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Modeling of health related quality of life using an integrated fuzzy inference system and linear regression

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Abstract

Health Related Quality of Life (HRQL) is one of the increasing subjects used for assessing health condition among patients who suffer from specific diseases or illness. It has been assumed that multiple variables of HRQL would provide the one's overall health conditions. However, devising the extent of contribution of multiple variables towards overall health conditions is not straight forward as the arbitrary nature of HRQL variables. This paper aims to model the relationship between HRQL variables using an integrated model of fuzzy inference system and linear regression. An experiment was conducted to measure the strength of the relationship between variables and health indices among patients with chronic kidney diseases (CKD). To model this relationship, thirty outpatients with CKD were recruited from a government funded hospital in Peninsular Malaysia. Linguistic data were collected via guided interview and fed into the fuzzy inference system to yield HRQL indices. Multi-linear regressions were then undertaken to establish the relationship between variables and HRQL indices. The model shows that the variable of 'unemployment' was identified as the highest impact factor for patients with CKD. The employment of the integrated model, fuzzy inference system and multi-linear regressions were successfully identified the strength of the relationship between the multiple variables of HRQL and the health status.

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*Keywords:*Fuzzy inference system; inference rule; health status; chronic kidney diseases; multi-linear regression

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1. Introduction

One of the most significant current discussions in modern living is quality of life. The conceptual definitions of quality of life are indeed varies depending on social stratification and local preferences. Some of the definitions of quality of life are extended specifically to health related issues and normally refers as health related quality of life (HRQL). Most of the conceptual definitions of HRQL refer to a person or group's perceived their physical and mental health. According to Hays and Reeve[1], HRQL concerns how well people are able to function and how they feel about physical, mental, and social dimension of their lives. HRQL also has been defined as a multi dimensional concept that reflects a person's perception of their physical, psychological, and social function and health classification[2]. Bowling[3] defines HRQL as optimum level of physical role, for example, work, career, parent and social functioning, including relationships and perceptions of health, fitness, life satisfaction and well-being. Some these definitions purposely explain HRQL as patient-assisted outcome measure, health classification, and functional classification or just as outcome measure. Patients with chronic diseases do not typically cause death, but has a substantial effect on health, fitness, and physical, emotional, and social functioning. Sharma[4], for example, describes HRQL as a multi-dimensional dynamic concept that has developed from the need to estimate the impact of diseases, which includes economic welfare, characteristic of community and environment, and health classification.

The impact of specific disease to general health status was discussed by Zakaria et al.,[5]. They employed a tool in measuring knee osteoarthritis patients and found that the patients was poor in quality of life due to the impact of the disease. One of the most frightening specific diseases that believe to bring huge impact on patients' health status is chronic kidney diseases (CKD). The kidney failure related diseases are one of the major health issues in the world and not just it associates with life expectancy but also it substantially impacts on patients' quality of life. The patients with CKD were hypothesized to less able perform physical activity hence some were forced to leave workplace. From psychological point of view, patients with CKD also may suffer some degree of emotional disturbances. A report from psychology centre reveals that both depression and less physical activity may play a major role in patients with kidney failure leaving the workforce[6]. Markell et al.,[7] reported that unemployment rate has increased among CKD patients. The major reasons for discontinuing work after starting dialysis treatment were subjective illness, followed by interference of the dialysis regimen with time necessary for work. In the study of Bowling et al.,[8] they found that CKD is associated with poor physical function. However, little is known about the longitudinal association between CKD and the decline of instrumental activities of daily living, inability to resume working life and emotional disturbances. Therefore, HRQL has been acknowledged as a good health indicator in measuring impact of the many chronic diseases including CKD.

In the midst of many research in HRQL, methodological issues in measuring the impact still require careful attention. Most data used in research of HRQL were assessed and measured using descriptive and inferential statistics approaches which is fundamentally depend on the data collection via questionnaire or survey. With statistical approaches, health related indicators are measured based on data collected via a questionnaire that administered to the patients. The largest study to date, regarding the HRQL in patients with CKD comes from the Dialysis Outcomes and Practice Pattern Study (DOPPS)[9]. DOPPS was a multinational, prospective, observational study of haemodialysis patients focusing on practice patterns and outcomes. HRQL was measured using both the instrument SF-36[10] and KDQoL-SF[11]. These types of quantitative research are mostly relying on a priori stated hypothesis regarding HRQL in order to meet the research objectives. Tools that have been used in accessing HRQL, ideally must fulfil some reliability tests and homogeneity of variance assumptions. As to avert the normality and statistical tests assumptions in quantitative research, other forms of health related research may opt to qualitative nature research such as interviews and observations. Abdullah and Jamal[12], for example, used closed end question during an interview with medical officers and nurses to collect linguistic judgment data over the health related status of patients with CKD. The applications of qualitative fuzzy decision making in health sciences and human well-being are not something new. The fuzzy theory, for example, has been applied in medical decision making[13,14,15,16], controller systems[17,18,19] and also in measuring quality of life[20,21]. This study proposes the integration model of intelligent system of decision making approach and linear regression in searching the interactions between physical and emotional variables of patients with CKD and patients' HRQL. This paper takes account the emotions, unemployment and physical activities as the input variables to unveil the extent of these variables impacting quality of life among CKD patients. Specifically, this paper aims to model the relationship between HRQL indices of

patients with CKD and the selected emotional and physical variables using the integrated approach of fuzzy inference system and multi linear regressions. This paper is structured as follows. A framework of the research is explained in Section 2. Implementation of the proposed integration model using the patients with CKD data is presented in Section 3. Finally this paper ends with conclusions in Section 4.

2. Research Framework

This framework is designed to aid in conceptualizing how the experiment was conducted to search the interaction between input variables and health status among patients with CKD. Thirty patients with CKD at a government funded hospital in Peninsular Malaysia were interviewed to tap their HRQL conditions specifically in the three areas. They were asked to respond in linguistics scales over the extent of 'emotion', 'unemployment' and 'daily activities' affect their quality of life. These input variables are fed into the fuzzy inference system (FIS) to established HRQL indices. These indices are then used as response variable in multi linear regression (MLR). The input variables were regressed with the indices to form a multi linear regression equation. The integration model is expected to be able to capture the most influential variable affecting quality of life among patients with CKD. In short, this research flow is divided into two phases. Phase I explains the step-wise procedures to obtain HRQL indices using fuzzy inference system (FIS). The Phase II presents the proposed step-wise procedures in obtaining multi linear regression (MLR) equation. This equation could be used to identify the most effective predictor of HRQL among patients with CKD. Summarily, the research framework can be depicted in Fig. 1.

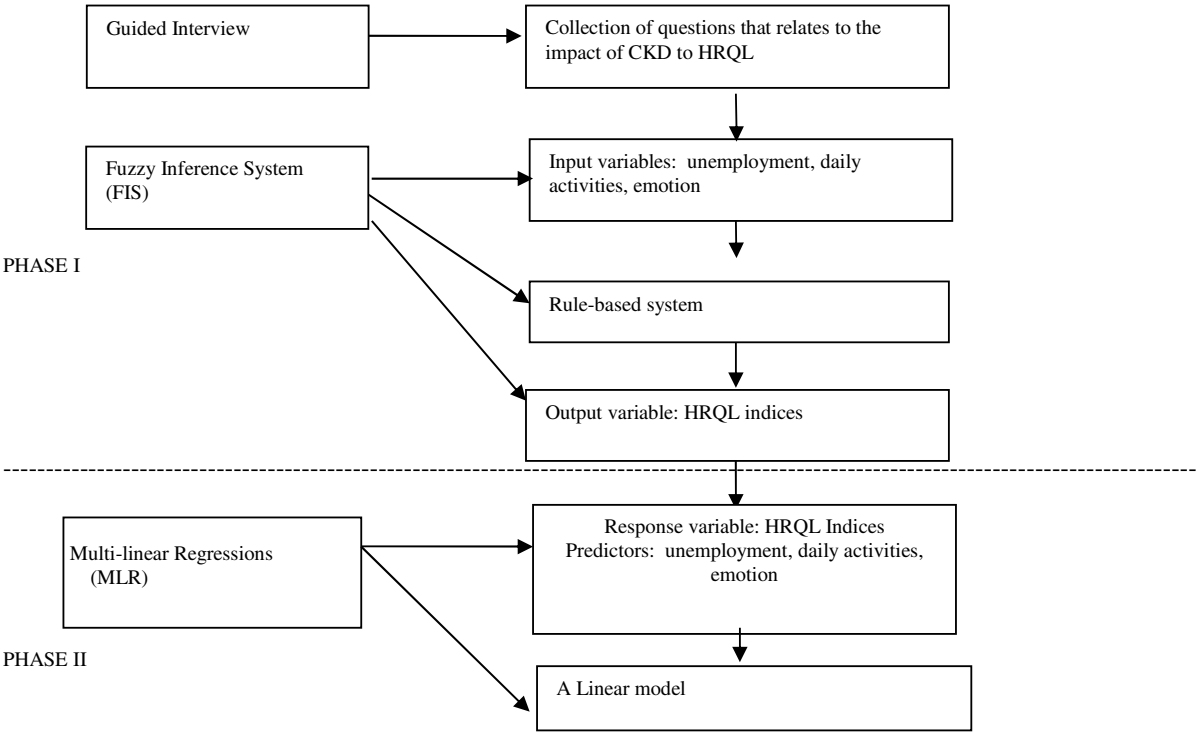

Fig. 1. Framework of the modelling flow

3. Implementation

This section explains the implementation of stepwise procedures to obtain HRQL classification using fuzzy inference system. The step-wise procedures could be used to classify HRQL status among CKD patients.

Step 1: Identify Input and Output Variables
The variables of HRQL among CKD patients are become the input of this Mamdani inference and the output of the system is the HRQL status. Input variables are Unemployment, Daily activities, Emotion and output variable is HRQL status. Fig 2 illustrates how the inputs related to the HRQL are being processed to classify into the predetermined output.

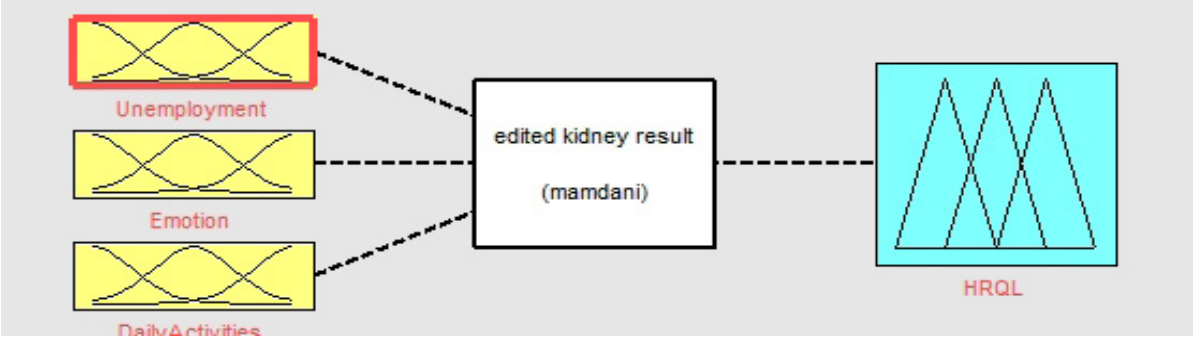

Fig. 2. Input and output of the system

Step 2: Fuzzify the variables.

The input variables are fuzzified by determining the degree to which they belong to each of the appropriate fuzzy set via membership functions. Input variable of emotion, for example, is fuzzified into five linguistics. Status of HRQL (output variable) is defuzzified into five linguistics of 'very high' to 'very low'.

Step 3: Creating Rules
According to Guillaume[22], fuzzy inference system contains fuzzy rules built from expert knowledge. Based on input variables Unemployment, Daily Activity and Emotion with five linguistics, thirty nine relevant 'IF–THEN' rules are created. The rules are designed by expert to describe the importance of the input variables over the possible status of HRQL At this step, information from patients are entered into the system. Based on the expert knowledge, this study expresses the problem in terms of logical rules. Parts of the rules are shown in Fig. 3.

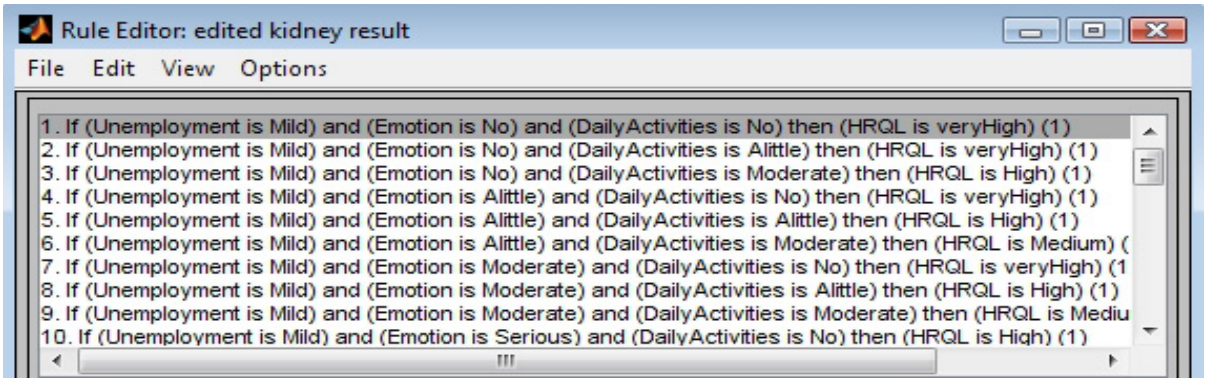

Fig. 3. Rules for determining HRQL status

Step 4: Defuzzification

Defuzzification using centroid or center of area (COA) is used to aggregate all the outputs into a single output. Center of the area under the aggregated output membership function is calculated using the following equation,

$$z_{COA} = \frac{\int \mu_A(z)\, z\, dz}{\int \mu_A(z) dz}$$

where, $\mu_A(z)$ is the aggregated output membership function. Once rules have been created, a single output can be calculated by inserting the patients' data in rule viewer. The HRQL index was successfully predicted by the system.

The FIS successfully composited all the three input variables to yield the HRQL indices. Nevertheless, the effect of every single input variable toward the indices is still inconclusive. As to deal with this problem, the analysis is resumed with the multi linear regression. The effects of the input variables toward HRQL index could be dealt from the multi linear regressions equation

Multiple-linear regression is a method used to model the linear relationship between a dependent variable and one or more independent variables. The dependent variable is sometimes called the response variable and the independent variables are called as the predictors. As to make the analysis more organized, the following steps are proposed.

Step 1: Identify predictors and response variable.
Predictors: Emotion, Daily activity, unemployment
Response variable: HRQL indices (output of the Phase I).

Step 2: Assumption of normality.
All variables are subjected to fulfil normality assumption. The normal P-P Plot of Regression is plotted as to observe the data distribution. Figure 4 shows the data are almost linear in P-P plot thereby the assumption of normality for multiple regression analysis is fulfilled.

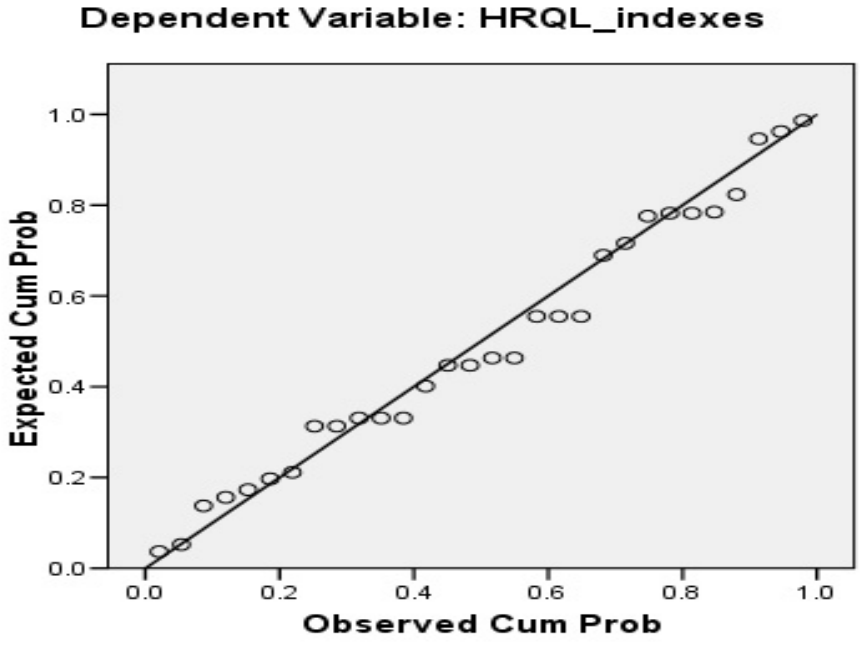

Fig. 4. Normality assumption test

Step 3: Testing the relationships.
The relationship between predictors and HRQL index are pre-tested using F-test based on the following hypotheses at significant level of $\alpha = 0.05$.
H_0 : The model is not suitable for predicting HRQL of patients with CKD
H_1 : The model is suitable for predicting HRQL of patients with CKD

Summary of the test is shown in Table 1.

Table 1. F-Test for the relationship

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	3534.856	3	1178.285	100.242	0.000
	Residual	305.613	26	11.754		
	Total	3840.470	29			

With the F-value at 100.242 and 0.000 significant probability, the null hypothesis is rejected at 0.05 significant level. There is a relationship between predictors and HRQL indices. Therefore, the multi linear regressions fulfil the linearity test in predicting the HRQL among patients with CKD.

Step 4: Obtain the multi-linear regression equation.
Multi linear regression equation in explaining the behaviours of predictors toward HRQL indices patients with CKD is obtained. The coefficients of the regression equation are presented in Table 2.

Table 2. Regression Coefficients

Model		Unstandardized Coefficients		t	Sig
		B	Std. Error		
	(Constant)	5.333	1.835	2.906	.007
	Unemployment	4.131	0.415	9.962	.000
	Emotion	1.422	0.402	3.540	.002
	D_activity	2.914	0.448	6.507	.000

From the table, the multi-linear regression equation can be written as,

$$\hat{Y} = 5.333 + 1.422(\text{Emot ion}) + 2.914(\text{Dail y activity}) + 4.131(\text{Unem ployment})$$

Out of the three predictors, the variable of 'unemployment' is the highest contributors toward HRQL indices patients with CKD. It is evident that the variable of 'emotion', daily activities' and 'unemployment' are positively contributed to the quality of life of patients with CKD. The findings of the current study are consistent with those of Lopes et al.,[16] who found the positive relation relationship between the dependent variable and independent variables.

4. Conclusions

This paper has successfully demonstrated that the integrated rules-based system and multi-linear regressions can be used to propose a linear relationship between health related quality of life indices and its variables among patients with CKD. The experiment was conducted to show the relationship between health indices and the three selected variables. Thirty patients with CKD were chosen as participants in this experiment. The fuzzy inference system provided the health indices whereby these indices were subsequently used as the response variable in the regression

analysis. It is demonstrated that the linear relationship can identify the best predictor for health related quality of life among patients with CKD. 'Unemployment' among the patients was identified as one of the significant variables in prescribing the impact of the disease toward patients. It is important to note that the impacting factors for quality of life among patients with CKD are not limited to the three selected variables. Future research may be undertaken to include greater number of participants and more variables to substantiate these findings.

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