RESEARCH ARTICLE

Determining the Cut-Off Points of the Self-Rated Health Visual Analogue Scale for Patients with Depression in Greece

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ABSTRACT

Introduction: Depressed individuals usually rate their health more poorly than non-depressed ones.

Aim: Because little is known regarding the correspondence between the scales used to measure self-rated health in patients with depression, the objective of this study is to determine the cut-off points of the Visual Analogue scale that indicate bad, moderate and good health for patients with depression.

Methods: For the purpose of this study, data from a Panhellenic cross-sectional survey were used. The survey was conducted in 2017 and used stratified random sampling. The study focused on 71 patients with depression. The respondents were asked to rate their health on a 5-point Likert scale and in a Visual Analogue scale. In order to determine the cut-off points of the Visual Analogue scale, an ordinal logistic model was applied. The dependent variable was the Likert scale and the independent variable was the Visual Analogue scale. In addition, a multinomial logistic model was applied and the 33.3rd and 66.6th percentiles of the Visual Analogue scale were calculated.

Results: According to the ordinal logistic regression model, the cut-off points of the Visual Analogue scale are 24 and 76. In addition, according to the multinomial logistic regression model, the cut-off points are 21 and 77. The cut-off points that correspond to the 33.3rd and 66.6th percentiles of the Visual Analogue scale are 50 and 70, respectively. Finally, the Gwet's AC2s of the regression methods were found to be significantly higher than the percentiles' method.

Conclusions: The results of this study confirm international bibliography in the sense that depression is positively related to poor perception of health. Because the cut-off point of poor health, which is based on the percentiles method, is relatively high, we argue that the percentiles method is inappropriate. This conclusion is also derived from the Gwet's AC2s' comparison.

Key words: Depression, Likert scale, percentiles, regression methods, self-rated health, visual analogue scale

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HIGHLIGHTS / KEY POINTS

- **The percentiles method is arbitrary**
- **The cut-off point corresponding to very bad and bad health, is low**
- **Researchers should adopt the regression methods**

INTRODUCTION

Depression is a major public-health issue and is one of the leading causes of disease burden globally (Moussavi et al 2007). Although depressive symptoms and poor perception of individual's health are strongly associated (Rantanen et al 2019), little is known regarding the correspondence between the scales that are used to measure self-rated health (SRH) in patients with depression.

SRH is a subjective assessment of one's health (Meng et al 2014) and constitutes the most widely used measure of health in medical, social, and behavioral surveys (Garbarski 2016). Although this assessment is subject to reporting error (Ichoku et al 2011), SRH has been found to be a predictor of mortality and morbidity (Bonner et al 2017) and is considered a valid and reliable measure (Cullati et al 2018, Arsandaux 2019). As a result, quantitative studies suggest that since SRH reflects physical, mental and social health and functioning, it provides an integrative summary of internal and external information of one's health (Benyamini 2016).

SRH may be used to identify individuals or groups at risk for poor health (Bardage et al 2005) and is a useful prognostic measure for the stratification of treatment allocations during clinical trials (Fayers & Sprangers 2002). In this sense, it is a useful concept not only in clinical medicine but also in healthcare planning (DeSalvo et al 2005). In addition, health-policy makers can use SRH to predict healthcare demand in order to effectively allocate resources, assess subjective effectiveness of treatments and identify areas of inequity that require special attention (Cislaghi & Cislaghi 2019).

Given that SRH can be measured in different ways, variations in wording, scale and number of response categories exist (Bowling 2005, Jurges et al 2008, Daniilidou et al 2010). SRH may be quantified via Likert scales using questions (Bowling & Windsor 2008, Hoshi 2018) such as "In general, how would you rate your health today?" (Subramanian et al 2010) or "In general, would you say your health is?" (Bombak 2013). In many cases SRH is measured on a Likert scale (Kondo et al 2009) using a single question with 5 (very good, good, moderate, bad, very bad or excellent, very good, good, fair, poor) (Wilson et al 2004) or 4 typical answers (excellent, good, fair, poor) (Manor et al 2000). However, SRH may also be captured on a Visual Analogue scale (VAS), anchored with 100 (best imaginable health state) at the top and 0 (worst imaginable health state) at the bottom (Rabin & de Charro 2001). Both VASs and Likert scales have pros and cons (Hasson & Arnetz 2005). For example, although the VAS allows for finer distinctions than the Likert scale, providing a greater amount of information to the researcher (Gorrall et al 2016), its interpretations is thought to be more difficult (Bowling 2009).

The difficulty in categorizing the VAS scores can be overcome, to some extent, by determining the correspondence between the VAS scores and the Likert scale (Badia Llach et al 1999). Nevertheless, in several studies, the VAS scores are arbitrarily interpreted (Szybalska et al 2018) using the calculation of percentiles as a method to interpret scores (Pedersen et al 2011, Krantz et al 2019), even if this method is considered to be arbitrary (Diouf et al 2015). In other cases that concern psychological health, the VAS scores have been divided into arbitrary categories (Kim et al 2017).

With these considerations, the objective of this study is to determine the cut-off points of the VAS that correspond to the bad, moderate and good health states of the Likert scale for patients with depression.

METHODS

For the purpose of this study, data from a Panhellenic cross-sectional survey were used (Zavras 2019). The survey was conducted in 2017 and used stratified random sampling. Sample selection strata were based on the 2011 Census of the Hellenic Statistical Authority; strata were defined by age, gender, urbanity status of permanent residence and prefecture based on Nomenclature of Territorial Units for Statistics II (NUTS II). A computer-assisted telephone interviewing (CATI) method was used for the data collection.

The sample size was 2003 individuals aged 18 years or over (n1=2003). However, the study focused on 71 patients with depression (n2=71).

The ethical approval from the Bioethics Committee of the Greek National School of Public Health was obtained for this study.

The respondents were asked to rate their health on a 5-point Likert scale. The answers of the Likert scale were: a) 1: very bad; b) 2: bad; c) 3: moderate; d) 4: good; and e) 5: very good. In addition, the respondents were asked to rate their health in a VAS. The value of 100 on the VAS scale represented the best health state imaginable and a value of 0 represented the worst health state imaginable.

In order to determine the cut-off points of the VAS, an ordinal logistic regression model was applied. The dependent variable was the Likert scale and the independent variable was the VAS.

Due to the low frequency of some classes of the original variables (the "very bad", "bad", "good" and "very good" categories)

these categories were collapsed (Preisser et al 2011). Although collapsing categories in the Likert scale results in loss of information, it is a valid approach (Armstrong & Sloan 1989).

According to the ordinal logistic regression model, the cut-off points are given by:

$$cut-off_1 = \frac{\ln(e^{-a_1} - 2\ e^{-a_2})}{\beta}$$

$$cut-off_2 = \frac{\ln(e^{-a_2} - 2\ e^{-a_1})}{\beta}$$

(Bersabé et al 2009)

where a_i the intercepts and β the coefficient of the VAS.

The proportionality of the odds assumption was tested using the Brant Test (Brant 1990). The model's goodness of fit was tested using the Lack of Fit test. The model was tested through the Link Test for specification error (Stata Corp 2013).

A multinomial logistic regression model was also applied. According to the multinomial logistic regression model, the cut-off points are given by:

$$cut-off_1 = \frac{a_1 - a_2}{\beta_2 - \beta_1}$$

$$cut-off_2 = \frac{a_2}{-\beta_2}$$

(Bersabé & Rivas 2010)

where a_i the intercepts and β_i the coefficients of the VAS.

The model's goodness of fit was tested using the Lack of Fit test.

The cut-off points that corresponded to two equal percentiles (Çelebioğlu & Çiçeklioğlu 2013), i.e., the 33.3rd and 66.6th percentiles of the VAS, were calculated.

In order to compare the cut-off points from the regression methods with that of the percentiles' method, the difference of Gwet's AC2s (Gwet 2016) was tested.

The STATA 14 and JMP 14 statistical software packages were used for the analysis.

RESULTS

The prevalence of depression was found to equal 3.54% (n2=71 out of 2003 respondents) of the study sample.

Approximately twenty-one percent (21.13%) of the patients were men and seventy-nine (78.87%) were women.

The average age in the sample was 56.37 years (±12.51).

All respondents answered the Likert scale and the VAS. 52.11% of respondents (the highest) rated their health as moderate in the Likert scale, while the percentage of the patients that rated their health as very bad and bad was 19.72% (Table 1).

(Table 1)

The mean of the VAS was found equal to 54.93 (±24.28), while the median equaled 60.

The diagnostic tests of the ordinal logistic regression model (Table 2) indicated a good fit.

(Table 2)

According to the Brant test (1990) (the STATA command brant (Long & Freese 2014) was used), the proportional odds assumption holds (p=0.847). In addition, the Lack of Fit test indicates good fit (p=0.14). Finally, according to the Link test, the model does not suffer from specification error (Table 3).

(Table 3)

According to the ordinal logistic regression model, the cut-off scheme (rounding of the regression coefficients was not used) is the following: a) very bad and bad health: 0-24; b) moderate health: 25-76; and c) good and very good health: 77-100. The frequency of the categories that correspond to the cut-off points that were derived from the ordinal logistic regression model is given in Table 4.

(Table 4)

The results of the multinomial logistic regression model are given in Table 5.

(Table 5)

The Lack of Fit test indicated a good fit (p=0.07). According to the multinomial logistic regression model, the cut-off scheme (rounding of the regression coefficients was not used) is the following: a) very bad and bad health: 0-21; b) moderate health: 22-77; and c) good and very good health: 78-100. The frequency of the categories that correspond to the cut-off points that were derived from the multinomial logistic regression model is given in Table 6.

(Table 6)

The frequency of the categories that corresponded to the cut-off points that correspond to the percentiles of the VAS is given in Table 7.

(Table 7)

In order to compare the cut-off points from the regression methods with that of the percentiles' method, the Gwet's AC2s were calculated (Table 8) and their difference was tested (the STATA command kappaetc (Klein 2018) was used).

(Table 8)

According to Table 8, the Gwet's AC2s for the cut-off schemes that were derived from the regression methods are higher than that derived from the percentiles method, and their difference (0.258) is significant (p<0.001).

DISCUSSION

According to the ordinal logistic regression model, the cut-off points of the VAS are 24 and 76. In addition, according to the multinomial logistic regression model, the cut-off points of the VAS are 21 and 77. From these results we can see that the cut-off points of the two methods are comparable.

Based on the ordinal logistic regression model, VAS scores between 0 and 24 (0-21 for the multinomial logistic regression model) correspond to very bad and bad health, i.e. the range of scores that correspond to the two lowest health states is equal to 24 (21 for the multinomial logistic regression model). In addition,

the range of the scores that correspond to moderate health (25-76) (22-77 for the multinomial logistic regression model) is equal to 51 (55 for the multinomial logistic regression model). Furthermore, the range of the scores that correspond to good and very good health (77-100) (78-100 for the multinomial logistic regression model) is equal to 23 (22 for the multinomial logistic regression model). So, it seems that the range of the VAS scores differs between health states. Emphasis should be given to this point, since in some cases the VAS scores are divided into a number of even categories, e.g. 0-20, 21-40, 41-60, 61-80, 81-100 (Yang et al 2018).

As mentioned above, in some cases, the calculation of percentiles is used as a method to interpret the VAS scores (Krijger et al 2014, Machon et al 2017). This point is also true in depression studies (Flores et al 2017). However, differences in the valuations between populations (König et al 2009, Heijink et al 2017) highlight the need for a calculation of cut-off points using regression methods.

Given that depressed individuals tend to rate their health more poorly (Williamson et al 2009), the numbers mentioned above, and the results of this study highlight the need to calculate the VAS cut-off points using regression methods, when studying self-perceived health in patients with depression.

The extent to which the VAS can be interpreted as the Likert scale requires the VAS to be best classified against the Likert scale in order to be applicable an agreement methodology (Lin et al 2012).

As a result, the comparison between the cut-off points derived from the three methods that are described in this study was made possible through Gwet's AC2s (Gwet 2014). According to the results, the Gwet's AC2 (when taking into account the Likert scale) is higher than the opposite case, and indicates that the percentiles method is inappropriate.

LIMITATIONS

The main limitation of this study is that we collapsed some categories of the Likert scale and lost information regarding the cut-off points for all the five health states.

CONCLUSION

According to the results of this study, the cut-off point corresponding to very bad health, which was calculated using regression methods, is low; a finding that confirms international bibliography. Indeed, depression, has a large contribution to poor self-rated health in individuals (Molarius & Janson 2002). Furthermore, the Gwet's AC2s' comparison indicates that the percentiles method is inappropriate.

The calculations of these cut-off points using ordinal or multinomial logistic regression is easy and all statistical software packages include routines for these methods, thus, researchers should adopt these methods when studying similar problems. However, both scales (Likert and VAS) shall be included in the surveys' questionnaire.

Table 1 Likert Scale

Category	n (%)
Very Bad	2 (2.82)
Bad	12 (16.90)
Moderate	37 (52.11)
Good	16 (22.54)
Very Good	4 (5.63)

Table 2 Ordinal Logistic Regression Model

Variable	Coefficient	p	95% Confidence Interval	
VAS	0.058	<0.001	0.033	0.082
Cut 1	1.310		0.027	2.592
Cut 2	4.436		2.752	6.121

Table 3 Link Test

Variable	Coefficient	p	95% Confidence Interval	
h	0.641	0.356	-0.720	2.001
h2	0.064	0.591	-0.170	0.298

Cut 1	0.918		-0.950	2.786
Cut 2	4.051		1.905	6.197

Table 4 Cut-Off Scheme that was Based on the Ordinal Logistic Regression Model

Cut-Off Scheme	n (%)
0-24 25-76 77-100	10 (14.08) 46 (64.79) 15 (21.13)

Table 5 Multinomial Logistic Regression Model

Category	Variable	Coefficient	p	95% Confidence Interval	
Very Bad & Bad	VAS	-0.088	<0.001	-0.133	-0.044
	Constant	4.454	0.001	1.823	7.086
Moderate	VAS	-0.047	0.009	-0.082	-0.011
	Constant	3.582	0.003	1.188	5.976

Table 6 Cut-Off Scheme that was Based on the Multinomial Logistic Regression Model

Cut-Off Scheme	n (%)
0-21	10 (14.08)
22-77	46 (64.79)
78-100	15 (21.13)

Table 7 Cut-Off Scheme that was Based on the Percentiles of the VAS

Cut-Off Scheme	n (%)
0-50	35 (49.30)
51-70	21 (29.58)
71-100	15 (21.13)

Table 8 Gwet AC2

Variables	Gwet AC2
Likert Scale-Cut-off Scheme Derived from the Ordinal Logistic Regression Model	0.706
Likert Scale-Cut-off Scheme Derived from the Multinomial Logistic Regression Model	0.706
Likert Scale-Cut-off Scheme Derived from the Percentiles of the VAS	0.448

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