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Application of Rasch model for evaluating the quality of life in blind war veterans

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Abstract

Background: Quality of life evaluates the general well-being of individuals and it can be considered as one of the important aspects in programming and giving service to disabled people. Blindness is one of the most important kinds of physical disability that has a direct effect on quality of life, so this study aimed to explore how war blindness influences the quality of life.

Methods: In this cross-sectional study, data from 71 blind war (Iran-Iraq) veterans in 2010 were collected using the Short Form Health Survey instrument (SF36). Rasch model was fitted by running WINSTEPS software and then item parameter (β), i.e. difficulty of items, and person parameter (θ), i.e. the ability or attainment level of respondents, were estimated.

Results: In a total of 71 cases**,** 69 cases (97 %) were male with a mean ($\pm SD$) age and blindness duration range of 48.97 ($\pm$10.655) yrs and 25.74 ($\pm$3.692) yrs, respectively. Item difficulty ranged from 2.962 to 4.441. Comparison of the SF36 scores and Rasch measurements showed that standard error of Rasch model estimates in physical and total scores are less than SF36 scores.

Conclusion: Due to the advantages and higher accuracy of the Rasch model, using this model can be a good alternative for the traditional models. With due regard to the relative low quality of life of blind war veterans in this study and other similar study, further investigation are recommended to be carried out to this group of society.

Keywords: Rasch model, Quality of life, Blind war veterans.

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Introduction

Quality of life (QoL) is a concept incorporating all the factors that might effect on an individual's life. In medical research it is more usual to consider health-related QoL. The World Health Organization (WHO) defined health in 1948 as "a state of complete physical, mental and social well-being and not merely the absence of infirmity and disease". This definition reflects the focus on a broad picture of health (1-3).

The term QoL has been used in many ways. Although the exa ct definition varies among authors, there is general agreement that QoL is a multidimensional concept that focuses on the impact of disease and its treatment on the well-being of an individual (4). In the broadest definition, the quality of our lives is influenced by our physical and social environment as well as our emotional

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and existential reactions to that environment. Kaplan and Bust proposed the use of the term health-related-quality of life (HrQoL) to distinguish health effects from other factors influencing the subject's perceptions, including job satisfaction and environmental factors (5).

QoL evaluates the general well-being of individuals and societies. Over the last ten years, this term has been seen increasingly in medical literatures. Studying QoL can provide information and solution about international development, healthcare, politics, programming and effectiveness of different treatments.

Nowadays, QoL is one of the important aspects in programming and giving service to disabled people and blindness is common kind of physical disabilities that has a direct effect on QoL. It takes away the man from the natural course of life and makes a lot of mental and physical problems (6).

War is one of the events that if occur in any society will cause enormous physical and psychological damage that each of them alone have many consequences. Blindness is one of the complications that occur in most of the world wars. Most of the blind war veterans suffer mental disorders, especially depression, in addition to their physical diseases (7,8). Mental problems have far-reaching effects on QoL and in some of the articles it has more health problems and that become more obvious when correlated with physical factors. As one of the longest modern wars, the Iran-Iraq War (1980-88) is no exception to this phenomenon and has produced many veterans with these injuries (9,10).

QoL has been examined in several studies and some of them have been working on war disabled and especially on blind war veterans. In most of them QoL is measured using a questionnaire (like SF36, GHQ, etc) and the effect of some variables have been investigated. In all these studies, a questionnaire has been used as a measurement tool and after measuring the QoL, these values are used as the response variables in the statistical procedures and models to examine the relationship between the some risk factors and QoL (11-15).

In this paper we want to show that QoL can be directly estimated using the latent trait models, without using classical summation methods (i.e., instrument's algorithm). Whereas QoL cannot been measured directly so it can be spot as a latent variable, so an alternative is to use item response theory (IRT) models such as the Rasch model (RM) (16,17).

The analysis of response data to test items requires psychometric methods to investigate characteristics of items and individuals that answer those items. One of the parameters that involved in responding to a question is item difficulty. It means that the difficulty level of each item has a direct impact on person's response and on the total score of QoL. If we use simple and traditional algorithm to compute questionnaire scores then we cannot consider the impact of difficulty parameter on total score of QoL. Using item IRT models, one can simultaneously include both the difficulty and ability parameters to assess the total scores more accurately (18-20).

The application of IRT modeling has increased considerably in recent years because of its utility in developing the different instruments. Some procedures (Structural Equation Models, Discriminant analysis) allow the links between the items and the latent variables to be defined, but none of them a direct estimate of latent variable (21-24). In 1960, George Rasch suggested a statistical RM that makes it possible to define these links and transforms the raw scores into linear continuous measures of person ability and item difficulty. In the Rasch model raw data from a rating scale is converted to an equal interval scale measured in logit scale (log odd units) that allows one to use more variant parametric statistics instead of nonparametric statistics (25).

In this manuscript, we use the RM for analyzing the data from 71 Iranian blind war veterans. We also compare the obtained results of RM with finding from SF36.

Methods

Questionnaire SF36

A new measure that consider as a measure of health status is the Short Form 36 (SF-36). The SF-36 is a generic tool that can be used for the general population and different patients groups developed by the Medical Outcomes Study in the United States. The SF-36 contains 36 items which measures the eight areas: social functioning (2 items), mental health (5 items), physical functioning (10 items), role limitations due to emotional problems (3 items), role limitations due to physical problems (4 items), energy/vitality (4 items), pain (2 items), and general health perception (5 items) and a single item, asking respondents about health change over the past year. It also provides two summary scales, namely Physical Component Summary (PCS) and Mental Component Summary (MCS). Scores on each of the subscales range from 0 to 100, with 0 representing the worst and 100 representing the best QoL status (26).

The SF36 questionnaire was translated into Persian and the psychometric properties assessment of the Persian version of the SF36 showed considerable evidence about the reliability of this questionnaire. The internal consistency of the different dimensions of the questionnaire was found to be 0.77 to 0.90. Finally Factor analysis produced a two factor solution for Persian version of SF36 (27).

Participants and data

The study population of this cross-sectional study consisted of all completely blind Iran-Iraq war veterans who were invited to the Foundation of Martyrs and Veterans Affair in 2010. Data was of a convenience sample of 71 out of an initial group of 250 invitees. There was no exclusion criterion and ethical considerations were taken into account when designing and executing this study. The quality of life assessment was done using the SF-36 Health Survey. Moreover, for these participants the demographic and other information like age, gender, blindness duration, additional ulcers, employment status and educational level were considered.

Rasch model

The RM is named by Danish mathematician George Rasch in 1960. The RM can be used for analyses the educational tests which are considered to capture a unidimensional construct. Because the responses to items are used to indicate the property that cannot be measured directly, so the RM is a latent trait model. This model can be used to cumulative data based on frequency items or Likert-style items and it is a useful tool for converting raw data into item difficulty and person ability estimates on an approximately linear measurement scale (17, 18, 20).

Now assume there are n examinees, $E_1, \dots, E_n$, drawn who respond to a set of J test items. Let x_{ij} denote the response of examinee i to item j. If $x_{ij} \in \{0, 1\}$ so we speak of dichotomous data and refer to the dichotomous RM. The dichotomous RM assumes that there is a parameter θ for each examinee, referred to as person parameter, and β for each item, subsequently referred to as item difficulty. For the probability of a response x_{ij}, the dichotomous RM is:

$$P(X = 1|\theta_i, \beta_j) = \frac{exp(\theta_i - \beta_j)}{1 + exp(\theta_i - \beta_j)}$$

That $P(x)$ is the probability of correct response, θ_i is ability of person i (in this paper is QoL) and β_j is difficulty of item j (18, 22). Small values of β show the easiest items, that is, they are attended in the many of respondents, also respondents with low ability. On the other hand, large values of β show the most difficult items, that is, only respondent with a high ability show them.

Three key assumptions are assumed in RM: specific objectivity, statistical sufficiency of raw scores and local independence of item responses. Specific objectivity describe that case essential to measurement in which "comparisons between individuals become independent of which particular instruments -tests or items or other stimuli- have been used. Symmetrically, it ought to be possible to compare stimuli belonging to the same class- measuring the same thing- independent of which particular individuals, within a class considered, were instrumental for comparison" (18). Specific objectivity is tested by comparing distribution of mean square residuals, normalized to expected response variance, to the expected chi-square distribution.

Statistical sufficiency of raw scores means that raw scores are sufficient statistics for person parameter and they have all the information there is in the dataset about the ability of the respondent (18). It is tested by correlation between person measures and test scores (based on raw scores).

Local independence means that the responses to an item are independent of the responses to any other items in the instrument. In other words, the way a person responds to an item depends on the person's parameter level and not on how the person responds to any other items in the instrument (18). Local independence assumption is checked through principal component analysis (PCA). In this paper, we used RM by running WINSTEPS software to fit the model and estimate the item and person parameters.

Results

In this cross-sectional study, a total number of 71 blind war veterans were studied. Among them, 97.1% (69 veterans) were male. The mean ($\pm SD$) age and blindness duration was 48.97 ($\pm$10.655) yrs and 25.74 ($\pm$3.692) yrs, respectively. In average, they had 2 additional ulcers in different parts of their bodies. The employment rate was 32.9% (23 veterans) among these veterans. About 70% (50) of the veterans had non-academic and 30% (21) had academic education. In order to fit the RM, we first checked the model assumptions.

For checking the sufficiency condition, we can see in table3 that correlations between person measures and test scores are high and it means that raw scores are sufficient statistics for ability parameter. As shown in Table 1, the unexplained variance was 6.4% so PCA results provide no additional structure and support a unidimensional and local independency underlying construct for SF36.

After checking the assumptions of the model, the RM that included 71 respondents was fitted to the data. Table 2 shows the obtained estimates for SF36 items difficulty and Fig.1 shows the frequency distribution of estimated QoL.

Item difficulty ranged from -2.962 to 4.441 and this finding shows that items "Lifting or carrying groceries", "Climbing several flights of stairs", "Climbing one flight of stairs", "Bending, kneeling, or stooping" and "Bathing or dressing yourself" have the lowest estimates and are the "easiest" items, that is, they are attended in the many of patients, also patients with a low QoL; instead, items "Moderate activities", "How much bodily pain have you had during the past 4 weeks" and "As healthy as anybody" have the highest estimates and are the most "difficult", that is, only people

Table 1. Principal Component Analysis (PCA) for Standardized residuals variance for checking the unidimensionality and local independency assumptions

Variance Component	Empirical		Model based
Total raw variance in observations	51.8	100%	100%
Raw variance explained by measures	26.8	51.80%	50.80%
Raw variance explained by persons	14.5	27.90%	27.40%
Raw Variance explained by items	12.4	23.80%	23.40%
Raw unexplained variance (total)	25	48.20%	49.20%
Unexplained variance in 1st contras	3	6.40%	12.20%
Unexplained variance in 2nd contrast	3	5.80%	12.00%
Unexplained variance in 3rd contrast	2.1	4.00%	8.40%
Unexplained variance in 4th contrast	2	3.90%	8.10%
Unexplained variance in 5th contrast	1.6	3.00%	6.30%

Table 2. The results from Rasch model for assessing the SF36 items difficulty

Item	estimate	standard error	p
General health	-0.6067	0.3111	0.0511
General health compare to one year ago	1.8271	0.3689	<.0001
Vigorous activities	1.8271	0.3689	<0.0001
Moderate activities	4.4419	0.6171	<.0001
Lifting or carrying groceries	-1.2839	0.3187	<.0001
Climbing several flights of stairs	-1.4857	0.3236	<.0001
Climbing one flight of stairs	-1.3841	0.3210	<.0001
Bending, kneeling, or stooping	-1.6943	0.3301	<.0001
Walking more than a mile	-0.2253	0.3118	0.4760
Walking several blocks	-0.8934	0.3128	0.0043
Walking one block	-0.2253	0.3118	0.4700
Bathing or dressing yourself	-2.9625	0.4111	<.0001
Cut down the amount of time you spent on work	1.2123	0.3420	0.0004
Accomplished less than you would like	0.2609	0.3173	0.4111
Were limited in the kind of work	0.4614	0.3210	0.1506
Had difficulty performing the work	-0.2253	0.3118	0.4710
Cut down the amount of time you spent on work	2.7412	0.4283	<.0001
Accomplished less than you would like	2.5685	0.4152	<.0001
Didn't do work or other activities as carefully as usual	0.1621	0.3158	0.6077
Emotional problems	0.0643	0.3145	0.8381
How much bodily pain have you had during the past 4 weeks	3.3352	0.4805	<.0001
How much did pain interfere with your normal work	2.5685	0.4152	<.0001
Feel full of pep	-0.5115	0.3109	0.1020
Very nervous person	-0.3209	0.3113	0.3026
Down in the dumps	2.1036	0.3843	<.0001
Calm and peaceful	1.9626	0.3762	<.0001
A lot of energy	0.9879	0.3345	0.0031
Downhearted and blue	0.7721	0.3283	0.0187
Worn out	0.1621	0.3158	0.6077
Happy person	-0.1293	0.3125	0.6790
Tired	1.9626	0.3762	<.0001
Time that your physical or emotional problems interfered with your social activities	1.6965	0.3624	<.0001
Get sick a little easier than other	2.5685	0.4152	<.0001
As healthy as anybody	3.1222	0.4605	<.0001
Expect my health to get worse	2.251	0.3934	<.0001
My health is excellent	1.4476	0.3512	<.0001

with a high QoL show them.

Regarding to the p-values item difficulty estimates, items “walking more than a mile”, “walking one block”, “accomplished less than you would like”, “were limited in the kind of work”, “had difficulty performing the work”, “didn’t do work or other activities as carefully as useful”, “emotional problem”, “feel full of pep”, “very nervous person”, “happy person” and “tired” are not significant, that is, difficulty of these parameter were not significantly upper or lower than population’s mean and we cannot say these are easy or difficult.

From Fig. 1 we can see that persons’ QoL estimates have different values in population and there is inconsistency in sample. Moreover values in a small neighborhood of zero often are not statistically significant, that is, their estimate of QoL were not significantly upper or lower than population’s mean.

In Table 3, the obtained QoL from RM and summation method and correlation between these two measurements in two dimensions of QoL (Physical and Mental) are presented.

By comparing the QoL estimates from RM and values obtained by SF36 algorithm, we can see that these two values are rather similar but the standard error of RM estimations in physical and total dimensions are less than values obtained from SF36. In addition, correlation coefficient between these two values is large which means there is high linear correlation between these two types of measurements.

Table 3. Comparison of SF36 scores and Rasch estimates in two dimensions and total scores of QoL

Dimension	QoL	min	max	mean	S.E	correlation	p
Physical	SF36	3	93	51.68	25.29	0.94	<0.0001
	Rasch	1	94	55.43	25.044		
Mental	SF36	2	97	56.44	27.584	0.946	<0.0001
	Rasch	4	93	65.76	32.557		
Total	SF36	2	91	53.44	25.675	0.972	<0.0001
	Rasch	3	89	53.99	24.345		

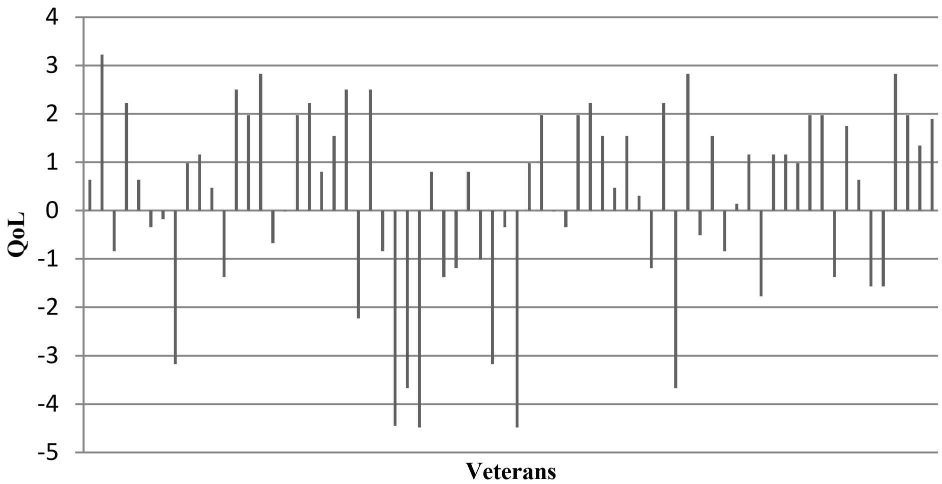

Fig.1. The distribution of estimated veterans' QoL using Rasch model

Discussion

The purpose of the paper was to introduce the RM and to show an application of this model in estimating the latent variable in quality of life research. RM usually provides more accurate assessment of health status as compared with traditional summation method (28).

Rasch analysis has several advantages. First, the possibility of direct examination of latent variable because we can consider such latent trait in this model and second, simplicity of coefficient interpretation. Although, latent variables are entered directly into the model but RM is in the context of multilevel models, so interpretation of the model coefficients are the same as interpretation of random and fixed effects on multilevel logistic model. Third, the RM is not based on the assumptions about the data, that is, in RM unlike other statistical and classical models, data have to meet the requirement of the model. Finally, The RM measures the relationship between a person's ability and an item difficulty, and models this as a probabilistic function. These two parameters are important factors that strongly affect on the total score of QoL but in summation methods do not consider these two important parameters (19, 22, 28).

During the recent decades, much use in numerous studies especially in developing the instruments is made of RM (19,25,29,30). For example, Hagquist and colleagues (19) used the RM in nursing research and developed the NSE tool by removing and recoding the questions of original questionnaire based on RM assumptions. Wuang and colleagues (31) conducted the Rasch analysis of the Bruininks–Oseretsky Test of Motor Proficiency-Second Edition (BOT-2) in intellectual disabilities. They used partial credit RM to examine the measurement properties of the BOT-2. In this study, after rescoring most items, revised BOT-2 showed good fit to the RM and demonstrated excellent reliability.

Bacci (17) has done something different from the others. She has used RM and a Multilevel model simultaneously and fitted longitudinal latent regression model (LLRM) to examine the effect of various factors on the quality of life of terminal cancer patients in Italy. Finally the comparisons between LLRM and classical two-step procedure showed the higher accuracy of the LLRM.

Many studies have been done in the QoL field and the determining the relationship between QoL and various factors (32-36). For example, Rodd and colleagues used multiple lagged regression analyses to assess the effect of dental conditions on children's health-related quality of life. Result showed that clinical variables were significant predictors of OHRQoL (32). Mesbah showed the procedure of joint analysis of a longitudinal latent variable and in this study, generalized estimating equations approach is used to overcome with the problem of need for numerical integrations (37).

Tran in a longitudinal study determined the changes in drug use patterns and health-related quality of life (HRQL) among HIV-positive drug users in the cohort in Vietnam, using the generalized estimating equations (GEE) models (38). Results shown by adjusting propensity scores in GEE models, ongoing heroin use during the study resulted in large decrements in all HRQL domains.

Our results showed that the blind war veterans' QoL have different values in population and there was inconsistency between the results. Also as shown in Haqani (6) and Chia (11) study on the blind war veterans, more than half of them have lower level of quality of life whereas this measure (QoL) was also much less in war disables with lower limb amputation but in mental subscale These two values did not differ much. Also in the study by Tavakol (7) on the children with blindness, the level of QoL was slightly higher than blind war veterans in our study.

Moreover, estimated item difficulties indicated that all SF36 items except than some of them are statistically significant in QoL assessment. By comparing the result from RM and summation method, RM estimations had smaller standard errors for both physical and mental summary components of SF36. Like the study by Raczek it has been suggested that RM provides more accurate estimates than summation method (SF36 algorithm), whereas there is high positive linear correlation between the two methods (39).

Conclusion

Although numerous studies have been carried out on QoL but little research has been done on blind war veterans' QoL. In this study, we utilized a probability function (RM) to estimate the unobservable (latent) QoL directly not from the questionnaire algorithm such as summation method and emphasize on the accurate estimation of RM Methods.

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