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Qualitative profiles of disability

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Abstract—This study identified profiles of functional disability (FD) paralleled by increasing levels of disability. We assessed 96 subjects using the World Health Organization Disability Assessment Schedule II (WHODAS II). Clustering Based on Rules (ClBR) (a hybrid technique of Statistics and Artificial Intelligence) was used in the analysis. Four groups of subjects with different profiles of FD were ordered according to an increasing degree of disability: "Low," self-dependent subjects with no physical or emotional problems; "Intermediate I," subjects with low or moderate physical and emotional disability, with high perception of disability; "Intermediate II," subjects with moderate or severe disability concerning only physical problems related to self-dependency, without emotional problems; and "High," subjects with the highest degree of disability, both physical and emotional. The order of the four classes is paralleled by a significant difference (<0.001) in the WHODAS II standardized global score. In this paper, a new ontology for the knowledge of FD, based on the use of ClBR, is proposed. The definition of four classes, qualitatively different and with an increasing degree of FD, helps to appropriately place each patient in a group of individuals with a similar profile of disability and to propose standardized treatments for these groups.

Key words: artificial intelligence, cluster analysis, disability profiles, functional disability, Knowledge Discovery, qualitative analysis, rehabilitation.

INTRODUCTION

Disability is usually defined as the difficulty or inability to independently perform basic activities of daily living or other tasks essential for independent living without assistance. Disability has no clear limits, and defining different levels in different patients is very difficult, particularly when referring to functional disability (FD). FD has to be intended as the result of the interaction of different individual components of compromised functions: physical, emotional, and cognitive aspects usually interact to produce a comprehensive disability, which is more than the simple addition of the single impairments, affecting the patient's global function and his or her self-dependency [1]. From a rehabilitation perspective, patients' functioning and health are associated with, but not merely a consequence of, a condition or disease. Furthermore, functioning and health must be seen in associated with a condition but also associated with personal

Abbreviations: AI = artificial intelligence, ClBR = Clustering Based on Rules, FD = functional disability, KB = knowledge base, WHODAS II = World Health Organization Disability Assessment Schedule II.

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and environmental factors and context. Rehabilitation interventions are targeted toward a person's functioning and health [2]. A multidisciplinary involvement in comprehensive rehabilitation programs has proven effective [3], and the positive interaction of mental and physical training has been studied [4–9].

Recent debate on the evaluation of treatment efficacy and effectiveness has requested that the treatments be objectively defined and protocol-based. These treatments cannot be defined without also specifying the nature of the population being treated [10]. The possibility of defining reliable profiles of disability represents a prerequisite for proposing standardized rehabilitative treatments for patients sharing the same pattern of FD—patients who at that point will be allowed to undergo a program of comprehensive rehabilitation instead of the treatment of single compromised functions.

However, the scientific community lacks consensus on how to measure disability and how to individuate subgroups of disabled individuals [11]. Many assessment scales have been proposed to correctly define disability. Clinicians' most widely used approach is to produce an absolute or relative score for each assessed patient [12–13] to classify him or her or his or her disability on a scale or a range of values. In these terms, the disability scores of each scale constitute an increasing or decreasing continuum of values related to individual degree of self-dependency. For one to better interpret data resulting from assessment scales, a possible solution is to identify different subgroups defined by cutoff values, which possibly can be associated with common characteristics. However, summarizing a multidimensional evaluation in a single result is difficult and these scores would then hardly play a substantial role in clinical practice and decision-making.

Cluster analysis is a more sophisticated approach that distinguishes (with higher definition) different groups of subjects on the basis of similar individual attributes. Cluster analysis allows the identification of groups of patients affected by different pathologies but with similar symptoms such as motor, cognitive, or mood alterations [14–16]. It has been applied in studies of psychiatric patients [17] and patients suffering from an alteration of pain perception [18]. However, the classical clustering techniques do not recognize the structure of certain sets of complex data and produce some nonsense classes [19]—in clinical terms—that experts cannot interpret and that do not correspond to real concepts in the medical domain. In fact, this occurs when dealing with "ill-structured domains" [20], in which relationships between variables are complex, either numerical or qualitative information has to be treated together, and additional semantic knowledge is available but not considered by classical clustering techniques.

Since the results of classical clustering methods are frequently difficult to apply clinically [21], we propose the interaction between statistical and artificial intelligence (AI) methods, which has already been successfully applied in the medical field [19,22–24]. The method is known as *Clustering Based on Rules* (ClBR) [25]. It is a hybrid technique that combines some inductive learning elements with statistical methods to improve clustering results on ill-structured domains. In fact, one of the main advantages of this approach is that it guarantees the semantic meaning of the resulting classes. Previously, it was successfully used for Knowledge Discovery in several real applications [19,26–27]. Discovering the underlying classes of a domain helps to organize and make explicit the knowledge about it, and it allows establishing what is known as *ontology* in AI environments [28].

The main goal of this research is to identify disability profiles on the basis of similar functional problems—possibly paralleled by increasing levels of disability—subsequently to propose an ontology for the target phenomenon. This attempt relies on the assumptions that individuating the multiple components of FD will help clinicians in making decisions about the most effective treatment strategies and that grouping patients in qualitatively defined profiles will provide the basis for standardized treatment.

METHODS

Sample

The sample included 96 subjects, 58 males (60.4%) and 38 females (39.6%); mean age was 56 years. Of these 96, 76 were neurological patients, aged 18 to 80 years, recovering from October 1999 to February 2000 at the IRCCS (Istituto di Ricovero e Cura a Carattere Scientifico) S. Lucia hospital in Rome, Italy. They included 20 spinal cord injury patients (mean age 47.20 ± 17.6 standard deviation [SD]), 20 Parkinson disease patients (mean age 69.25 ± 6.53 SD), 20 stroke patients (mean age 63.40 ± 15.96 SD), and 16 depressed patients (mean age 46.56 ± 11.15 SD). The control group included 20 healthy subjects (mean age 55.05 ± 15.57 SD). A trained physician interviewed each subject according to the World Health Organization Disability Assessment Schedule II

(WHODAS II) scale. The only inclusion criterion was the absence of cognitive disorders, according to a prior clinical evaluation by a neurologist.

The WHODAS II Scale

We derived data from use of the WHO evaluation scale, which provides the necessary information about disability on the basis of quality and quantity. The WHODAS II [29] is a multidimensional evaluation scale for measuring level of functioning and disability across a variety of conditions. One added advantage of the WHODAS II is that it assesses functioning and disability at the individual level instead of the disorder-specific level. The WHODAS II is undergoing reliability and validity testing (in 16 centers across 13 countries) and health services research studies to test sensitivity to change and predictive validity [30]. The WHODAS II has shown an excellent internal validity and convergent validity in the primary care setting [31], and it has been used in the study of depressive disorders [32].

In the same set, the WHODAS II incorporates instruments for the detection of both physical and mental health factors related to disability. The WHODAS II version 3.1a (June 1999, interviewer-administered version) is a scale containing 96 items for the assessment of disability levels according to the ICF (International Classification of Functioning and Disability). This interview measures self-reported difficulty in functioning in six major domains considered important in most cultures: Understanding and Communicating (six items), Getting Around (five items), Self-Care (four items), Getting Along with People (five items), Life Activities (eight items), and Participation in Society (eight items). The WHODAS II employs a 5-point rating scale for all items in which “1” indicates no difficulty and “5” indicates extreme difficulty or inability to perform the activity. The WHODAS II standardized global score ranges from 0 (nondisabled) to 100 (maximum disability).

Analysis

ClBR was used to analyze data collected from the sample of 96 subjects. Gibert and Cortés originally presented this method in detail [25]. It consists of a mixture of two main elements: on one hand, an AI process that manages a knowledge base (KB), which includes prior medical knowledge, even if partial, and on the other hand, a later clustering process that is biased on the basis of some induction on the KB.

The KB is processed and used to induce a first structure on the sample, mainly consisting of the identification of certain groups of patients, called *rules-induced classes*. If the KB is partial, it will not involve certain objects, and these will constitute what is called the *residual class*. Then clustering is carried out in every rule-induced class; a prototype of each rule-induced class is built and clustered together with the residual class, thus constructing a single global hierarchy including all the objects.

The additional knowledge provided by the expert is expressed by means of logical rules, with the structure:

$$r = (A \rightarrow C), \text{ and written as } r\text{: If } A \text{ then } C,$$

which is read as “occurrence of A implies membership to C,” where A is a Boolean expression either on the variables of the database or some transformation on them, and C is a group label. The KB is a set of rules r, and it may be a partial description of the domain: in ill-structured domains, building a complete explicit KB for the domain is usually difficult because of the large quantity of implicit knowledge experts unconsciously use.

With respect to the underlying clustering method, in this particular application, the reciprocal neighbors algorithm is used, with Ward criteria (which is based on the concept of inertia and has the property of giving priority to the formation of homogeneous groups of objects). A particular property of the ClBR is that it allows treatment of heterogeneous databases (with both numerical and categorical variables), measuring distances between objects by means of “Gibert mixed metrics” [33]:

$$d^2_{(\alpha,\beta)}(i,i') = \alpha \underbrace{\sum_{k:X_k} \frac{(x_{ik}-x_{i'k})^2}{s_k^2}}_{\text{numerical}} + \beta \frac{1}{n_Q^2} \underbrace{\sum_{k:X_k} d_k^2(i,i')}_{\text{qualitative}}$$

where x_{ik} is the value taken by variable X_k for object i, $x_{i'k}$ is the value taken by variable X_k for object i', and n_Q^2 is the number of qualitative variables with $(\alpha, \beta) \in [0,1] \times [0,1]$, $s_k^2 = \mathrm{Var}(X_k)$; and $d_k^2(i, i')$ a rewriting of χ^2 metrics, calculated with qualitative variables and supporting symbolic representation. The rules used in this application concern the items of the WHODAS II that inquire about emotional behavior.

Four of the test questions are related to emotional behavior. They are—

1. B4 = How do you rate your mental or emotional health in the past 30 days?

2. B9 = How much worry or distress have you had about your health in the past 30 days?
3. S5 = How much have you been emotionally affected by your health condition?
4. R2 = How much have the difficulties been caused by mental health or emotional problems?

People who give higher values to these questions are considered to have an emotional problem of some kind. So, the proposed KB for biasing the cluster is—

KB = {*r*1: If B4 is in [4,5], then emotional problems,
*r*2: If B9 is in [4,5], then emotional problems,
*r*3: If S5 is in [4,5], then emotional problems,
*r*4: If R2 is in [4,5], then emotional problems},

where *r*1, *r*2, *r*3, and *r*4 are the "rules"; B4, B9, S5, and R2 are the WHODAS II items just reported; [4,5] are the highest (worst) scores for the items considered, meaning high (4) or extremely high (5) difficulties.

One can interpret classification in a nonautomatic way by analyzing conditional distributions of the WHODAS II items against classes and using medical expertise. The significance of differences among classes for different variables is assessed with the Kruskal-Wallis test (since nonnormality holds) for numerical variables and χ^2 independence test for qualitative ones. Differences of mean standardized global scores among classes are analyzed with analysis of variance (ANOVA).

RESULTS

ClBR suggested a set of seven classes, three of which contained isolated patients confirmed as outliers (**Figure**). The four remaining classes were kept for interpretation. The classes identified four groups of subjects with different profiles of FD and could be ordered according to an increasing degree of disability. The most characteristic items in each class were also identified (fields in gray in the **Table**). The **Table** reports the mean scores ± SD of each item in the four classes.

On the basis of the conditional distribution of the scores of different variables versus classes, a qualitative description was made of features outlining major differences among classes (codes in parentheses refer to the original WHODAS II items):

- Cr93 (mean ± SD standardized global score: 10.4 ± 10.5): (B2) good physical health, (B9) mild worry or distress, (S1) can stand up for 30 minutes, (S7) no difficulty in walking for a long distance, (S8) no difficulty in toileting the whole body or (S9) dressing, (R1) no difficulty related to physical or (R2) mental problems, (B1) 45 percent of the subjects reported some physical problems, and (B3) 35 percent some emotional problems.
- Cd52 (mean ± SD standardized global score: 27.3 ± 10.6): (B2) moderate physical health, (B9) mild or moderate worry or distress, (S1) moderate difficulty in standing up for 30 minutes, (S6) mild difficulty in concentrating for 10 minutes, (S7) extreme difficulty in walking for a long distance, (S12) mild difficulty in daily work, (R1) extreme difficulty related to physical problems, (R2) moderate difficulty related to emotional problems, (B1) 91 percent of the subjects reported some physical problems, and (B3) 71 percent reported some emotional problems.
- Cr89 (mean ± SD standardized global score: 34.1 ± 15.4): (B2) moderate physical health, (B9) mild or moderate worry or distress, (S1) extreme difficulty in standing up for 30 minutes, (S7) extreme difficulty in walking for a long distance, (S8) extreme difficulty in toileting the whole body and (S9) dressing, (R1) extreme difficulty related to physical problems, (R2) moderate difficulty related to emotional problems, (B1) 100 percent of the subjects reported some physical problems, and (B3) none reported emotional problems.
- Cd53 (mean ± SD standardized global score: 48.6 ± 12.6): (B2) extremely bad physical health, (B9) extreme worry or distress, (S1) moderate difficulty in standing up for 30 minutes, (S3) extreme difficulty in learning a new task, (S4) extreme difficulty in participating in community activities, (S5) extreme emotional involvement in life conditions, (S6) extreme difficulty in concentrating for 10 minutes, (S7) extreme difficulty in walking for a long distance, (P4.1) extreme difficulty in daily work related to interaction with others, (B1) 75 percent of the subjects reported some physical problems, and (B3) 90 percent reported some emotional problems.

The mean standardized score shows a clear increase and statistically significant difference (<0.001) among the four profiles (**Table**).

DISCUSSION

The efficacy and effectiveness of rehabilitative treatment [34] are of critical concern for their implications for quality of life, healthcare policies, and healthcare

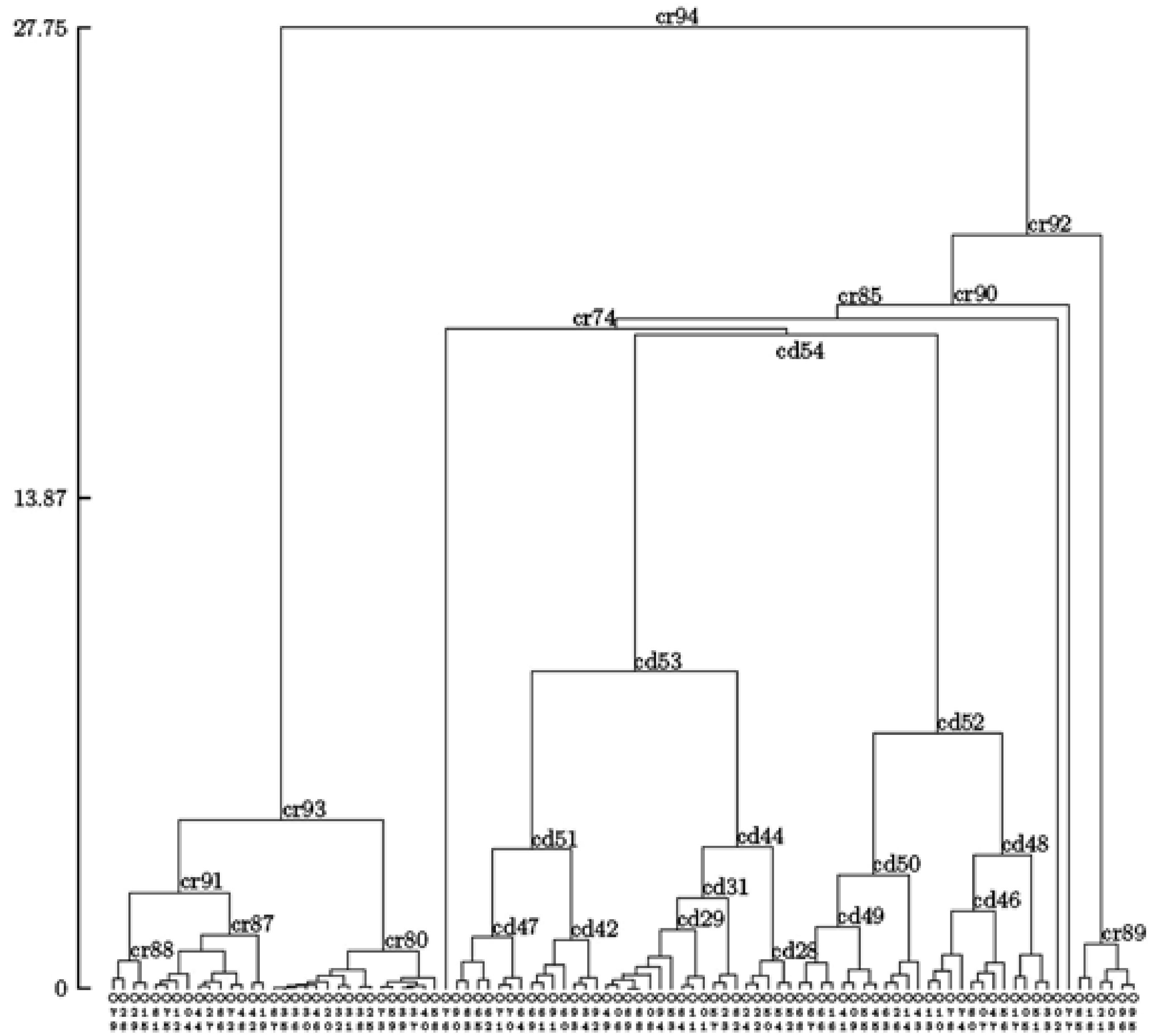

Figure.
Dendrogram for ClBR (Clustering Based on Rules). As usual in any ascendant hierarchical clustering, each leaf of the tree corresponds to one patient (which is identified by a history number). Patients are successively grouped into classes on basis of some distance. First, more similar patients are grouped. Classes are represented as internal nodes of the dendrogram. Height of each class corresponds to distance between components of class, which is why classes in the bottom contain similar patients while classes in the top are much more general (and bigger). A partition is determined by subtrees emerging by a horizontal cut of dendrogram. Elements composing each class are found by searching all leafs of corresponding subtree. ClBR produces particular dendrograms, including in general classes, of hierarchy induced by rules. Nodes labeled with prefix "cd" correspond to hierarchical structure of class induced by rules, i.e., class of "patients with emotive problems."

expenditures [10]. The need for proving the cost-effectiveness of different treatments has forced the debate and the research toward a better definition of rehabilitative care. Main topics of the debate are the treatment itself, the treatment outcome, and the population to be treated. In these terms, for one to respond to both the needs of standardized treatments and individualized care, the question to ask becomes "What works for whom?" [35]. One of the terms

Table.
Taxonomy of four qualitative profiles of increasing disability. Mean scores, mean standardized global scores (standard deviations [SDs]), and qualitative rank of most characteristic items are included.

Item	Measure	Classes				*p*-Value
		Cr93	Cd52	Cr89	Cd53	
		Functional Disability				
		Low	Intermediate I	Intermediate II	High	
Physical Problems (B1) (perceived)	Proportion	45%	91%	100%	75%	0.004
Emotional Problems (B3) (perceived)	Proportion	35%	71%	0%	90%	0.001
Physical Health (B2) (perceived)	Mean score qualitative rank	2.19 good	2.83 moderate	2.83 moderate	3.25 extreme	<0.001
Worry or Distress (B9) (perceived)	Mean score qualitative rank	1.77 mild	3.50 mild/moderate	2.50 mild/moderate	3.93 extreme	<0.001
Standing Up for 30 Minutes (S1) (difficulty in)	Mean score qualitative rank	1.43 none	2.70 moderate	4.16 extreme	3.43 moderate	<0.001
Walking for a Long Distance (S7) (difficulty in)	Mean score qualitative rank	1.74 none	3.66 extreme	4.66 extreme	4.03 extreme	<0.001
Toileting Whole Body (S8) (difficulty in)	Mean score qualitative rank	1.19 none	2.75 moderate	3.50 extreme	3.46 extreme	<0.001
Dressing (S9) (difficulty in)	Mean score qualitative rank	1.16 none	2.16 mild/moderate	3.66 extreme	3.21 moderate/ extreme	<0.001
Difficulty Due to Physical Problems (R1) (perceived)	Mean score qualitative rank	1.74 none	3.66 extreme	3.83 extreme	3.43 extreme	<0.001
Difficulty Due to Mental Problems (R2) (perceived)	Mean score qualitative rank	1.32 none	2.45 moderate	1.33 moderate	3.21 extreme	<0.001
Concentrating for 10 Minutes (S6) (difficulty in)	Mean score qualitative rank	1.41 none	2.16 mild	1.16 none	2.81 extreme	0.001
Daily Work (S12) (difficulty in)	Mean score qualitative rank	1.51 none	2.83 mild	3.33 moderate/ extreme	4.18 extreme	<0.001
Learning a New Task (S3) (difficulty in)	Mean score qualitative rank	1.22 none	1.41 mild	1.16 none	2.81 extreme	<0.001
Participating in Community Activities (S4) (difficulty in)	Mean score qualitative rank	1.25 none	1.41 mild	2.0 moderate	3.46 extreme	<0.001
Emotional Involvement in Life Conditions (S5) (perceived)	Mean score qualitative rank	1.67 mild	3.25 extreme	2.50 moderate	4.15 extreme	<0.001
In Daily Work Related to Interaction with Other Persons (P4.1) (difficulty in)	Mean score qualitative rank	1.29 none	2.29 moderate	2.16 moderate	3.00 extreme	<0.001
Standardized Global Score	Mean ± SD	10.4 ± 10.5	27.3 ± 10.6	34.1 ± 15.4	48.6 ± 12.6	<0.001

Note: Fields in gray refer to items that qualitatively characterize four classes. Codes in parentheses refer to original World Health Organization Disability Assessment Schedule II (WHODAS II) items:
B1 = Do you have any physical health problems?
B3 = Do you have any mental or emotional health problems?
B2 = How do you rate your physical health in the past 30 days?
B9 = How much worry or distress have you had about your health in the past 30 days?
S1 = How much difficulty did you have in standing for long periods such as 30 minutes?
S7 = How much difficulty did you have in walking a long distance such as a kilometer?
S8 = How much difficulty did you have in washing your whole body?
S9 = How much difficulty did you have in getting dressed?
R1 = How much have the difficulties been caused by physical health problems?
R2 = How much have the difficulties been caused by mental health or emotional problems?
S6 = How much difficulty did you have in concentrating on doing something for 10 minutes?
S12 = How much difficulty did you have in your day-to-day work?
S3 = How much difficulty did you have in learning a new task, for example, learning how to get to a new place?
S4 = How much of a problem did you have joining in community activities (i.e., festivities, religious, or other activities) in the same ways as anyone else can?
S5 = How much have you been emotionally affected by your health condition?
P4.1 = How much did these difficulties in getting along with people interfere with your life?

of the problem (the population to be treated) becomes crucially important in the judgment of treatments: the value of a specific protocol is not to be considered as an absolute one, but it has to be related to the characteristic of the group of patients who undergo the procedure.

In rehabilitation, because several outcomes are usually relevant and relevant outcomes are affected by multiple factors [36–38], the definition of subgroups of patients to be treated must rely on the possibility of both quantitative and qualitative information being considered.

A preliminary analysis of the data collected in this study clarified that the amount of information provided was hardly manageable with the use of the proposed standardized global score, with the risk of missing the whole potential of the test. Only a clear separation between disabled and nondisabled subjects is supplied by this kind of analysis, as already presented in a previous paper [21]. This loss of information hinders any attempt to clearly define different levels and profiles of disability. The individual score adds too little knowledge to the classical clinical assessment. More importantly, major characteristics common to subgroups of patients are lost when all information is summarized in a single score.

To use all the information collected more comprehensively in this research, even summarizing it into meaningful specific characteristics, we decided to use a more sophisticated analysis, i.e., ClBR, which is a hybrid AI and statistics technique. In addition to the classical clustering analysis, ClBR allows combining database and additional semantic information, which can be considered when the clustering process is properly biased. In other words, through the intervention of experts who suggest “rules,” their clinical experience represented in a KB can be considered in the analysis. In this specific case, medical experts’ opinions have been used to generate the rules to be introduced to bias the clustering process. Different knowledge structures could, however, be used as KB. The introduction of diagnostic or treatment guidelines is also possible and of peculiar interest, since greater levels of adherence to rehabilitation guidelines have been shown to be associated with improved patient outcomes and the use of guidelines has been considered as a quality-of-care indicator [39]. An important property of the method is that semantic restrictions implied by the KB are satisfied by final clusters, and this guarantees interpretability of results and consistency with knowledge initially provided for the KB.

In this particular application, the classification obtained by classical clustering methods [21] was especially unsatisfactory for those items of the scale referring to emotional problems and depressive symptoms. As a matter of fact, a direct influence of depressive symptoms on general functioning is known: patients with either current depressive disorder or depressive symptoms tend to have worse physical, social, and role functioning and worse perceived current health than other subjects with no chronic conditions; depressed patient functioning is worse than or comparable to that of patients with major chronic medical conditions. Depression and chronic medical conditions have unique and additive effects on patient poor functioning [40].

The additional knowledge provided by the experts then focused on this topic, and the KB used in this application introduced a semantic bias referring to how to handle the items of the WHODAS II that investigate emotional behavior, and inducing the system to select at a first step all patients reporting high scores in such items. The final hierarchy, obtained after combining the KB management with the clustering, suggests a subdivision of these patients into two classes: one (Cd53) comprising patients with greater emotional and physical problems and the other (Cd52) patients with milder problems (**Figure**). The composition of the emerging classes corresponds to different profiles of FD. In particular, the classification of the emotionally compromised patients, influenced by the experts’ rules, made possible the distinguishing between two intermediate degrees of disability that are qualitatively different mainly in terms of being or not being burdened by emotional problems, confirming the just-mentioned different performance of emotionally compromised, depressed patients.

The possibility to individuate a different self-perception of one’s objective disability is important because rehabilitation implies (with the exception of passive treatments) active engagement and motivation in tasks that are supposed to improve function: patients with higher levels of depressive symptoms or history of depression use rehabilitative services less efficiently and progress slowly in regaining basic functional capacities [41]; depressive symptoms, even if mild, show a negative impact on functional recovery after stroke [42–43] with slower recovery and poorer final scores [44]. On the other hand, Loong et al. showed that the mood of depressed patients improved at the end of rehabilitative treatment [45].

Apart from the result of a higher definition in classifying depressed or emotionally impaired subjects, the analysis clarifies the most characteristic items in each class and, at the same time, defines the degree of impairment connected to single functions. As a consequence, the classes can be ordered according to the severity of the FD and a new taxonomy of four profiles of increasing disability can be proposed (**Table**): Low (Cr93), self-dependent subjects, with no physical or emotional problems (includes all control patients and a few patients without apparent FD); Intermediate I (Cd52), subjects with a low to moderate degree of both physical and emotional disability, with high perception of disability, worse than the objective (milder) clinically defined disability; Intermediate II (Cr89), subjects with moderate to severe disability concerning only physical problems related to self-dependency, without emotional problems; High (Cd53), subjects with the highest degree of disability, both physical and emotional. The proposed order of the four classes—in terms of worsening global function—is paralleled by a significant difference (<0.001) in the standardized global score (**Table**). Furthermore, the proposed profiles are not directly associated with underlying pathologies equally distributed over the four classes (not shown). We must note that the discrimination between patients with different perceptions of their impairments is no longer present in the high-level disability class. Perhaps in this group of subjects, the handicaps, diseases, and clinical conditions achieve such a state of seriousness to overwhelm a possible underlying different emotional response.

The method presented here offers the opportunity of a better classification of disabled patients—especially those with an intermediate degree of disability—and could help clinicians to evaluate a patient's potential for rehabilitation at an early stage, thus facilitating effective treatment strategies, as well as helping in deciding the most efficient use of services: both clinicians and administrators have a need to identify patients who are likely to benefit from rehabilitation. Determining in advance who will be a suitable candidate for which kind of rehabilitation should help to guarantee efforts and resources to be expended productively. [46–48]. The need to develop protocol-based treatments, the need to specify the nature of the population to be treated, and the definition of the outcomes represent basic requisites of the research on treatment efficacy and effectiveness [49] and, as a consequence, of the study of cost-effectiveness in rehabilitation medicine [50–52].

Of course, an appropriate analysis of data is a basic condition for obtaining good results. Indeed, one can obtain poor results by using either a univariate approach on the basis of the standardized global score or a multivariate approach using only classical clustering [21]. This paper shows once again that analyzing complex domains requires something more. We propose the use of a mixed technique (ClBR) that combines AI and statistical methods to improve quality of results. In this domain, integration of clinical knowledge in the analysis is fundamental for proper interpretation. None of the classical statistical methods allow expert knowledge to influence the data analysis. The use of ClBR greatly improved the results.

A potential bias in this study is represented by the nonexplicit formulation of rules regarding cognitive impairment to be introduced in the KB to influence the clustering. Cognitive impairment has been correlated with limited functional gains and poor rehabilitation outcome [53–54]. Specific studies among elderly patients with stroke led to the assumption that these patients should not be considered suitable candidates for active rehabilitation programs [55–57]. However, other studies have shown that cognitive impairment may not interfere with effective rehabilitation of elderly stroke patients [58–60]. The preliminary analysis of the groups of patients individuated by the classical clustering method did not evidence any substantial bias with regard to the cognitive performance. This finding probably depends on the fact that a criterion of inclusion was the absence of a diagnosis of cognitive impairment, based on the answers to the questionnaire's items self-reported. Furthermore, the relatively young mean age of the sample (56 years) does not introduce biases connected to the subclinical presence of cognitive impairment, a problem which becomes typical in older ages. A future sample will include both older and cognitively impaired patients, and the analysis will specifically control for this parameter.

Another aspect of the study that needs further research is the possibility of immediately classifying a single patient in one of the four classes. This possibility bases itself on the use of the scores reported in those items resulted as characteristic for each class (i.e., the fields in gray in the **Table**) and on the weight assigned to each score for each class. Based on this concept, we are currently developing an interpretative grid to be used in clinical practice.

A substantial improvement of the model will be realized with the introduction of guidelines (for diagnosis and treatment) as a major component of the KB. A preliminary project for this development is currently under study.

CONCLUSIONS

In this paper, we have proposed the definition of four classes of disability, qualitatively different among them and of increasing degree of FD (Low, Intermediate I, Intermediate II, and High) that helps to appropriately place each patient in a group of individuals with a similar profile of disability and to propose standardized treatments for these groups—an approach that is occurring in the field of rehabilitation. The advantage of a multivariate approach that properly analyzes the rich source of information and produces useful results has been shown. A new way of analyzing assessment scales (ClBR) produced interesting results. The introduction of medical knowledge in the clustering process produced benefits and helped improve the actual knowledge on the domain of disability, proposing a new ontology for disabilities that can be used to support the decision-making process in this field. These results represent a first step toward defining a new ontology to improve the clinical knowledge about the multifaceted phenomenon of FD. This step forward will contribute to the efforts of other research groups [61–64] who are trying to define new taxonomies to be used operatively in the fields of research and clinical treatment of rehabilitative medicine, since classification is basic to the advancement of scientific understanding [65].

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