualité de vie (fonctionnement physique, rôle physique), alors que les autres dimensions de qualité de vie (vitalité et santé mentale) étaient moins visibles. **Conclusion** : Les réseaux neuronaux artificiels avaient prouvé l'exactitude du diagnostic et peuvent être utilisés pour influence la perception de la qualité de vie du patient atteint d'une maladie chronique.

Mots-clés : perception de la maladie ; qualité de vie ; réseaux neuronaux artificiels (RNA) ; fonction à base radiale (RBF).

اقتراح مقاربة جديدة باستخدام تقنية الشبكات الاصطناعية العصبية : للتنبؤ بجودة الحياة من خلال ادراك المرض لدى المصابين بالمرض المزمن

ملخص:

الهدف من الدراسة: اصابة الكثير من الجزائريين بالمرض المزمن نتج عنه العديد من المشاكل المتعلقة بجودة الحياة. ولذلك بات من الممكن الكشف عن امكانية التنبؤ بجودة الحياة المتعلقة بالصحة من خلال مدركات المريض ازاء حالته الصحية. ولهذا هدفت هذه الدراسة إلى اقتراح مقاربة جديدة للتنبؤ بجودة الحياة المتعلقة بالصحة من خلال ادراك المرض المزمن ، وهذا باستخدام برنامج الحزمة الإحصائية (SPSS) وباستخدام تقنية: الشبكات العصبية الاصطناعية من نوع (شبكة وظائف الاشعاع الأساسي) . **المنهج:** قد شملت عينة البحث من 316 مريضا مصابا بالمرض المزمن ، والقاطنين بمدينتي أريس و باتنة بالجزائر. وقد استعملت في الدراسة مقياسين هما: مقياس ادراك المرض المعدل(IPQ-R)، ومقياس جودة الحياة (SF-36V2). **النتائج:** قد أسفرت نتائج الدراسة إلى إمكانية التنبؤ بجودة الحياة المتعلقة بالصحة من خلال ادراك المرض المزمن ، و أن هناك ارتباط بين قيمة التنبؤ والقيمة الحقيقية للمتغير التابع تتراوح بين قيمة0,34 الى0.43 مما يفسر صلاحية تقنية الشبكات العصبية للتنبؤ بجودة الحياة المتعلقة بالصحة. وهذا ما توضحه اهمية ظهور المتغيرات التابعة من لوحة الانتشار لكل من مدة المرض وكذا ابعاد جودة الحياة المدركة (الحيوية البدنية، الدور البدني) بالاضافة الى الظهور الاقل بالنسبة لمتغيري (الحيوية والصحة النفسية المدركة). **خاتمة**: استطاعت تقنية الشبكات الاصطناعية العصبية من كشف النتائج المرجوة من خلال تشخيصها في وجود تاثير لادراك المرض المزمن على جودة حياة المريض.

الكلمات المفتاحية: ادراك المرض المزمن ، جودة الحياة ، الشبكات العصبية الاصطناعية، شبكة وظائف الاشعاع الأساسي

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INTRODUCTION

Advances in many disciplines of health care sciences have resulted in a dramatic decrease in the number of deaths from illness. This decrease in mortality has resulted in an increase in the prevalence of chronic illnesses. These illnesses are managed in a variety of settings, including home, at work, and in the community setting, rather than within the medical system at a hospital or nursing facility [1]. An increasing number of Algerians are affected by chronic health conditions. People with a chronic health condition often have to face a broad range of problems related to their chronic health condition. Consequently, there is a growing interest in identifying factors that influence people's health-related quality of life in a positive, as well as in a negative way. The individuals' ways of life and the never-ending advances in health care will continue to have a major influence on health and overall well-being and will result in an increase in the incidence and prevalence of chronic illnesses. Because many chronic conditions are rarely linked to a specific cause, they are managed but not cured.

In Algeria, 20 million people currently live with a chronic condition [2]. Chronic illnesses are now the leading cause of death and disability in developed countries and their prevalence is increasing as the population ages [3, 4]. With the advances that have occurred in health care technology, research regarding chronic illness has changed from identification of measures that will extend life to the development, testing, and implementation of measures to support health-related quality of life.

Many intelligent systems have been developed for the purpose of enhancing health-care and providing a better health care, reduce costs … etc. As expressed by many studies [5-8], an intelligent system was developed to assist users particularly doctors and patients, and provide early diagnosis and prediction to prevent serious illnesses. Even though the system is equipped with "human" knowledge, the system will never replace human expertise as humans are required to frequently monitor and update the system's knowledge. Therefore, the role of medical specialists and doctors (or medical practitioner) is important to ensure system validity. Artificial Neural Network (ANN) is one of the powerful techniques that has the capability to learn a set of data and constructs weight matrixes to represent the learning patterns. ANN is a network of many simple processors or units. It simulates the function of human brain to perform tasks as a human does. As an example, a study on approximation and classification in medicine with incremental neural network shows superior generalization performance compared with other classification models [9].

ANN has been employed in various medical applications such as coronary artery [10], myocardial infarction [11], cancer [12], pneumonia [13] and brain disorders [14]. The desire for an improved quality of life has become a particularly important outcome of medical service provision [15]. Individuals with both acute and chronic illnesses are taking a more active role in their health care and expect their beliefs regarding their illness to be considered in medical consultations and selection of treatment [16]. In order to interpret and respond to the wide variety of problems encountered when dealing with a chronic illness, individuals create their own models or representations of their illness [17]. These representations include factors such as chronicity, consequences, and severity and subsequently determine the coping strategies that are used both directly and indirectly to deal with the illness.

It is evident that an individual's representation of the chronic illness guides the development and achievement of goals and the evaluation of the outcomes of coping strategies. As well, quality of life may be related to these cognitive representations of illness and treatment [18]. A lack of congruity between the health care practitioners and the patient's beliefs regarding the cause of the chronic illness and subsequent management can impact the psychological and physiological outcomes of their disease process [19]. Many researchers had identified a relationship between the patient's perception of illness and quality of life [20-22]. A definition that describes both the physical and psychological components of chronic illness is appropriate.

Han *et al*. [1] define chronic illness as "a state of disease with irrevocable pathological change, lasting for more than three months and eventually causing permanent disability." Germino (1998) further describes chronic illness as unremitting, persisting over time, pervading all aspects of life, and having a trajectory that varies in its predictability and controllability. Chronic illness is continuous and without a predictable resolution [23, 24]. Dealing with the transition from diagnosis to treatment and management of a chronic illness can be difficult. Chronic illness has a significant impact on the quality of life of affected individuals and the range of problems experienced varies greatly from one to another [25].

The study about chronic illness perception in the Algerian sample used a version of the IPQ-R adapted for chronic illness patients. This questionnaire was translated to Arabic since there were no published Arabic scales that measure the illness representation of chronic illness. The purpose of this study is to examine the relationship between illness representation and quality of life. By using the ANN, as a conceptual framework, it is possible to investigate the prediction ability of quality of life dimensions as a function of demographical factors in addition to illness perception dimensions. This paper highlights a new approach exploring the ANN in this sample in order to consider both the empirical value and further knowledge regarding the importance of psychotherapeutic interventions in chronic illness.

METHODS

Participants

We have analyzed a sample of 316 persons having chronic illness, 48.73 % women. The majority of the participants were married (53.8 %), 3.8 % were divorced, and 36.08 % were never married. Concerning education, 22.78 % of the participants reported never having attended school, 14.56 % said they achieved primary school, 27.21 % had middle school level, 25.32 % were secondary school graduates, and 10.12 % had higher education. The majority of the participants had median economic level (75.32 %). Four illness groups have been created from the regions of Arris and Batna. All patients were able to read and write in Arabic and had a medical diagnosis of their condition to be included in the study. All eligible patients who attended the clinic were invited to participate. The characteristics of the four illness groups are presented in Table 1.

Measures

The Illness Perception Questionnaire Revised (IPQ-R) (Predictor)

Table1. Characteristics of Patient Samples

Illness Group	N	Gender (% Male)	Length of Illness Mean (SD) years	Age Mean (SD) years
Asthma	62	63.3	10.90(10.03)	40.73(13 .98)
Diabetes	74	64.6	5.64(4.96)	45.29(16.02)
HBP	82	36.5	10.09(7.38)	55.17(14.07)
Chronic Kidney disease	98	60	6.46(5.63)	35.62(11.96)

Development of the Illness Perception Questionnaire Revised (IPQ-R): The IPQ-R is divided into three sections, with the identity and causal dimensions presented separately from the remaining dimensions. The identity scale is presented first and consists of the 12 commonly experienced symptoms included in the original IPQ: pain, nausea, breathlessness, weight change, fatigue, stiff joints, sore eyes, headaches, upset stomach, sleep difficulties, dizziness and loss of strength. Two new symptoms, sore throat and wheeziness, were added to the list. The instructions for this scale were also altered. The IPQ-R firstly asks patients to rate whether or not they have experienced each symptom since their illness using a yes/no response format. They are then asked whether or not they believe the symptom to be specifically related to their illness using the same format. The sum of the yes-rated items on this second rating forms the illness identity subscale.

The general symptom experience subscale is not included in the IPQ-R but was used in the current study to assess the validity of the identity subscale. In the following section the identity, consequences, timeline acute/ chronic, timeline cyclical, coherence and emotional dimensions of the IPQ-R are rated on the original 5-point Likert type scale: strongly disagree, disagree, neither agree nor disagree, agree, and strongly agree. The causal dimension is presented as a separate section which uses the same Likert-type scale. The number of attributional items was extended from 10 to 18 [26]. These sub-scales had adequate internal consistency in the prior study of Arabic version [27], and in the present sample (Cronbach's alpha ranging from 0,45 to 0,88).

Short-Form 36 Health Survey Version 2.0 (SF-36v2) (Outcome)

Short-Form 36 Health Survey Version 2.0 (SF-36v2): The SF-36v2 is a multipurpose health survey that measures overall health status, functional status, and health-related quality of life. It is a generic measure and its use is not restricted to a single disease state. Using an eight-scale profile of physical and mental health summary measures, the SF-36 is a valid and reliable tool that allows comparisons between and within clinical and general populations. The SF-36 is used to monitor specific and general populations to estimate disease burden After deployment, the SF-36 can be used to quantify the severity of an individual's post-deployment health issue at any point in time as well as allowing comparisons of his or her health status over time.

- The survey produces 8 scale scores:- Physical Functioning (PF)- Role Physical (RP)- Bodily Pain (BP)- General Health Perceptions (GH)- Vitality (VT)- Social Functioning (SF)- Role Emotional (RE)- Mental Health (MH).
- Two summary scales can be used: - Physical Component Score (PCS): Combines PF, RP, BP, and GH - Mental Component Score (MCS): Combines VT, SF, RE, and MH. [28]. These subscales had adequate internal consistency in the present sample (Cronbach's alpha ranging from 0.50 to 0.89).

Prediction of life quality through illness perception dimensions

In order to get an accurate analysis of the acquired data, radial-basis function (RBF) network models were developed under the SPSS statistical package. We specified the relative number of cases assigned to the training: testing samples should be 7:3. This assigned 7/10 of the cases to training and 3/10 to testing. Before using the input data records to the ANN, a normalization process took place so that the values with wide range do not prevail over the rest. The auto scaling approach was applied. This method outputs a zero mean and unit variance of any descriptor variable [29].

Use of Radial Basis Function in estimating the quality of life

The Radial Basis Function (RBF) produces a predictive model for one or more dependent (target) variables based on values of predictor variables.

Preparing the Data for Analysis

Running the Analysis

From the RBF analysis, 316 cases (77 %) were assigned to the training sample, (15 %) to the testing sample, and (8 %) to the holdout sample. 116 data records were excluded from the RBF analysis.

RESULTS AND DISCUSSION

Table 2 displays the corresponding information from the RBF network. There appears to be more errors in the predictions of several dimensions, in the training and holdout samples. The difference between the average overall relative errors of the training (0.865), and holdout (0.925) samples must be due to the small data set available, which naturally limits the possible degree of complexity of the model [30].

Table2. Model summary

Training	Sum of squares error		164,399
	Average Overall Relative Error		0,865
	Relative Error for Scale Dependents	PF	0,838
		RP	0,804
		VT	0,921
		MH	0,852
		RE	0,911
	Training time		00:00:02,453
Testing	Sum of squares error		33,875[a]
	Average Overall Relative Error		0,966
	Relative Error for Scale Dependents	PF	1,456
		RP	1,038
		VT	0,976
		MH	0,848
		RE	0,819
Holdout	Average Overall Relative Error		0,925
	Relative Error for Scale Dependents	PF	0,772
		RP	0,690
		VT	0,915
		MH	1,084
		RE	1,041

a. The number of hidden units is determined by the testing data criterion: The "best" number of hidden units is the one that yields the smallest error in the testing data.

Model Summary

In Table 2 parameter estimates for input and output layer are given for the RBF network.

Predicted-by-Observed Charts

Figure1 shows the predicted by observed chart for physical functioning likewise each observed value of perceived mental health and vitality.

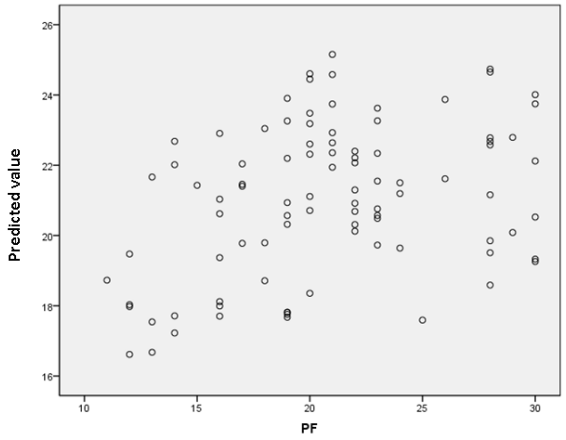

Figure 1. Predicted-by-observed chart for physical functioning.

Physical functioning and physical role involve the functions from several human systems, including the musculoskeletal and neurologic systems, as well as supplemental systems, such as the cardiovascular and respiratory systems. Physical functioning of chronic condition patients is a result of the cumulative effect of physical change from the threat process. Generally, the physical functioning of patients deteriorates because of the degeneration of their physiology. Physical functioning plays an important role in human adaptation as proposed from the human response model. Having good physical functioning supports the ability for adaptation, whereas loss of physical functioning makes the patient vulnerable to disability and weakens his ability for adaptation with his healthy situation. For scale-dependent variables, the predicted-by-observed chart displays a scatterplot of predicted values on the y axis by observed values on the x axis for the combined training and testing samples. Ideally, values should lie roughly along a 45-degree line starting at the origin. The points in this plot form vertical lines at each observed emotional role. Looking at the plot, it appears that the network does a reasonably good job of predicting RE. The general trend of the plot is off the ideal 45-degree line in the sense that predictions for observed RE.

For scale-dependent variables, the predicted-by-observed chart displays a scatter plot of predicted values on the y axis by observed values on the x axis for the combined training and testing samples. Ideally, values should lie roughly along a 45-degree line starting at the origin. The points in this plot form vertical lines at each observed value of perceived mental health and vitality. Looking at the plot, it appears that the network does a reasonably good job of predicting perceived vitality.

For other remaining dependant variables (PF, RP), we can obtain similar behavior of the artificial neural network in terms of prediction performance.

Residual-by-Predicted Charts

The residual-by-predicted chart displays a scatterplot of the residual (observed value minus predicted value) on the y axis by the predicted value on the x axis. Each diagonal line in this plot corresponds to a vertical line in the predicted-by-observed chart, and we can more clearly see the progression from over-prediction to under-prediction of the PF as the observed PF increases (see figure 2).

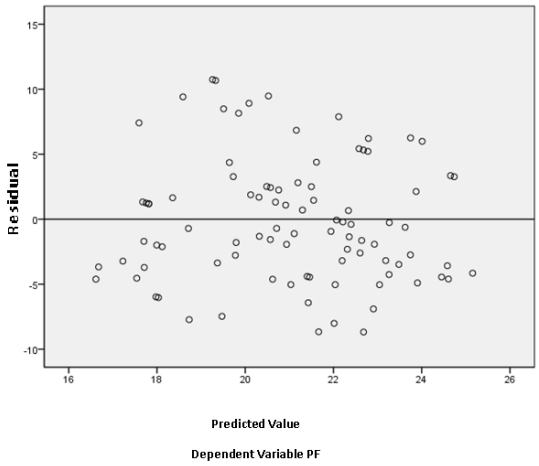

Figure 2. Residual-by-predicted chart for physical functioning.

Likewise, for patients observed in the predicted-by-observed plot for physical role, the residual-by-predicted chart shows a progression from over-prediction to under-prediction of quality of life as the observed increase. The effect of demographic information during the illness threat are still clearly visible, but it is also easier to see the other variables such as behavioral attributions.

The residual-by-predicted chart displays a scatterplot of the residual (observed value minus predicted value) on the y axis by the predicted value on the x axis. Each diagonal line in this plot corresponds to a vertical line in the predicted-by-observed chart, and you can more clearly see the progression from over-prediction to under-prediction of the mental health as the observed MH increases. (similarly to figure 2)

For other remaining dependant variables (vitality), we can obtain similar behavior of the artificial neural network in terms of prediction performance.

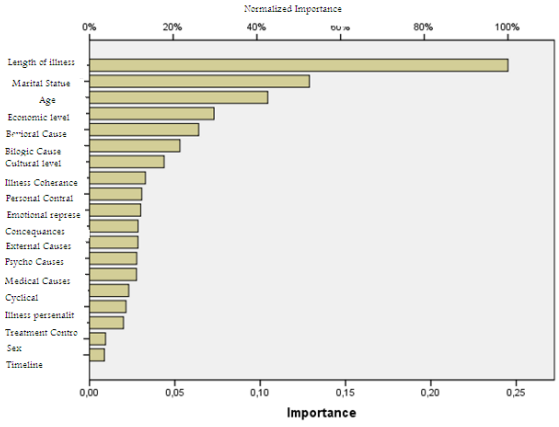

Figure 3. Independent variable importance chart

The importance chart shows that the results are dominated by the length of illness, followed distantly by the marital statue, followed distantly by the remaining predictors. The importance of length of illness is visible in the plots for perceived quality of life (PF, RP) and other quality of life dimensions (VT and MH) are less visible. Although, the effect of length of illness and marital status on quality of life dimensions appear to be visible in the participants having the largest observed vitality and mental health (see figure 3).

The correlation between the predicted and real values

Table 3 presents the main results of the correlation between the predicted and real values of quality of life dimensions.

Table 3. Correlation between the predicted and real values of quality of life dimensions.

	Real value of RE	Real value of MH	Real value of VT	Real value of RP	Real value of PF
Predicted value of RE	0,353	-	-	-	-
Predicted value of MH	-	0,397	-	-	-
Predicted value of VT	-	-	0,346	-	-
Predicted value of RP	-	-	-	0,433	-
Predicted value of PF	-	-	-	-	0,417

CONCLUSIONS

In this study, we have aimed at the evaluation of artificial neural network ability in Quality of life prediction through illness perception and demographic information with chronic illness patients. The radial-basis function neural network with supervised learning has been proposed to prediction purposes. It shows significant results in dealing with data represented by both independent and dependent variables (input and output respectively). The obtained results have indicated satisfactory performance, showing that the correlation between the predicted and real values of quality of life dimensions is appropriate. The artificial neural networks has proved the diagnosis results to be correct and could be useful for assessment of the influence of patients' chronic health condition perception on the quality of life. Unlike traditional statistical methods, the neural network models have provided dynamic output as further data is fed to it, while they do not require performing and analyzing sophisticated statistical methods. The future investigation will focus more attention to evaluate ANN in other psychological assessments ; therefore, impressive results may be obtained with the proposed method and improving the performance of ANN using high-performance computing techniques. In addition, the combination of the approaches mentioned above can yield an efficient classifier for a lot of applications and open new research directions.

Conflicts of interest

The authors have no conflicts of interest to declare.

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