Perception of disability in a public health perspective: a model based on fuzzy logic

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Fuzzy sets; Disability; Health states; Health indicators; Quality of life; Public health informatics

Summary
Measures of functional levels, commonly used to assess the safety and quality of life of individuals and populations, have not yet been derived from a fuzzy framework. The aim of this study is to estimate the degree of disability associated with varying functional levels, through a model based on fuzzy sets theory. A fuzzy linguistic model was developed to measure varying levels of functional disability, in accordance with the definitions of an individual’s social and physical activities and mobility. One year of an adult’s life whose mobility, social and physical activities were somewhat limited, was judged to be equivalent to 0.575 years free of functional disability. Results obtained from the fuzzy model approach those obtained with the quality of well-being scale (QWB), used as a conceptual framework. Such findings are encouraging, since the QWB is considered a consistent and valid approach for disability assessment and quality-of-life evaluation.

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1. Introduction

Measures of health have played an essential role in the analysis of health status and quality of life, at individual and population levels. So far, they have been used mainly in the setting of health policy priorities and goals, and in the monitoring of medical and health care effectiveness.

As societies evolve, health problems change and new health measures are needed to adequately reflect such changes. Usually, death rates are suitable indicators of health [1]. Another reason for this is that the aims of the health care system have expanded in order to incorporate the achievement of physical, mental and social well-being [2].

The need for the development of new health indicators based on both fatal and non-fatal health outcomes has been stressed since the late 1960’s [3], when functional disability began to emerge as a major public health problem worldwide due to its hazardous consequences upon economic production, social welfare and population well-being. Since then, efforts have been aimed to develop composite measures of morbidity and mortality, as well as of general morbidity prevalence levels, have changed the emphasis on death rates alone, as suitable indicators of health [1].
intended to provide a rationale for the allocation of health care and research resources—encompassing the prevention, treatment and rehabilitation of functional disability due to both fatal and non-fatal diseases and injuries—as well as social assistance expenditures aimed at the disabled population. Considering the limited availability of resources, policy makers need to reduce uncertainty to an utmost degree when establishing priorities and goals based on the assessment of the health status of populations [4].

So far, a variety of methods have been developed in order to adjust the time lived at different functional levels. In general, these methods are intended to provide quantitative estimates of subjective phenomena, such as value judgements or preferences for different health states or functional levels. Opinions on which method is best vary widely, although a consensus exists around the need of a thorough understanding of the underlying mechanisms involved in functional disability measurement within quality-of-life research [4].

Nowhere in the field of biosciences is the need for tools to deal with uncertainty more critical than in medicine and epidemiology. Disease diagnosis involves several levels of imprecision and uncertainty, particularly in epidemiological studies. A single disease may manifest itself quite differently in different patients. Further, a single symptom may be indicative of different diseases, and the presence of several diseases in a single patient may disrupt the expected symptom pattern of any of the diseases. This may lead to a tremendous amount of imprecision and uncertainty in the interpretation of effect measures of covariates of interest. Also, the best and most useful descriptions of disease entities often use linguistic terms that are inevitably vague.

In addition, the classic and current view of disease is that health and disease are opposites and that they are dual and contradictory attributes. It is said that health is the absence of disease and vice versa. The fuzzy logic approach, otherwise, considers health and disease as, at least partially, complementary states [5], and better fits the concepts of health states and health-related quality of life, as used in public health and quality of life research [6].

Since first introduced by Zadeh, fuzzy sets have been recognised as a potential tool for use in contexts full of uncertainties. This ability to deal with uncertainties and linguistic terms is one of many features that led to the immense application of the fuzzy theory in the study of biomedicine problems [7–10]. Nevertheless, none of the methods for the assessment of quality of life developed so far has been based on a fuzzy framework. In this paper, we present a fuzzy model developed for measuring the degree of functional disability, and illustrate its potential use in public health.

2. Fuzzy sets theory

Fuzzy logic is a superset of conventional logic that has been developed to handle the concept of partial truth—truth values situated between ‘‘completely true’’ and ‘‘completely false’’. The fuzzy sets theory was first proposed by Lotfi Zadeh of University of California, Berkeley, in the 1960’s, as a means to model the uncertainty within natural language [11]. The mechanics of fuzzy sets theory was set forth in 1965, based on Zadeh’s key notion of membership degrees, according to which a set could have members who belonged to it partially [12,13]. So, if we assume X as a set serving as the universe of discourse, a fuzzy set A of X is associated with a characteristic function:

$$\mu_A(x) \rightarrow [0, 1]$$  \hspace{1cm} (1)

which is generally called membership function. The idea is that for each x, \(\mu_A(x)\) indicates the degree to which x is a member of the set A; this membership degree indicates the compatibility degree of the assertion ‘‘x is A’’.

Sometimes, a fuzzy set could represent linguistic concepts, such as very small, small, high and so on, as interpreted in a particular context, resulting in the named linguistic variable. The ability to operate with linguistic variables is one of the most important characteristics of fuzzy sets theory and its successful applications.

A fuzzy linguistic model is a rule-based system that uses fuzzy sets theory to deal with particular phenomena [14,15]. Its basic structure includes four main components: (1) a fuzzifier, which translates crisp (classical number valued) inputs into fuzzy values; (2) an inference engine, which applies a fuzzy reasoning mechanism to obtain a fuzzy output (in the case of Mamdani’s inference rule); (3) a knowledge base, which contains both a set of fuzzy rules and a set of membership functions that represents the fuzzy sets of the linguistic variable, and (4) a defuzzifier, which translates the fuzzy output into a crisp value. The decision process is performed by the inference engine according to the rules contained in the rule base. These fuzzy rules define the connection between the fuzzy input and output. A typical fuzzy rule has the form: If antecedent then consequent, where antecedent is a fuzzy expression composed by one or more fuzzy sets connected by fuzzy operators, and consequent is an expression that assigns fuzzy values to the output.
variables. The inference process evaluates all rules in the rule base and combines the weighted consequents of all relevant rules into a single output fuzzy set (Mamdani’s rule of composition) [16]. In many applications of the fuzzy sets theory, it is necessary to produce a crisp value as the result of an approximate reasoning process. The fuzzy output set may then be replaced by a “crisp” output value obtained through a process called defuzzification. A number of defuzzification methods can lead to distinct results, as we see in the literature. Each method is based on some rationale, but in all of them the crisp value found means the best representation of the defuzzified fuzzy set [14,15].

Three defuzzification methods have been predominant in the literature on fuzzy systems: the Center of Area Method, the Center of Maxima Method and the Mean of Maxima Method.

The Center of Area is one of the most used methods to find the crisp number that best represents the fuzzy output. The other two methods tend to reinforce in the defuzzification processes the influence of maximum values. In contrast, the Center of Area method considers the area under the graph of the membership function, and results in a single value that could be interpreted as an expected value of the variable under study.

For the reason discussed, we chose a Center of Area Method to defuzzify the fuzzy output of our proposed model.

3. Methods

A fuzzy linguistic model based on experts opinions was developed for measuring the degree of functional disability. Three fuzzy input variables were considered, according to social activity, mobility and physical activity.

Social activity (S) refers to the performance of activities usual for a person’s age and social role, according to: to play for pre-schoolers below 6 years old, study for the 6—17-year-old age group, work and/or housekeeping for the 18—64-year-old age group and housekeeping and leisure from 65 years on. Mobility (M) is related to the range and to the freedom to travel from one place to another. Physical activity (P) is concerned mainly with walking, but includes other physical movements of the trunk and extremities, such as standing and stooping. These three dimensions of health are as those defined in the quality of well-being scale [17].

A set with 100 fuzzy rules was derived and considered as consequent for each rule the degree of functional disability (D), which describes the overall functional level of an individual, based on the previous three dimensions. The set of 100 fuzzy rules was derived by relating the fuzzy sets representing the functional levels of each input variable, namely social activity (five levels), mobility (five levels) and physical activity (four levels). A knowledge base was then developed according to the definitions presented in the original QWB scale approach [17].

The fuzzy sets related to each linguistic-variables were also derived from the original QWB scale framework—not as a direct translation of its definitions—taking into account an underlying ordinal measurement scale. Expert knowledge was acquired through a standard questionnaire. Following the presentation of essential concepts regarding fuzzy sets theory, the experts were asked to: (i) define the membership functions related to the fuzzy sets representing the functional levels of each input variable as well as the output variable (functional disability); (ii) define the consequent part of each of the 100 fuzzy rules; (iii) assign a value within the [0,10] interval—the fuzzy rating scale—to each of the three fuzzy input variables; and (iv) assign a value within the [0,10] interval to each of the 100 combinations of the functional input variables, as in the QWB scale approach.

The fuzzy linguistic model has the form.

\[ \text{If } S \text{ is } S_i \text{ and } M \text{ is } M_j \text{ and } P \text{ is } P_k \text{, then } D \text{ is } D_l \]

Also

\[ \text{Also if } S \text{ is } S_i \text{ and } M \text{ is } M_j \text{ and } P \text{ is } P_k \text{, then } D \text{ is } D_l \]

where \( S, M, P \text{ and } D \) are the fuzzy representation of social activity, mobility, physical activity and the degree of functional disability, and \( S_i, M_j, P_k \text{ and } D_l \) are the fuzzy sets concerning the magnitude of \( S, M, P \text{ and } D \), respectively (Table 1). The linguistic terms represent different levels of functional disability and reflect the uncertainty and imprecision that underlie the measurement of such subjective concepts.

The rules were defined by a neurology expert; only the combinations of fuzzy sets considered to be clinically meaningful and plausible were considered.

Each of the fuzzy linguistic variables are numerically represented by the set of real numbers, included in the interval [0,10]. Disposed as a rating scale, such numbers express the functional level for each dimension of health, along a continuum that ranges from optimal function to death, represented by the extreme values 10 and 0, respectively.

In order to model the evaluation of functional disabilities with a fuzzy structure, we chose the Mam-
Table 1 Linguistic variables and respective fuzzy sets related to functional levels

<table>
<thead>
<tr>
<th>Linguistic variables</th>
<th>Fuzzy sets (functional levels)</th>
<th>Symbol</th>
</tr>
</thead>
<tbody>
<tr>
<td>Social activity (S)</td>
<td>Extremely limited</td>
<td>$S_1$</td>
</tr>
<tr>
<td></td>
<td>Very much limited</td>
<td>$S_2$</td>
</tr>
<tr>
<td></td>
<td>Limited</td>
<td>$S_3$</td>
</tr>
<tr>
<td></td>
<td>Somewhat limited</td>
<td>$S_4$</td>
</tr>
<tr>
<td>Mobility (M)</td>
<td>Extremely limited</td>
<td>$M_1$</td>
</tr>
<tr>
<td></td>
<td>Very much limited</td>
<td>$M_2$</td>
</tr>
<tr>
<td></td>
<td>Limited</td>
<td>$M_3$</td>
</tr>
<tr>
<td></td>
<td>Somewhat limited</td>
<td>$M_4$</td>
</tr>
<tr>
<td>Physical activity (P)</td>
<td>Extremely limited</td>
<td>$P_1$</td>
</tr>
<tr>
<td></td>
<td>Very much limited</td>
<td>$P_2$</td>
</tr>
<tr>
<td></td>
<td>Limited</td>
<td>$P_3$</td>
</tr>
<tr>
<td></td>
<td>Plenty</td>
<td>$P_4$</td>
</tr>
<tr>
<td>Degree of functional disability (D)</td>
<td>High</td>
<td>$D_1$</td>
</tr>
<tr>
<td></td>
<td>Moderate</td>
<td>$D_2$</td>
</tr>
<tr>
<td></td>
<td>Low</td>
<td>$D_3$</td>
</tr>
<tr>
<td></td>
<td>None</td>
<td>$D_4$</td>
</tr>
</tbody>
</table>

activity, mobility, physical activity and functional disability, respectively. Each of the four axes comprises the real numbers $x$, $y$, $z$ and $w$, respectively, bounded within the interval $[0,10]$. Such numbers are meant to express quantitatively the degree of disability associated with different functional states, within each health dimension considered in the fuzzy model. The values in $W$—the axis representing the functional disability dimension—are dependent upon the values in $X$, $Y$ and $Z$.

The aggregation of the $n$ rules, as implied by the also connective, is accomplished via the standard fuzzy union of the individual fuzzy relations.

$$R = \bigvee_{m=1}^{n} R_m$$

The membership function $R(x, y, z, w)$ of the fuzzy relation $R$ is:

$$R(x, y, z, w) = \bigvee_{m=1}^{n} R_m(x, y, z, w)$$

where $\bigvee$ is the max operator [18].

For a given input combination of fuzzy sets $S = S_i$, $M = M_j$ and $P = P_k$, the fuzzy output $D_l$ is defined by the max–min inference rule, whose membership function is:

$$D_l(w) = \bigvee_{x,y} S_i(x) \land M_j(y) \land P_k(z) \land R(x, y, z, w)$$

Membership functions of the fuzzy sets, on the fuzzy rating scales, were determined by the neurology expert. Such functions were all trapezoidal membership functions, generally expressed as:

$$f(x) = \begin{cases} 
\frac{x - \alpha}{\beta - \alpha} & \text{if } \alpha \leq x \leq \beta \\
1 & \text{if } \beta < x \leq \gamma \\
\frac{\gamma - x}{\gamma - \delta} & \text{if } \gamma < x \leq \delta \\
0 & \text{otherwise}
\end{cases}$$

where $\alpha$, $\beta$, $\gamma$ and $\delta$ are parameters that define a particular function as depicted in Fig. 1.
As discussed above, the thresholds denoted by the parameters $\alpha$, $\beta$, $\gamma$ and $\delta$ were defined by the neurology expert through a standard questionnaire and interviews (Table 2).

These membership functions of input and output variables are shown in Figs. 2–5.

For each functional level presented in Table 3, a crisp value was assigned on the proper fuzzy rating scale. Multidimensional functional levels, derived from the combination of single-dimensional functional levels, as in the QWB [17], were evaluated through the fuzzy model, as already explained.

In the present model we chose the FATI methodology, where the fuzzy information are aggregated first and inference is performed after. This process is common in diagnostic decision, where the experts collect and aggregate information to procedure the decision based on this aggregation.

4. Results

As an example, we present the evaluation of one multidimensional functional level, derived from the combination of the B categories of each single-dimensional level (Table 3). The crisp values $(x, y, z)$ assigned to the social activity, mobility and physical activity fuzzy rating scales were eight, seven and six, respectively. In words, social activity was judged to be between somewhat limited and mobility and physical activity were evaluated as being somewhat limited. From the membership functions presented in Table 2, the fuzzy output set $D'_l$ was derived. A crisp value $d$, expressing the degree of disability associated to the multidimensional functional level (B, B, B), was determined through the centre of area defuzzification method [13,14], as expressed by the equation

$$d = \frac{\sum_{l=1}^{N} w_l \mu_I'(w_l)}{\sum_{l=1}^{N} \mu_I'(w_l)}$$

In this example, $d$ was equal to 5.75. When normalized with reference to a scale bounded by the limits 0 and 1, it simply becomes equal to 0.575. From the original QWB, $d$ was estimated as 0.5402, a value which can be considered fairly close to the one obtained with the use of the fuzzy model.

With reference to a well-known composite health indicator, the health status index [17], this estimate means that one year lived in such functional...
Fig. 3 Membership functions of mobility.

Fig. 4 Membership functions of physical activity.

Fig. 5 Membership functions of the degree of functional disability.

Table 3 Function level of fuzzy input variables

<table>
<thead>
<tr>
<th>Function level</th>
<th>Social activity</th>
<th>Mobility</th>
<th>Physical activity</th>
</tr>
</thead>
<tbody>
<tr>
<td>A</td>
<td>Did work, school, or housework, and other activities</td>
<td>Drived car or used public transport without help</td>
<td>Walked without physical limitations</td>
</tr>
<tr>
<td>B</td>
<td>Did work, school, or housework, but other activities were limited</td>
<td>Did not drive, or had help to use public transport</td>
<td>Walked with physical limitations</td>
</tr>
<tr>
<td>C</td>
<td>Limited in amount or kind of work, school or housework</td>
<td>In house</td>
<td>Moved own wheelchair without help</td>
</tr>
<tr>
<td>D</td>
<td>Performed self-care, but not work, school or housework</td>
<td>In hospital</td>
<td>In bed or chair</td>
</tr>
<tr>
<td>E</td>
<td>Had help with self-care</td>
<td>In special care unit</td>
<td></td>
</tr>
</tbody>
</table>

Adapted from [1].
state is worth 0.575 years in perfect health, for which \( d = 1 \). Inversely, the value given by \( 1 - d \) expresses the amount of time lost in one year, due to a determined functional level (0.325 years, in the present example). Consequently, 10 years lived in functional state (B, B, B), irrespective of its underlying cause, implies a loss of 3.25 years of well life, with reference to perfect health. In case of death, \( d \) is estimated as 0.

The estimates of \( d \) varied according to the different functional levels evaluated. For less severe functional disabilities, characterised by functional states (A, B, A) and (A, A, B) (Table 3), \( d \) was estimated as 7.00; for more severe functional disabilities, such as states (B, C, B) and (B, B, C), lower estimates of \( d \) were obtained (4.90 and 2.80, respectively). Considering the whole range of conditions evaluated, the estimates of \( d \) tended to decrease as the functional states moved away from the absence of disabilities ("perfect health") towards the death extremes, thus establishing—as expected from any consistent method—a grading system for quality-of-life evaluation.

In order to assess the model, we submitted all functional levels to the evaluation of two other experts. An agreement analysis was carried out, concerning the estimates of the degree of functional disability for different (three-dimensional) conditions obtained through the fuzzy model and through a direct assignment on the fuzzy rating scale; this latter approach—named "direct" model—resembles the method used in the original QWB scale.

Agreement was assessed by means of the intraclass correlation coefficient (ICC), in two different ways, as follows: (i) considering the results obtained from each of the two approaches—i.e. the fuzzy model and the direct approach—separately, as defined by each of the three experts—namely, between-observers agreement; and (ii) considering the results obtained from each of the two approaches for each neurology expert separately—namely, between-methods agreement.

Between-experts agreement was higher for the results obtained from the fuzzy model (ICC = 0.666; 95%CI: 0.568–0.751) when compared to the estimates originated from the direct model (0.496; 95% CI: 0.220–0.681), considering the estimates provided by the three neurologists altogether. In this sense, the fuzzy model constitutes a consistent alternative for disability measurement, since it provides more stable results when compared with the original crisp approach.

Comparing the performance of the fuzzy model with the direct (QWB) method at the level of the single expert neurologist, results varied widely. While there was poor agreement between the two methods for expert 1 (ICC = 0.309; 95%CI: 0.065–0.666), the estimates provided by expert three were found to be reasonably reliable (ICC = 0.791; 95%CI: 0.218–0.919) [19]. Considering the average of experts opinions and model results, we found the ICC equal to 0.742 (95%CI: 0.112–0.899). The high ICC estimates suggest that the fuzzy model is as good as the original QWB approach, in what concerns functional disability measurement. Such findings support the hypothesis about the validity of the results obtained from the fuzzy model, since the QWB scale is widely recognised as a consistent and valid approach in quality-of-life research [6].

The estimates of \( d \) for a selected sample of conditions evaluated by the experts, as derived from the fuzzy and the "direct" models, are shown in Table 4.

An additional advantage of the fuzzy model over the crisp approach is that it allows a better understanding of how different scales—qualitative, linguistic, ordinal scales and quantitative, numer-

<table>
<thead>
<tr>
<th>Functional level of fuzzy input variables*</th>
<th>Social activity</th>
<th>Mobility</th>
<th>Physical activity</th>
<th>Functional disability degree estimates (d)</th>
</tr>
</thead>
<tbody>
<tr>
<td>A</td>
<td>A</td>
<td>A</td>
<td></td>
<td>0.94</td>
</tr>
<tr>
<td>B</td>
<td>A</td>
<td>B</td>
<td></td>
<td>0.73</td>
</tr>
<tr>
<td>C</td>
<td>B</td>
<td>A</td>
<td></td>
<td>0.73</td>
</tr>
<tr>
<td>C</td>
<td>C</td>
<td>B</td>
<td></td>
<td>0.51</td>
</tr>
<tr>
<td>E</td>
<td>C</td>
<td>A</td>
<td></td>
<td>0.51</td>
</tr>
<tr>
<td>E</td>
<td>C</td>
<td>C</td>
<td></td>
<td>0.30</td>
</tr>
<tr>
<td>E</td>
<td>D</td>
<td>C</td>
<td></td>
<td>0.30</td>
</tr>
<tr>
<td>E</td>
<td>D</td>
<td>D</td>
<td></td>
<td>0.10</td>
</tr>
</tbody>
</table>

* As described in Table 3.
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5. Discussion

The amount of well years of life can be used as a common denominator to assess the impact of medical and public health interventions, both preventive and curative. Such an approach, when applied at a population level, has been considered a useful tool for priority-setting and decision-making purposes in public health, particularly when related to cost estimates [4].

However, its foundations rely on value judgements, which are not easily expressed in an objective manner. Uncertainty is inherent in functional disability measurement, and it is not restricted to random variation. Functional levels and health states are usually characterised by linguistic terms, many of which are markedly vague and imprecise, but, at the same time, meaningful enough to be used in common practice.

In fact, such evaluations are too complex to be handled objectively by the human mind. First, because they take into account multiple dimensions simultaneously. Second, and most important, because of the limitations that underlie the conversion of linguistic terms, defined on an ordinal scale into precise, numerical values, laying on an interval or ratio scale.

The fuzzy model is intended to emulate human thinking, in order to adequately deal with such an imprecise measurement process. In this sense, the measurement process was fragmented into distinct sequential steps. First, the original functional states used in the QWB approach were related to categories intentionally vague, represented by the fuzzy sets. Through the overlaying of such fuzzy sets on the rating scales, and by relating them through the fuzzy rules, the model allowed a smooth conversion of linguistic, qualitative judgements, into numerical, quantitative evaluations. The final “crisp” estimates of the functional disability degrees $d$ are meant to be numerical summaries of the resultant fuzzy sets. The intrinsic imprecision involved in the estimation of $d$ is clearly incorporated into each of the model’s steps. It is important to highlight that the three underlying dimensions—social activity, mobility and physical activity—were considered separately by the neurology experts.

The fuzzy model was easily implemented. Its principles, as well as its underlying concepts, were readily understood by the neurology experts involved in this work. Data processing and analysis required common up-to-date PC-type computers.

Artificial intelligence (AI) theories have been introduced in several medical and health areas, and the high number of publications in this area testify the value of these theories in the improvement of current biomedical science. In this context, it is important to analyse the differences and similarities between AI techniques in order to find more adequate biomedical models.

To perform the majority of AI techniques, it is essential to have a functional information about the systems behaviour, and/or a large set of data that provide this information. Sometimes, one has a large data collection about the system behaviour, besides the opinion of experts. As discussed in [20], in this situation a good way to design a model is to mix the experience of the human controller and a sample of input–output pairs of the system. Hybrid models as, for instance, genetic algorithms and neural networks, have been used with success in similar situations. The majority of AI techniques require a large data to model the system, as Neural Network, Genetic Algorithms and the Bayesian approach, where the data and functional information assume an important role to define prior probabilities. However, in many health areas, data sets and functional information are not available. In these cases, structures based on experts knowledge and opinion play an important role.

One of the most relevant techniques to deal with experts knowledge is the fuzzy linguistic model framework. The absence of functional disabilities measures and data collection in the problem here analysed led us to develop a fuzzy model based on experts opinion. This fuzzy structure presents an important advantage compared with other AI methodologies when applied in the biomedical context: it is easily understandable for professionals that have not mathematical background. It is particularly important when the model produces decision-making information. In our experiences, we note that the health authorities and public health professionals tend to accept easier, the results that they may be able to understand the modelling. Fuzzy sets incontestably satisfy this requirements.
The tests performed suggest that the results obtained from the fuzzy model match those from the QWB scale, from which its conceptual and structural framework was derived. Such findings are encouraging, since the QWB scale is considered a consistent and valid approach for disability assessment and quality-of-life evaluation [21–23]. In addition, the fuzzy model provided comparable estimates of disability degree with the neurologists’ opinions.

The results obtained from the agreement assessment are encouraging, although they must be carefully interpreted. The fuzzy model showed a better performance in terms of between-observers agreement compared to the direct model. Since the latter approach is much similar to the original QWB scale method, we interpreted this finding as an evidence that supports the assumption about the appropriateness of the fuzzy model to deal with an essentially subjective measurement process. However, functional disability estimates derived from experts two and three fuzzy models showed a little variation in the whole range of functional conditions evaluated; this might partially explain the higher ICC estimates observed. In other words, the results derived from experts two and three fuzzy models showed limited ability to discriminate among rather different functional levels, defined according to the three dimensions already mentioned. One possible explanation for these findings is the close resemblance among the fuzzy variables sets and the functional levels defined in the original QWB scale, which, in fact, provided the basis for the fuzzy model’s structure. Such resemblance might have induced experts two and three to superpose the original QWB scale functional levels with the fuzzy variables sets, thus restricting the experts capability to differentiate among the varying functional states.

Further investigations are now being developed, taking into account the opinion of groups of varying medical experts, as a source for reliability analysis. Such analysis includes the method comparisons using the estimates provided by the QWB scale as well as within-and between-observers agreement evaluations concerning different aspects of the fuzzy model. The results will be presented in a forthcoming paper. In the near future, such investigations will be extended to other health professionals, such as nurses, as well as to samples of the general population. We expect that, based on the results of such a comprehensive approach, the fuzzy model will become a consistent alternative for further estimation of the burden of different health problems, as well as of the impact of available interventions in public health research.

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