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THE RASCH APPROACH TO “OBJECTIVE MEASUREMENT” IN THE PRESENCE OF SUBJECTIVE EVALUATION FROM “JUDGES”

**(APROXIMACIÓN AL MODELO DE “MEDICIÓN OBJETIVA” DE RASCH EN
PRESENCIA DE LA EVALUACIÓN SUBJETIVA POR JUECES)**

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RESUMEN

Algunas de las actividades humanas -deporte, educación, economía, investigación, desarrollo profesional, alimentación- requieren la participación de jueces en la evaluación de aspectos que son difíciles de medir de forma directa. Como estas evaluaciones pueden tener consecuencias relevantes para los sujetos examinados, es necesario investigar la máxima objetividad del proceso evaluador. El modelo de Rasch es el único procedimiento estadístico que asegura la medición objetiva, incluso en el proceso evaluador de jueces. Este artículo repasa la teoría del modelo de Rasch y propone una aplicación de datos relativos a la evaluación de proyectos financiados. Se examinan también las alteraciones significativas que se detectan cuando se emplean los modelos de las mediciones de Rasch.

ABSTRACT

A variety of human activities - sport, education, finance, research, professional development, feeding - require the participation of judges in order to evaluate aspects that are difficult to be measured directly. As this evaluations may have important consequences on the examined subjects, it is necessary to research the maximum objectivity in the evaluation process. The Rasch model is the unique statistical model that assures the construction of objective measurements, even in the presence of judges evaluations. This paper reviews Rasch models theory and proposes an application to data concerning the evaluation of projects presented for a funding competition. The serious alterations that arise from the use of the rough scores instead of the Rasch measures are explored.

1. INTRODUCTION

A variety of human activities - sport, education, finance, research, professional training, feeding - involve the judgement of aspects that are difficult to be measured directly, and then called "latent traits". Such situations are characterised by the presence of three sets: the set A of subjects to be judged with respect to some characteristics, the set B of tests able to provide useful informations on the measure of the latent trait, the set C of judges who observe how the subjects perform in the various tests and give them a judgement. The judgement of subject $a \in A$ on test $b \in B$ submitted to the evaluation of judge $c \in C$ provides the result $r=r(a,b,c)$. R is the set of all possible results. The collection of this 4 sets constitute the (three factors) reference system $F=\{A, B, C, R\}$ for the measure of the latent trait (Rasch, 1977)². As this evaluations may strongly influence career, success and income of the examined subjects, it is necessary to research the maximum objectivity in the evaluation process. The objectivity degree of the evaluation depends on two fundamental factors: a) the possibility of eliminating the subjectivity in the measure of the latent trait, which arises from the subjective judgement of the evaluators, and the weights assigned to each test; b) the content validity, that means the tests appropriateness with respect to the latent trait to be measured³ (Bond, 2003). In order to solve such problems, there exists a general methodology. It is based on a mathematical model which attributes the evaluations received to three factors: the subject ability⁴, the test difficulty, and the judge severity⁵. The construction of such model is based on the research developed by the Danish mathematician Georg Rasch (1960). Reasoning about what characterises the superiority of natural sciences respect human sciences, Rasch concluded that the concept of "science" is related to the possibility of developing methods for transforming observations into measurements, according to rules that satisfy the specific objective principle. Intuitively, such principle means that the measurement method provide a measure of some latent trait of the subject independently of other subject features, other subjects or characteristics of the tool use for measuring. To this end, it is necessary modelling the observations in the reference system $F=\{A, B, C, R\}$ according to the Rasch model family (Gori, et al., 2005). It is important distinguishing the statistical approach, that tries to find the model that better fits data, from the Rasch approach, that requires the data to fit a model developed on the basis of the specific objectivity principle. Some authors state that the principle "*there is nothing more practical than a good theory*" is a necessary condition for a good research, both in experimental and observational studies (Embretson and Hershberger, 1999; Masters and Keeves, 1999; Rowe and Cilione, 2001; Wilson and Engelhard, 2000; Wright and Mok, 2000).

2. THE RASCH MODEL FAMILY

The Rasch model family is founded on three assumptions (Hambleton and Swaminathan, 1985):

A1. Unidimensionality. There exists an unidimensional latent trait θ_n , called

latent ability, associated to a generic subject n , that determines his capacity of succeed the test submitted to him; the tests are related to this unique dimension⁶ and are characterised by a difficulty $\delta_i=1, 2, K, I$; the judges are characterized by a parameter $\gamma_j, j=1, K, J$ called severity.

A2. Monotonicity. X_{nij} represents the evaluation obtained by subject n , on test i , from judge j and constitutes a random variable which satisfies the condition that $P(X_{nij} > t | \theta_n, \delta_i, \gamma_j)$ is a monotonic function of the ability θ_n , for each i and t . Subjects with higher abilities have a greater probability of getting an higher evaluation. This assumption allows for utilizing the vector of observations on subject n in the various tests, $\mathbf{X}_n = \{X_{nij}, X_{n2j}, K, X_{n1j}\}$, as repeated measures on the same subject.

A3. Local independence.

$P(\mathbf{X}_n | \theta_n, \delta_1, \delta_2, \dots, \delta_I, \gamma_1, \gamma_2, \dots, \gamma_J) = \prod_{i=1}^I \prod_{j=1}^J P(X_{nij} | \theta_n, \delta_i, \gamma_j)$, that is: conditioning on subject ability, test difficulty and judge severity, the random variables $\mathbf{X}_n = \{X_{nij}, X_{n2j}, K, X_{n1j}\}$ are independent.

2.1 The binary case (absence of judges)

Every test submitted to subjects presents a binary response (correct/wrong, succeed/fail, ecc.). In this case, the Rasch model is

$$(1) \quad P(X_{ni} = 1) = \frac{e^{\theta_n - \delta_i}}{1 + e^{\theta_n - \delta_i}}$$

and it is the only IRT model that satisfies the *specific objectivity* condition. Such model is derived from the condition

$$(2) \quad \ln \frac{P(X_{ni} = 1)}{P(X_{ni} = 0)} = \theta_n - \delta_i$$

that, referred to two subjects m and n , and to any test i , allows to express the difference between the person parameters as function of the probabilities

$$(3) \quad \ln \frac{P(X_{mi} = 1)}{P(X_{mi} = 0)} - \ln \frac{P(X_{ni} = 1)}{P(X_{ni} = 0)} = (\theta_m - \delta_i) - (\theta_n - \delta_i) = \theta_m - \theta_n,$$

that does not depend on the item parameter δ_i ⁷.

2.2 The partial credit and rating scale models (absence of judges)

In the case that responses are of ordinal type (i.e. on a Likert scale), the binary model is extended to the *partial credit* model (Masters, 1982) or to the *rating scale* model (Andrich, 1978a):

$$(4) \quad P(X_{ni} = k) : \ln \frac{P(X_{ni} = k)}{P(X_{ni} = k-1)} = \theta_n - (\delta_i + \tau_{ik}), \quad k = 0, 1, 2, \dots, K_i \quad (\text{partial credit});$$

$$(5) \quad P(X_{ni} = k) : \ln \frac{P(X_{ni} = k)}{P(X_{ni} = k-1)} = \theta_n - (\delta_i + \tau_k), \quad k = 0, 1, 2, \dots, K \quad (\text{rating scale}).$$

(Both these models result unidentified, and require the constrains $\sum_{k=1}^{K_i} \tau_{ik} = 0, \forall i$ or $\sum_{k=1}^K \tau_k = 0$, to be estimated.)

The parameter δ_i represents the average difficulty of test i , and τ_{ik} is the additional difficulty of attain level k in test i . The *rating scale* model (particular case of the *partial credit* model) assumes such parameters constant across tests. In empirical applications it is possible the presence of tests with different responses types, so it is necessary the specification of a mixed response model, where some tests present the binary Rasch specification and other tests present the *partial credit* or *rating scale* specification. For example, a recent research aimed to evaluate students knowledge level in history (Irer, 2005) uses different evaluation criteria for the items (cfr. tab. 3). For example, the evaluations of some items are expressed on a Likert scale with 3 levels, while the evaluations of other items are expressed on a Likert scale with 4 levels: the choice is guided by the minimisation of erroneous classifications and by the suitability with the item.

2.3 The multifacet model

When the tests are evaluated by judges, the model that satisfies the specific objectivity principle was developed by Linacre e Wright (1997) and is called *multifacet* (or *many facets*). Denoting by X_{nij} the response given by judge j to subject n with respect to test i , the model takes the following form

$$(6) \quad P(X_{nij} = 1) : \ln \frac{P(X_{nij} = 1)}{P(X_{nij} = 0)} = \theta_n - \delta_i - \gamma_j$$

In this version judge j establish if subject n has failed ($X_{nij} = 0$) or not ($X_{nij} = 1$) test i . This is then a binary model with an additional parameter γ_j that can be interpreted as judge severity. Here it is important to highlight that often results natural (but not necessary) administering all the tests to all the persons, but it is rather impossible get the evaluations of each judge for every subject in every test. This is the case, for example, of the evaluation of projects by a couple of evaluators chosen in a larger set of evaluators. Model (6) is straightforward to extend to the case of ordinal response items:

$$(7) \quad P(X_{nij} = k) : \ln \frac{P(X_{nij} = k)}{P(X_{nij} = k-1)} = \theta_n - \delta_i - \gamma_j - \tau_k$$

(items and judges have the same thresholds),

$$(8) \quad P(X_{nij}) : \ln \frac{P(X_{nij} = k)}{P(X_{nij} = k - 1)} = \theta_n - \delta_i - \gamma_j - \tau_{ik}$$

(every item has different thresholds),

$$(9) \quad P(X_{nij}) : \ln \frac{P(X_{nij} = k)}{P(X_{nij} = k - 1)} = \theta_n - \delta_i - \gamma_j - \tau_{jk}$$

(every judge has different thresholds)

$$(10) \quad P(X_{nij}) : \ln \frac{P(X_{nij} = k)}{P(X_{nij} = k - 1)} = \theta_n - \delta_i - \gamma_j - \tau_{ijk}$$

(every judge has different thresholds for each item)

where the parameters τ_{jk} can be interpreted, likely the *partial credit* and *rating scale* models, as the additional difficulties to attain level k . The first two models (7) and (8) correspond to the *rating scale* and *partial credit* versions in presence of judges; model (9) assumes that the thresholds can be different according to the judge, while model (10) presents thresholds that vary across judges and items (the constrains $\sum_{i=1}^k \tau_{ki} = 0$, $\sum_{i=1}^k \tau_k = 0$, and $\sum_{i=1}^k \tau_{jk} = 0$ $\sum_{i=1}^k \tau_{ijk} = 0$, helps in interpreting δ_i and γ_j as average difficulties and severities, Linacre, 1998). Also in this cases, the models satisfy the specific objectivity condition. However, "...allowing each judge his own rating scale weakens inference because it lessens the generality of the measures obtained. Were a new judge included, it would be necessary to estimate not only his level of severity but also his own personal manner of using the rating scale"⁸. We can then conclude that a major objectivity is attained by model (7), as it does not require additional parameters that reduce estimation efficiency and imply measurement scale with particularities that should be avoided for a better comparability over time and space.

Interactions between judges and items, or between judges and subjects are not admitted in the model as they compromise the *specific objectivity* property: interactions between judges and subjects imply favouritism of judges respect to some subjects, interactions between judges and items imply disagreement between judges about the importance of items. This interactions produce bias in the measurement process.

2.4. Analysis of the presence of bias

Lynch and McNamara (1998) propose a method for assessing the presence of judge bias with respect to items or persons. To this aim, an interaction term is included in the model (for example in model (7)).

$$(11) \quad P(X_{nij}) : \ln \frac{P(X_{nij} = k)}{P(X_{nij} = k-1)} = \theta_n - \delta_i - \gamma_j - \tau_k + \begin{cases} C_{nj} [1] \\ C_{ni} [2] \\ C_{ij} [3] \\ C_{nij} [4] \end{cases} .$$

Where:

- in case [1] there is an interaction between subjects and judges that allows for detecting the judge equality with respect to subjects ($C_{nj} = 0 \forall n$), or the assignment of higher or lower scores to some subject compared to the evaluations given to the others;
- in case [2] there is an interaction between subjects and items that allows for detecting the equal functioning of the item with respect to subjects ($C_{ni} = 0 \forall n$), or the major difficulty of the item for some persons;
- in case [3] there is an interaction between items and judges that allows for discovering the judge equality with respect to items ($C_{ij} = 0 \forall i$), or a different behaviour of the judge in some item;
- in case [4] there is an interaction between items, judges and subjects that allows for detecting the equal behaviour of a couple item-judge with respect to subjects, or the presence of higher or lower evaluations from some couple item-judge.

2.5 The centrality of the goodness of fit

In the contest of the Rasch models, the goodness of fit indexes have a fundamental role, as the researcher does not search a model that better fits data, but requires the data to fit the model. Consequently, if some items do not fit the model these have to be eliminated or reformulated (Bond, 2003); if subjects give responses different from model predictions these have to do the test again or they have to be eliminated from the analysis; if judges presents biases with respect to subjects or items, they have to be substituted or adequately trained.

The fit indexes proposed and implemented in the most common software depend on the model used. They can then regard subjects or items, but also judges in the multifacet version. Such indexes (Wright and Masters, 1982) are based on the differences between observed and expected values, divided by the standard deviation (both computed under the hypothesis that the model is adequate), then

$$(12) \quad z_{ni} = \frac{x_{ni} - E(X_{ni})}{\sqrt{V(X_{ni})}} ,$$

where

$$(13) \quad \hat{E}(X_{ni}) = \sum_{k=1}^{k_i} k \cdot \hat{P}(X_{ni}=k), \quad \hat{V}(X_{ni}) = \sum_{k=1}^{k_i} (k - \hat{E}(X_{ni}))^2 \cdot \hat{P}(X_{ni}=k),$$

and $\hat{P}(X_{ni})$, is the probability specified by the Rasch model, computed with the estimated parameters. There are two types of indexes: *Infit* and *Outfit*, and they are reported in Table 1. The first one is more sensible to large differences in theoretical values around 0.5 (that present a larger variance), while the second one is more sensible to large differences in theoretical values around zero and one.

Tab. 1 - Fit indexes in the Rasch model

Index	Person	Item
<i>Infit</i>	$I_n = \frac{\sum_{i=1}^I V(X_{ni}) \cdot z_{ni}^2}{\sum_{i=1}^I V(X_{ni})}$	$I_i = \frac{\sum_{n=1}^N V(X_{ni}) \cdot z_{ni}^2}{\sum_{n=1}^N V(X_{ni})}$
<i>Outfit</i>	$O_n = \frac{1}{I} \sum_{i=1}^I z_{ni}^2$	$O_i = \frac{1}{N} \sum_{n=1}^N z_{ni}^2$

Values of the indexes greater than 1 indicate the presence of a larger variability than expected from the model (this happens when the responses to a test are given by chance); values smaller than 1 indicate a dependence in the data major than that hypothesized⁹. When data fit the model, these indexes have an expected value of 1 and, using the transformations of Wilson-Hilferty (Wright and Masters 1982), they can be approximated with a standard normal random variable, under the null hypothesis that the true model is the Rasch one. The goodness of fit of an item or a subject to the model, using this transformation, can then be performed referring to the standard interval (-2,+2) for a significance level of about 5%. When, instead, the indexes of infit and outfit are used, it is possible to refer to the practical rules reported in literature (tab. 2) (Bond and Fox, 2001). As Linacre highlights¹⁰, however, keeping in the analysis the observations (subjects, items or judges) that present low values of the goodness of fit indexes would not alter the meaning of the measure, but it would reduce the precision increasing the standard errors of the estimates.

Tab. 2 - Intervals for the Infit and Outfit indexes
 (Bond and Fox, 2001)

Type de test	Interval
Multiple responses (1)	0.8 - 1.2
Multiple responses (2)	0.7 - 1.3
Rating scale (Likert scale)	0.6 - 1.4
Clinical observations	0.5 - 1.7
Judges presence	0.4 - 1.2

- (1) the exam has important consequences for the student
- (2) the exam is aimed to research

It is important to recall here that some authors (Nickerson and McClelland, 1984) showed, through simulation studies, that these indexes tend overestimate the goodness of fit. This is attributed to the computation of the theoretical probabilities on the basis of the same data used for the computation of the indexes. Recently, some alternative and more powerful indexes have been proposed (Karabatsos, 2001), especially for verifying assumptions A1-A2-A3. However, these are very difficult to compute and they are not yet implemented in standard softwares. Curtis (2004) also highlighted the necessity of developing more sensible indicators".

3. THE PROBLEM AND THE DATA AVAILABLE

3.1 Projects evaluation

The application described in the following regards the evaluation of projects presented to an Italian region for a funding competition. Projects selection was composed by two phases:

1. A preliminary investigation aimed to verify the formal correctness and the completeness of the application, of the documentation and the coherence of the projects with the objectives established in the announcement.
2. Evaluation of the contents and projects ranking on the basis of criteria defined in the announcement.

An evaluation committee performed the second phase, that was composed by three steps, each requiring the assignment of a score to several criteria:

1. Technical and scientific evaluation, aimed to verify the technical and scientific quality of the project, the competence and the operative capability of the proponents, the quality of the plan for exploiting and transferring the results, the coherence of the finance plan. In order to reach the successive step, the project must attain a minimum score in each of these aspects.
2. Evaluation of the regional priority elements defined in the announcement; in particular, the priority of the specific objective chosen, the involvement of other subjects interested in the results, the co-funding of other subjects interested in the research, the transferability of the results to public technical services, the annual length of the project.
3. Evaluation of the coherence with the regional programs, referring also to the economical/social importance of the area interested.

The preliminary investigation selected 123 projects for the content evaluation. Using rough scores the committee produced a ranking of these projects and the first 85 projects were considered suitable for being financed. The funding availability allowed for finance 36 of them.

3.2 The technical and scientific evaluation process

Judges evaluations were given by assigning to each project a score in each of the 14 criteria reported in table 3 and grouped in four groups :

1. technical and scientific quality and originality of the project,
2. possibility of transferring and exploiting the results,
3. competence and operative capability of the proponents,
4. coherence and management of the resources.

Tab. 3- Description of the criteria utilized for evaluating the projects

Cod.	Criteria description
v11	Description of the state of the art and analysis of the needs
v12	Clarity and practicability of the project objectives
v13	Scientific quality and innovative level of the research
v14	Suitability of the methodological approach and the operative plan
v15	Quality of the costs/benefits analysis
v21	Presence of indicators on the result and their coherence
v22	Quality of the program about informative initiatives and transferring of the results
v23	Utility of the results and time necessary for using them
v31	Competence of the proponents (on the basis of the curriculum)
v32	Suitability of structures and equipment available for the project
v33	Presence of all the necessary competences (also as partners or consultants)
v41	Suitability of the management system of the project and of the partnership
v42	Suitability of the length with respect to the objectives
v43	Suitability of the financial resources

Scores were expressed on a scale from 0 to 5, where the values have the following meaning:

- 0 = unacceptable;
- 1 = seriously insufficient;
- 2 = insufficient;
- 3 = sufficient;
- 4 = good;
- 5 = optimum.

It was allowed to assign intermediate scores, so the scale resulted formed by 11 values: 0, 0.5, 1, 1.5, 2, 2.5, 3, 3.5, 4, 4.5, 5. Scores were given independently by at least two evaluators for each project; one of them has the role of coordinator, the other is the support.

3.3 Preliminary analysis of the judgements received from a subset of projects

From the 123 projects to be evaluated, 89 projects have been selected for the application of the *multifacet* model. For each project, the scores given by the judges (they were 44) were collected and transformed on a scale from 0 to 10. Generally, all the evaluators gave a score to all the criteria and missing data are less than 2,5%, with the exception of criteria 1.5 that presents 6.1% of missing data. Anyway, this do not constitute a problem for the estimation of the Rasch model, provided that an evaluation in any criteria is available for each project.

Figure 1 represents the average, minimum and maximum score obtained by each project in all the criteria from all the judges. The figure shows important divergences between the evaluators that, in some cases, goes from 6 to 9.

Fig. 1 - Minimum, maximum and average rough score received by each project

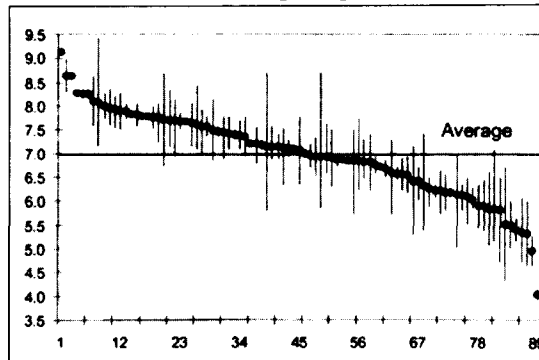
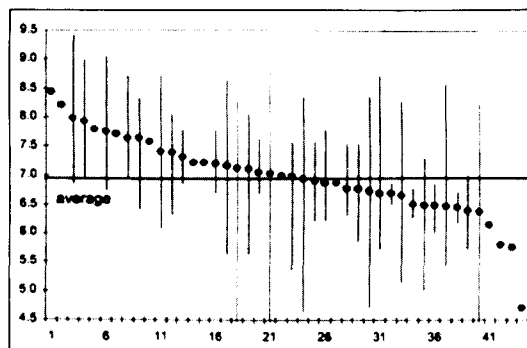


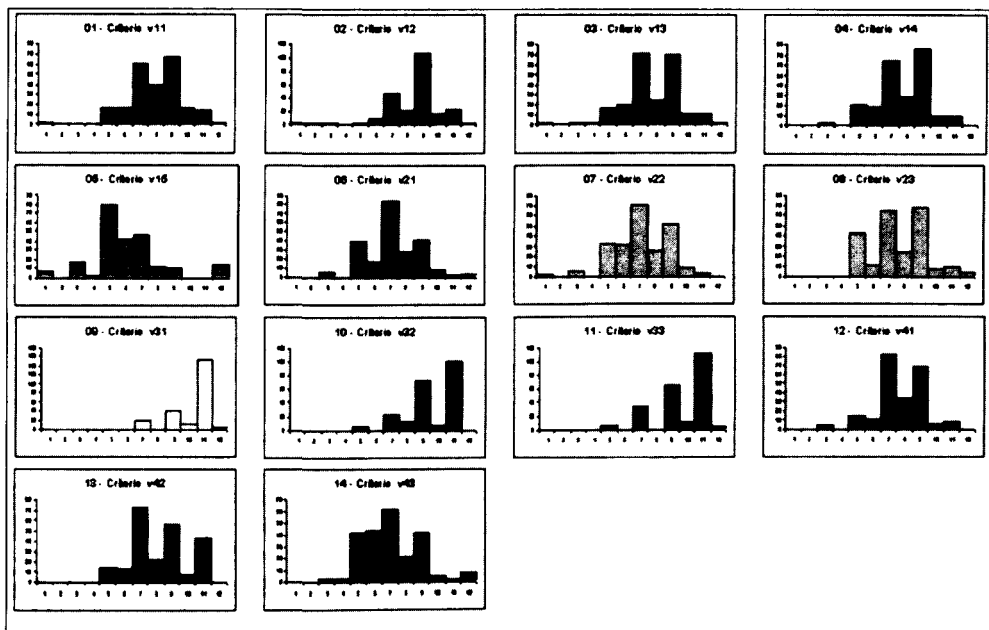
Figure 2 represents, instead, the minimum, maximum and average score given by each judge: in the hypothesis that projects were randomly assigned to the evaluators, the figure shows a large difference in severity between judges. These discrepancies could favour or not some project, and this will be further showed by the application of the *multifacet* model.

Fig. 2 - Minimum, maximum and average rough score assigned by each evaluator



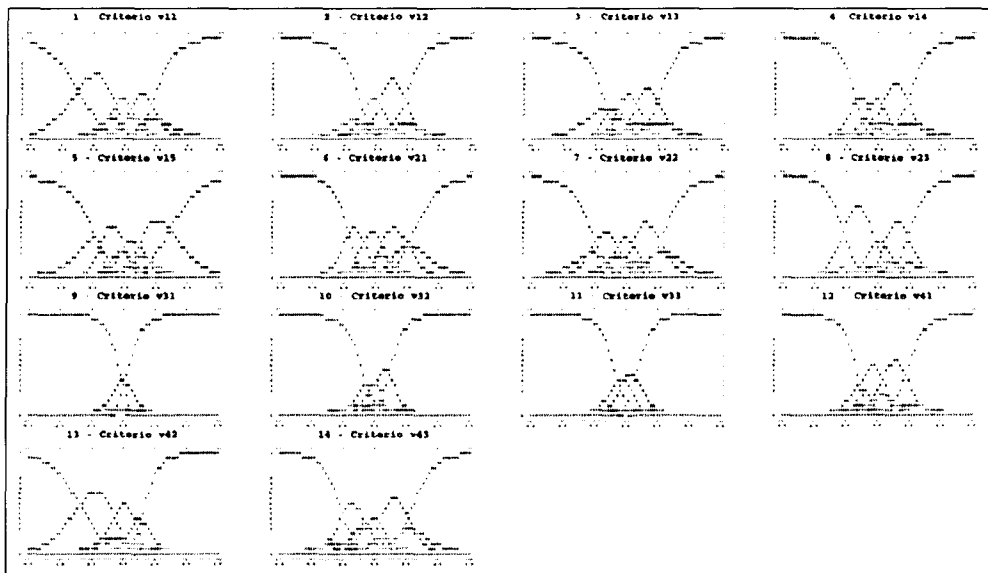
Finally, Figure 3, that represents scores distribution (from 0 to 10 + the missing data) for the different criteria, shows that not all the values were utilized and that a scale with 2 or 3 values would frequently be sufficient. This reduces the errors that judges commit in giving evaluations.

Fig. 3 - Use of the 11 values for the evaluation of the criteria



On the basis of this representation and of a first application of the model, a transformation on a new scale results appropriate. The model that was fitted is the partial credit model (8), estimated with the program FACETS (Linacre, 1998). Figure 4 represents the probabilities of receiving each of the 11 values on the basis of the model estimates. The large overlap of the curves indicates that the use of a big number of values increases the presence of errors in the evaluation process. This is confirmed by the indexes (Figure 7) for the interactions between evaluators and criteria and between projects and criteria and by the presence of a large number of misfitting indexes (Figure 6) for all the aspects (evaluators, criteria and projects).

Fig. 4 - Probability curves of receiving a score using the original scale on 11 values
(*partial credit model (8)*): every criteria has different thresholds



A transformation on a different scale, with less values, was individuated through various and successive attempts, in order to attain a better separation of the probability curves and a better fit of the model. Figure 5 reports the final choice, that uses 3 values (like insufficient, sufficient, good) for all the criteria with the exception for criteria 9 (that is v31) that was expressed on a binary scale (unsuitable, suitable). The figure shows that curves present now a good separation, reducing in this way the errors that judges committed assigning scores.

The final model presents different thresholds for different groups of criteria, leading to a special case of model (8). The groups are represented with different colours in Figure 3 and the transformation applied to the scores is reported in Figure 5.

The goodness of fit results quite improved. Figure 6 compares the infit and outfit indexes for the three aspects (evaluators, projects and criteria) before and after the transformation:

- *Evaluators*: using a scale with 11 values, 11 infit indexes and 9 outfit indexes were out the limits; after the transformation on a scale with 3 values these are respectively 6 and 5;
- *Projects*: before the transformation there were 15 infit indexes and 14 outfit indexes out of the limits; after the transformation these are 9 and 10;
- *Criteria*: before the transformation there were 2 infit indexes and 3 outfit indexes out of the limits, after transformation there these are both 0.

Figure 7 represents the bias due to interactions between evaluators and projects, between evaluators and criteria, and between projects and criteria, before

(left side) and after (right side) the transformation. The figure shows that after the transformation there are less interactions that result significative.

The final model presents good reliability indexes, that are equal to 83% for the evaluators, to 92% for projects (that is the measure of major interest) and to 97% for criteria.

Fig. 5 - Probability curves of receiving a score after the scale transformation (special case of model (8) with threshold constant within groups of criteria)

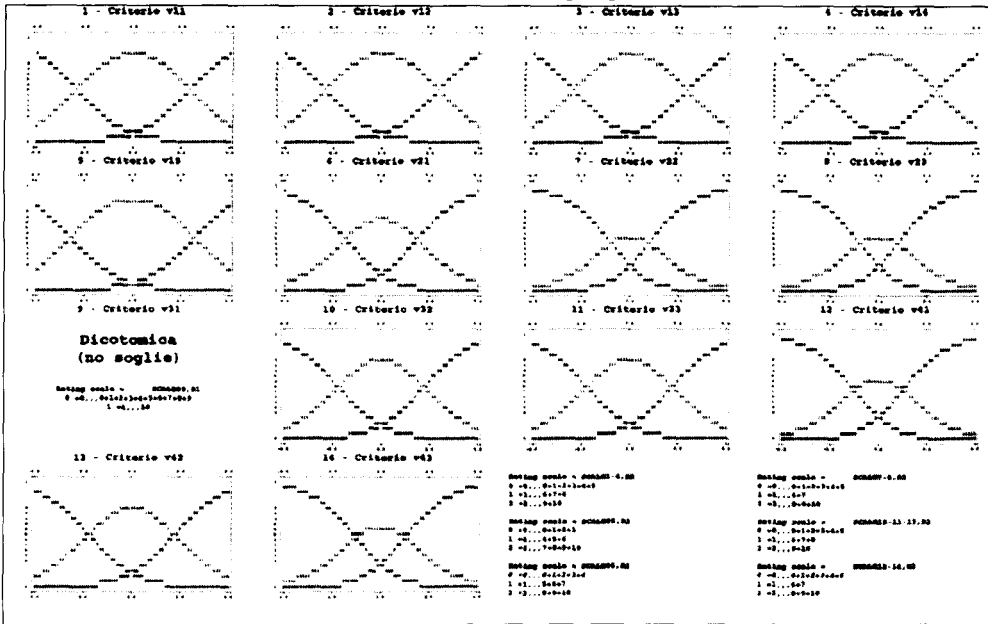


Fig. 6 - Standardized Infit and Outfit indexes before and after the scale transformation

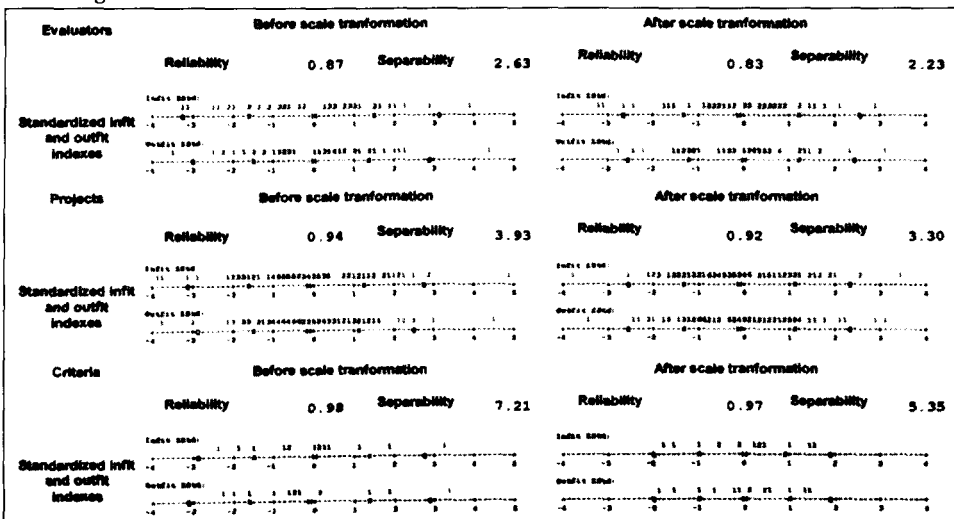
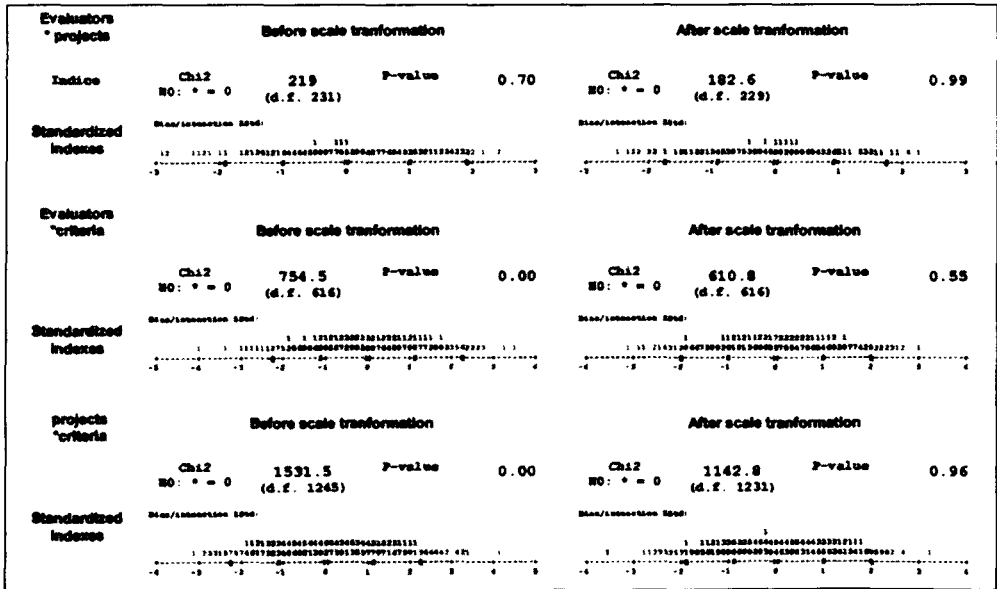
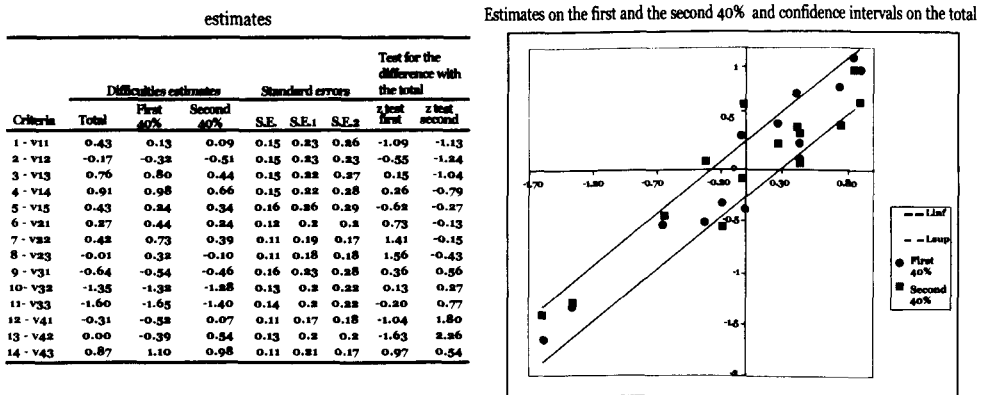


Fig. 7 - Indexes for detecting interaction bias, before and after the transformation of the scale



In order to further evaluate the goodness of fit of the model about the stability of the estimates of the criteria difficulties, the model was applied separately to the first 40% and the last 40% of the projects (ranked on the basis of their goodness). Figure 8 represents the comparison of the difficulties estimated on all the projects with those estimates on the two groups and shows a good similarity between them, with the exception of only one criteria (the 13th, that is v42).

Fig. 8 - Estimates of the criteria difficulties on all the projects and on the first and last 40%



Data available for the analysis, after the transformation of the scale, present an optimal fit to the Rasch model, that can be then utilized to obtain estimates of projects goodness, judges severities, and criteria difficulties.

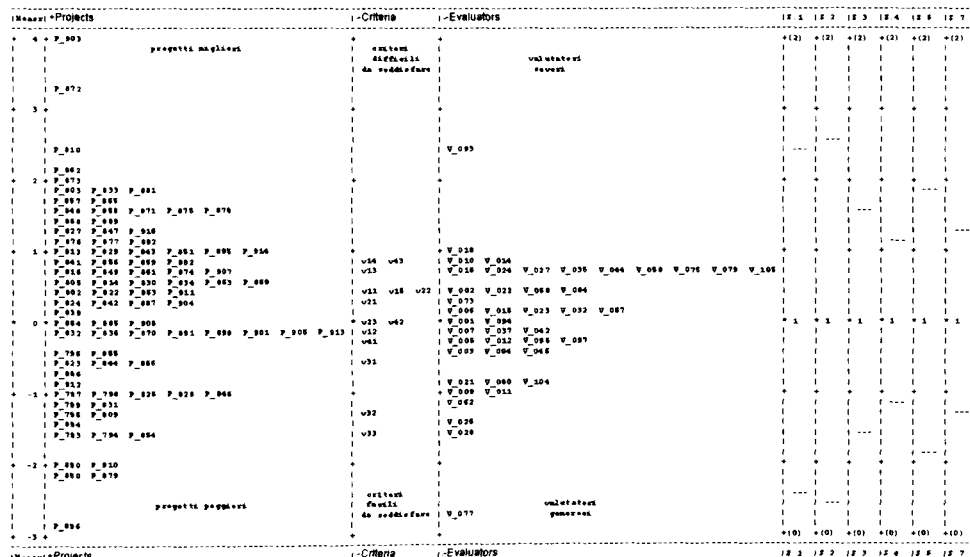
3.4 Estimation results of the multifacet model

The model utilized in the following is a special case of model (8), with thresholds kept constant within groups of criteria.

The model presents a good general fit, and the *Data log-likelihood chi-square* index is 4.45 with 3163 responses. An empirical rule, based on this index, for establishing the goodness of fit (Linacre, 1998) is the following: when the index is greater than [number of responses + 4*sqrt(number of responses)], then there is a bad general fit (significance level 5%). In this case, instead, 4.45 is largely smaller than such critical threshold.

Figure 9 represents some synthetic results of the estimation. On the left side there is the Rasch scale (from -3 to +4); then there are the projects collocated according to their goodness (the worse is project 896, the best is project 903); then there are the criteria (the most difficult are v14 and v43, the easiest is v33); on the next column there are the evaluators (the most severe is 93 and the most generous is 77); finally, on the right, there are the thresholds.

Fig. 9 - Map of the measures of the different aspects (Projects (P_), Criteria (v), Evaluators (V_)), and of the thresholds (S.)

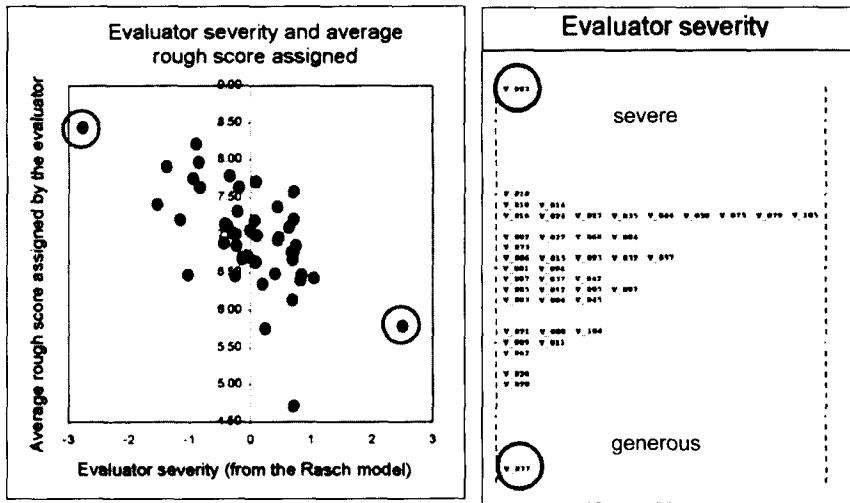


The appendix reports the estimated values of severities, goodness and difficulties. They all present acceptable infit and outfit indexes (between 0.8 and 1.2). The appendix reports also the thresholds estimates.

3.5 Bias induced by the use of rough scores

These analysis confirm the bias induced by the use of rough scores instead of the Rasch measures of projects goodness. Figure 10 shows that there is an inverse relation between the average score assigned by judges and their severity. The most severe is the 93 that gives on average scores between 5.5 and 6, while the most generous is the 77 who gives on average a score equal to 8.5.

Fig. 10 - Judges severity and scores assigned



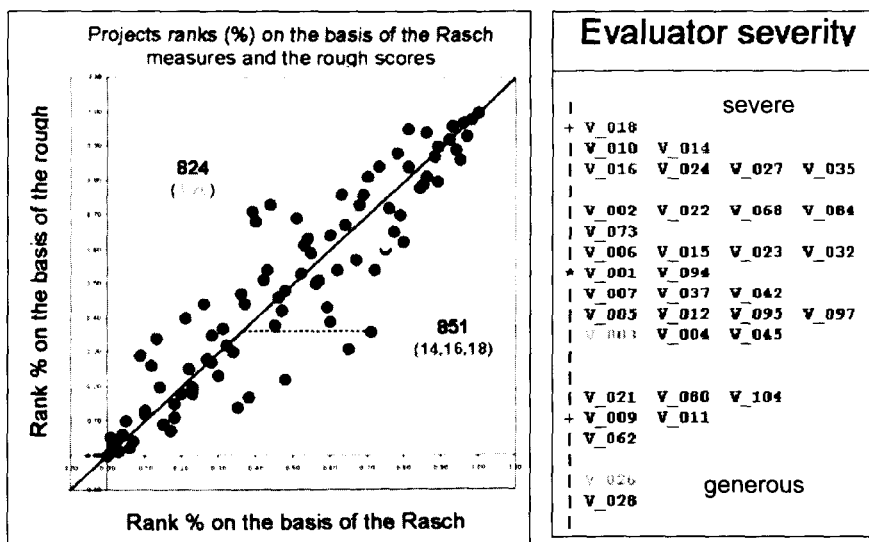
On the basis of the rough scores and the Rasch measures two different ranks for each project were obtained. This ranks were expressed on a percentual scale and the differences between the two percentual ranks for each project were computed. Table 4 reports the frequencies of such differences (grouped in classes). The 29% of the projects presents a gap grater than 10%, that means that, using the rough scores, 29 projects (on 100) unfairly overcome al least 10 projects (on 100).

Tab. 4 - Discrepancies in the percentual rank of the projects on the basis of the rough scores and the Rasch measures

rank (%) difference	frequencies	decumulate
=0	7	1 . 00
0 . 00 < x <= 0 . 05	32	0 . 92
0 . 05 < x <= 0 . 10	24	0 . 56
0 . 10 < x <= 0 . 15	9	0 . 29
0 . 15 < x <= 0 . 20	7	0 . 19
0 . 20 < x <= 0 . 25	4	0 . 11
0 . 25 < x <= 0 . 30	3	0 . 07
0 . 30 < x <= 0 . 35	3	0 . 03
Total	89	

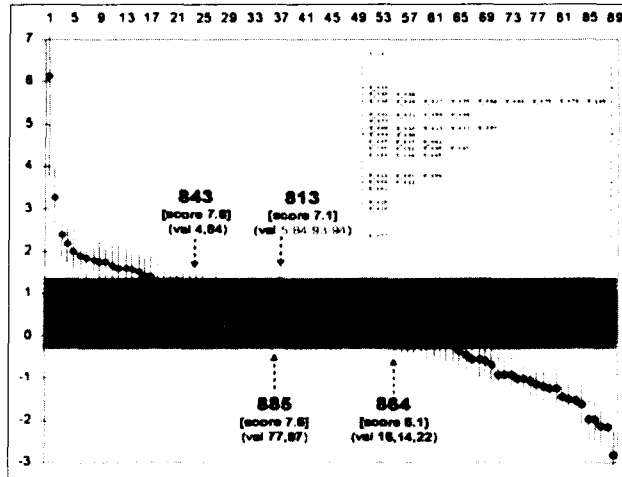
Figure 11 represents the plot of the percentual ranks on the projects in the two scales (rough scores and Rasch measures). Project 824 has a very good position (over 70%) when evaluated using the rough scores, but it has a percentual rank smaller than 40% using the Rasch measure. On the contrary, project 851 presents a percentual rank over 70% on the Rasch scale, but it is very penalized on the scores scale (about 35%). These discrepancies are due to the evaluators that judged the projects: the first one was evaluated by judges 3 and 26 that, on the severity scale, are collocated in the lower part (they are then more generous), while the second was evaluated by judges 14, 16 and 18 that are collocated in the upper part of the scale.

Fig. 11 - Judges severity effect on the percentual ranks discrepancies



Finally, considering that only 36 projects on 123 were financed, and assuming that the same proportion of financed ones is present between the 89 projects considered here, we can imagine that 26 projects would be financed. Figure 12 represents the group of the 26 projects that are financed on the basis of the rough scores (on the left) and the 63 ones that are excluded (on the right). Inside the two groups the ranking is given by the Rasch measures, that are represented with the 95% confidence interval. The figure shows that there is an important overlapping zone (that we call litigation zone) between the financed projects and the excluded ones. In particular, the best of the excluded projects, the 813, presents the same goodness of the 843 (that was financed on the basis of the rough scores). This is due to the fact that the first was evaluated by severe judges, while the second by more generous evaluators. Similarly, the worst of the financed projects, the 885, presents the same goodness of the 864, that is excluded. The judges who evaluate the first one were more generous than the evaluators of the second one.

Fig. 12 - Analysis of the collocation of the projects that would be financed on the basis of the rough scores. Projects are divided in two groups and ordered on the basis of the Rasch measures



4. CONCLUSIONS

The analysis presented in this paper shows that the data concerning projects evaluations, in the particular contest considered, can be adequately utilized for constructing objective measures by means of a special case of the multifacet model (8), with thresholds kept constant within groups of criteria. The only condition required is the use of a transformation of the original scale on which the judge evaluations are expressed in a scale with only 3 values, that allows for a reduction of the errors produced by the large number of values than can be assigned.

The model so obtained presents good infit and outfit indexes, a good general fit and an optimal reliability of the estimates of the three aspects. It is not present bias due to interaction between them (see § 2.4), and in particular that between evaluators and projects which is the most preoccupant as it may hidden favouritisms.

The criteria seem well structured for constructing the scale, and successive analysis with new data could confirm their validity if the difficulties remain constant over time and space.

Only a couple of judges present extreme severity parameters and, probably, in the future they could be excluded or adequately trained, together with the judges who present misfitting indexes.

The use of the rough score, compared with the results what would produce the Rasch measures, highlights the serious alterations of the projects ranking and motivates a litigation that, in this moment, is excluded only because the rough scores and the methods utilized to obtain them have all the legal requirements, but they are certainly not scientific and objective measures that would be necessary in this contest.

APPENDIX

Tab. A1 - Estimates of evaluators severity (γ_j = measure)
(ordered according to the identification number)

Obsvd Score	Obsvd Count	Obsvd Average	Fair-M Average	Model Measure	Model S.E.	Infit MaSq ZStd	Outfit MaSq ZStd	PCBis	Exact Obs %	Agree. Exp %	Num EVALUATORI
289	294	1.0	1.05	-.03	.11	1.0 0	1.0 0	.36	59.6	54.9	1 V_001
293	291	1.0	.92	-.45	.11	.9 -1	.9 -1	.41	63.7	54.9	2 V_002
330	292	1.1	1.15	-.30	.12	1.1 1	1.1 1	.36	67.4	55.7	3 V_003
214	194	1.1	1.16	-.42	.14	.9 0	.9 -1	.40	81.4	55.9	4 V_004
233	222	1.0	1.12	-.20	.13	1.2 1	1.1 1	.38	58.4	54.0	5 V_005
44	42	1.0	1.02	-.07	.29	.9 0	.9 0	.32	83.9	55.5	6 V_006
53	42	1.3	1.09	-.19	.31	1.0 0	.9 0	.22	44.0	56.7	7 V_007
01	69	1.2	1.30	-.95	.24	1.1 0	1.4 1	.42	72.6	54.1	9 V_009
55	67	.8	.81	-.03	.23	.9 0	.9 0	.24	65.5	51.5	10 V_010
43	51	.8	1.32	-1.02	.26	.7 -1	.8 -1	.38	59.0	48.0	11 V_011
19	14	1.4	1.34	-.34	.54	.7 0	1.0 0	.31	81.0	56.7	12 V_012
04	95	.9	.81	-.05	.19	1.2 1	1.1 0	.25	58.5	54.4	14 V_014
73	04	.9	.90	.21	.23	1.1 0	1.1 0	.53	61.9	57.2	15 V_015
85	94	.9	.84	.71	.20	.7 -2	.8 -1	.31	67.4	54.6	16 V_016
22	27	.8	.75	1.05	.37	.9 0	.9 0	.19	73.1	54.7	18 V_018
69	94	1.3	1.27	-.03	.20	1.1 0	1.0 0	.28	58.7	56.1	21 V_021
38	40	1.0	.93	-.42	.30	1.1 0	1.2 0	.12	63.5	54.6	22 V_022
43	42	1.0	1.01	.10	.30	.9 0	1.0 0	.41	69.6	54.3	23 V_023
10	14	1.3	.84	-.72	.53	.6 -1	.5 -1	.12	78.6	56.4	24 V_024
119	04	1.4	1.41	-1.30	.24	1.1 0	.9 0	.37	61.9	54.3	26 V_026
93	93	1.0	.86	-.68	.20	.9 0	.8 -1	.10	63.6	54.0	27 V_027
66	56	1.2	1.43	-1.53	.27	1.1 0	1.3 1	.29	57.1	51.4	28 V_028
17	14	1.2	1.02	.10	.52	1.0 0	1.4 0	.17	56.0	56.5	32 V_032
15	14	1.1	.94	.71	.51	.2 -3	.2 -2	.32	78.6	56.4	35 V_035
34	28	1.2	1.10	-.20	.37	2.0 2	2.3 3	.14	35.7	55.3	37 V_037
01	04	1.0	1.00	-.34	.21	.9 0	.8 -1	.43	86.4	56.2	42 V_042
101	98	1.0	.86	-.65	.20	.9 0	.8 -1	.40	53.4	54.2	44 V_044
31	20	1.1	1.16	-.44	.36	1.1 0	1.1 0	.13	61.4	54.2	45 V_045
15	14	1.1	1.01	.11	.51	.5 -1	.5 -1	.37	75.0	56.0	57 V_057
20	20	1.0	.89	-.69	.36	1.0 0	1.1 0	.20	53.7	55.6	58 V_058
14	14	1.0	1.33	-1.15	.50	1.2 0	1.7 1	.15	39.3	47.1	62 V_062
08	03	1.1	.93	.40	.21	1.0 0	1.1 0	.20	57.6	55.0	68 V_068
23	28	.8	.97	.24	.36	1.6 2	1.0 2	.22	33.9	53.9	73 V_073
17	28	.6	.85	.70	.37	1.0 0	1.0 0	.18	66.1	51.7	75 V_075
23	14	1.6	1.71	-2.76	.64	1.4 0	1.1 0	.17	38.5	42.0	77 V_077
7	14	.9	.84	.72	.56	1.6 1	1.7 1	.00	42.5	50.6	79 V_079
37	42	1.4	1.27	-.04	.32	1.0 0	.7 -1	.39	58.0	51.7	80 V_080
111	96	1.2	.91	-.45	.28	1.1 0	1.1 0	.21	68.5	54.7	84 V_084
0	14	.6	.90	2.50	.53	.9 0	.9 0	.07	45.2	37.5	93 V_093
30	93	1.1	1.05	.00	.20	.6 -3	.6 -2	.19	59.9	53.1	94 V_094
01	04	1.0	1.11	-.74	.22	.7 -2	.7 -2	.42	83.9	56.2	95 V_095
54	56	1.0	1.10	-.22	.26	1.2 0	1.2 0	.37	71.9	52.3	97 V_097
21	14	1.5	1.20	-.00	.50	1.2 0	1.3 0	-.03	78.4	53.5	104 V_104
15	14	1.1	.83	.75	.51	1.5 1	1.1 0	-.05	76.2	53.9	105 V_105

Obsvd Score	Obsvd Count	Obsvd Average	Fair-M Average	Model Measure	Model S.E.	Infit MaSq ZStd	Outfit MaSq ZStd	PCBis	Exact Obs %	Agree. Exp %	Num EVALUATORI
75.1	71.9	1.1	1.04	.00	.32	1.0 -1	1.0 .0	.25			Mean (Count: 44)
70.0	74.1	.2	.23	.06	.14	.3 1.3	.4 1.2	.14			S.D.

MSE (Model) .35 Adj S.D. .70 Separation 2.23 Reliability .03
 Fixed (all same) chi-square: 310.1 d.f.: 43 significance: .00
 Rater agreement opportunities: 2010 Exact agreements: 1795 = 63.9% Expected: 1527.6 = 54.4%

Tab. A2 - Estimates of the projects goodness (θ_n = measure)
 (ordered according to the goodness)

Obsvd Score	Obsvd Count	Obsvd Average	Fair-M Average	Measure	Model S. E.	Infit MsSq Std	Outfit MsSq Std	PtRis	Num	PROGETTI
54	28		6.13	1.85	(Maximum)				27	903 P_903
49	28	1.8	1.75	3.28	.55	.9 0	.8 0		32	872 P_872
43	28	1.5	1.58	2.37	.42	1.0 0	1.0 0		31	810 P_810
66	42	1.6	1.54	2.18	.35	.8 0	.7 -1		27	862 P_862
38	28	1.4	1.50	2.01	.38	.9 0	.8 0		40	873 P_873
60	42	1.4	1.47	1.89	.32	.6 -1	.5 -2		14	881 P_881
41	28	1.5	1.46	1.86	.40	1.3 1	1.4 1		20	833 P_833
59	42	1.4	1.45	1.79	.32	.7 -1	.7 -1		45	803 P_803
40	28	1.4	1.44	1.74	.40	2.2 3	2.2 2		22	865 P_865
37	27	1.4	1.43	1.74	.40	.8 0	.9 0		31	857 P_857
40	29	1.4	1.41	1.64	.40	1.2 0	1.3 0		06	875 P_875
43	29	1.5	1.40	1.59	.42	.9 0	1.5 1		32	848 P_848
39	28	1.4	1.40	1.59	.39	.9 0	.8 0		26	878 P_878
53	41	1.3	1.39	1.58	.31	.7 -1	.7 -1		24	871 P_871
57	42	1.4	1.38	1.52	.32	.9 0	.9 0		30	858 P_858
62	42	1.5	1.35	1.42	.34	1.2 0	1.3 0		17	869 P_869
37	28	1.3	1.35	1.42	.38	1.4 1	1.5 1		12	868 P_868
31	27	1.1	1.31	1.27	.37	.9 0	.8 0		39	847 P_847
50	41	1.2	1.31	1.25	.31	.9 0	.8 -1		30	827 P_827
54	41	1.3	1.30	1.22	.31	1.0 0	1.0 0		12	916 P_916
71	56	1.3	1.27	1.12	.27	1.0 0	.9 0		14	877 P_877
56	42	1.3	1.27	1.11	.31	.8 0	.9 0		30	892 P_892
47	42	1.1	1.26	1.08	.30	.5 -2	.5 -2		31	876 P_876
35	28	1.3	1.26	1.07	.37	.9 0	.7 -1		32	843 P_843
60	56	1.1	1.26	1.08	.26	1.0 0	1.0 0		27	813 P_813
57	42	1.3	1.26	1.03	.25	1.1 0	1.1 0		16	854 P_854
37	28	1.3	1.25	1.02	.38	1.5 1	1.3 1		32	914 P_914
67	54	1.2	1.24	1.00	.27	.9 0	1.0 0		22	829 P_829
36	28	1.3	1.24	.99	.38	1.2 0	1.2 0		26	895 P_895
30	28	1.1	1.22	.92	.36	1.2 0	.9 0		32	841 P_841
28	28	1.0	1.21	.87	.36	.8 0	.7 -1		30	882 P_882
32	28	1.1	1.20	.85	.36	1.0 0	1.2 0		32	856 P_856
57	42	1.4	1.20	.84	.32	1.0 0	1.0 0		14	859 P_859
47	42	1.1	1.18	.78	.30	1.2 1	1.3 1		20	874 P_874
40	41	1.0	1.17	.76	.29	.9 0	1.0 0		17	861 P_861
31	28	1.1	1.17	.76	.36	.8 -1	.7 -1		39	907 P_907
58	55	1.1	1.17	.74	.26	.7 -1	.6 -2		15	816 P_816
31	28	1.1	1.16	.72	.36	1.0 0	.8 0		22	849 P_849
31	28	1.1	1.14	.62	.36	1.6 2	1.8 2		20	814 P_814
75	69	1.1	1.13	.60	.22	1.5 1	1.2 1		09	830 P_830
36	28	1.3	1.13	.58	.38	1.4 1	1.3 0		21	863 P_863
32	27	1.2	1.12	.56	.38	.8 0	.7 0		39	808 P_808
39	37	1.1	1.10	.52	.31	.8 0	.8 0		33	869 P_869
36	28	1.3	1.10	.50	.38	.5 -2	.6 -1		31	834 P_834
44	42	1.0	1.10	.49	.29	.8 -1	.9 0		39	802 P_802
29	28	1.0	1.09	.45	.36	.6 -2	.6 -1		03	911 P_911
47	52	.9	1.10	.42	.26	1.6 2	1.8 3		13	853 P_853
31	28	1.1	1.07	.37	.36	.9 0	1.2 0		39	822 P_822
46	42	1.1	1.06	.35	.29	1.7 2	1.7 2		17	887 P_887
36	28	1.3	1.05	.32	.38	1.5 1	1.4 1		25	824 P_824
29	28	1.1	1.05	.31	.37	1.0 0	.8 0		15	904 P_904
31	28	1.0	1.04	.27	.37	1.0 0	1.0 0		19	842 P_842
31	27	1.1	1.02	.20	.38	.7 -1	.7 -1		45	829 P_829
51	40	1.3	.98	.06	.32	1.1 0	1.0 0		32	885 P_885
33	42	.8	.96	.00	.29	.9 0	.9 0		27	864 P_864
39	42	.9	.95	-.05	.29	1.1 0	1.1 0		35	908 P_908
27	27	1.0	.94	-.08	.36	.3 -3	.3 -3		45	832 P_832
38	53	.7	.95	-.09	.26	.7 -1	.8 -1		20	905 P_905
37	42	.9	.93	-.12	.29	1.0 0	1.0 0		32	891 P_891
24	28	.9	.93	-.14	.36	.8 0	.8 0		18	901 P_901
50	53	.9	.92	-.17	.26	.8 -1	.8 0		24	898 P_898
34	42	.8	.91	-.18	.29	1.1 0	1.2 1		14	913 P_913
20	25	.8	.90	-.20	.38	.9 0	.9 0		23	870 P_870
29	28	1.0	.91	-.20	.37	1.3 0	1.3 1		40	836 P_836
25	26	1.0	.86	-.37	.37	1.1 0	1.4 1		39	855 P_855
43	42	1.0	.84	-.46	.30	1.0 0	1.0 0		22	796 P_796
37	42	.9	.81	-.57	.28	1.0 0	1.0 0		12	866 P_866
21	28	.8	.80	-.57	.36	1.4 1	1.4 1		38	844 P_844
36	42	.9	.79	-.62	.29	1.1 0	1.1 0		15	823 P_823
27	28	1.0	.77	-.69	.36	1.2 0	1.0 0		21	886 P_886
22	28	.8	.71	-.92	.36	1.5 1	1.3 1		21	912 P_912
21	28	.8	.71	-.93	.36	.6 -1	.6 -1		25	825 P_825
31	42	.7	.71	-.93	.29	1.2 0	1.3 1		33	797 P_797
36	54	.7	.68	-1.01	.27	1.2 0	1.2 1		16	846 P_846
31	42	.7	.68	-1.03	.30	.9 0	1.1 0		20	828 P_828
28	42	.7	.67	-1.06	.30	1.1 0	1.1 0		26	798 P_798
25	28	.9	.65	-1.14	.36	1.2 0	1.3 0		29	799 P_799
31	41	.8	.63	-1.19	.30	1.0 0	1.0 0		21	831 P_831
29	42	.7	.62	-1.25	.30	.7 -1	.7 -1		42	795 P_795
29	42	.7	.62	-1.25	.30	.6 -2	.6 -2		33	809 P_809
25	28	.9	.57	-1.44	.36	.8 0	.8 0		18	894 P_894
27	42	.6	.55	-1.51	.30	.7 -1	.7 -1		04	794 P_794
15	27	.6	.54	-1.52	.38	1.5 1	1.5 1		25	854 P_854
19	27	.7	.53	-1.63	.37	1.0 0	1.1 0		03	793 P_793
16	27	.6	.43	-1.98	.38	1.4 1	1.3 1		30	910 P_910
11	28	.4	.43	-1.99	.41	1.0 0	1.0 0		16	890 P_890
22	42	.5	.40	-2.13	.32	.8 0	.8 0		43	879 P_879
14	27	.5	.38	-2.17	.39	.7 -1	.6 -1		07	850 P_850
8	28	.3	.26	-2.82	.45	1.3 1	1.1 0		10	896 P_896

Tab. A3 - Estimates of the projects goodness
 (ordered according to the identification number)

Obevd Score	Obevd Count	Obevd Average	Fair-M/ Average	Measura	Model S.E.	Infat [Mn]q	Std	Outfit [Mn]q	Std	PtBis	Num	PROGETTI
19	27	.7	.531	-1.63	.37	1.0	0	1.1	0	.03	793	P_793
27	42	.6	.551	-1.51	.30	.7	-1	.7	-1	.04	794	P_794
29	42	.7	.621	-1.25	.30	.7	-1	.7	-1	.42	796	P_796
43	42	1.0	.841	-.46	.30	1.0	0	1.0	0	.22	796	P_796
31	42	.7	.711	-.93	.29	1.2	0	1.3	1	.33	797	P_797
28	42	.7	.871	-1.05	.30	1.1	0	1.1	0	.26	798	P_798
25	28	.9	.651	-1.14	.36	1.2	0	1.3	0	.29	799	P_799
44	42	1.0	1.101	-.49	.29	.8	-1	.9	0	.39	802	P_802
59	42	1.4	1.451	1.79	.32	.7	-1	.7	-1	.45	803	P_803
32	27	1.2	1.121	-.56	.38	.8	0	.7	0	.39	805	P_805
29	42	.7	.681	-1.25	.30	.6	-2	.6	-2	.33	809	P_809
43	28	1.5	1.581	2.37	.42	1.0	0	1.0	0	.11	810	P_810
60	56	1.1	1.261	1.06	.26	1.0	0	1.0	0	.27	813	P_813
31	28	1.1	1.141	.62	.36	1.6	2	1.8	2	.20	814	P_814
58	55	1.1	1.171	.74	.26	.7	-1	.6	-2	.15	816	P_816
31	28	1.1	1.071	.37	.36	.9	0	1.2	0	.39	822	P_822
36	42	.9	.791	-.62	.29	1.1	0	1.1	0	.15	823	P_823
36	28	1.3	1.051	.32	.38	1.5	1	1.4	1	.25	824	P_824
21	28	.8	.711	-.93	.36	.6	-1	.6	-1	.25	825	P_825
60	41	1.2	1.311	1.28	.31	.9	0	.8	-2	.30	827	P_827
31	42	.7	.681	-1.03	.30	.9	0	1.1	0	.20	828	P_828
67	54	1.2	1.241	1.00	.27	.9	0	1.0	0	.22	829	P_829
69	69	1.1	1.131	.60	.43	1.3	1	1.2	1	.09	830	P_830
31	41	.8	.631	-1.19	.30	1.0	0	1.0	0	.21	831	P_831
27	27	1.0	.841	-.08	.36	.3	-3	.3	-3	.45	832	P_832
41	28	1.5	1.461	1.86	.40	1.3	1	1.4	1	.20	833	P_833
36	28	1.3	1.101	.50	.38	.5	-2	.6	-1	.31	834	P_834
29	28	1.0	.911	-.20	.37	1.3	0	1.3	1	.40	836	P_836
31	27	1.1	1.021	.20	.38	.7	-1	.7	-1	.45	839	P_839
30	28	1.1	1.221	.92	.36	1.2	0	.9	0	.32	841	P_841
29	28	1.0	1.041	.27	.36	1.0	0	1.0	0	.19	842	P_842
35	28	1.3	1.261	1.07	.37	.9	0	.7	-1	.32	843	P_843
21	28	.8	.801	-.57	.36	1.4	1	1.4	1	.38	844	P_844
36	54	.7	.691	-1.01	.27	1.2	0	1.2	1	.16	846	P_846
31	27	1.1	1.311	1.27	.37	.9	0	.8	0	.39	847	P_847
43	28	1.5	1.401	1.59	.42	.9	0	1.5	1	.32	848	P_848
31	28	1.1	1.161	.72	.36	1.0	0	.8	0	.22	849	P_849
14	27	.5	.381	-2.17	.39	.7	-1	.6	-1	.07	850	P_850
57	55	1.0	1.261	1.03	.25	.8	-1	.8	-1	.16	851	P_851
47	32	.9	1.101	.42	.26	1.6	2	1.8	3	.13	853	P_853
15	27	.6	.541	-1.52	.38	1.3	1	1.5	1	.25	854	P_854
25	26	1.0	.861	-.37	.37	1.1	0	1.4	1	.39	855	P_855
32	28	1.1	1.201	.85	.36	1.0	0	1.2	0	.32	856	P_856
37	27	1.4	1.431	1.74	.40	.8	0	.9	0	.31	857	P_857
57	42	1.4	1.381	1.52	.32	.9	0	.9	0	.30	858	P_858
57	42	1.4	1.201	.84	.32	1.0	0	1.0	0	.14	859	P_859
40	41	1.0	1.171	.76	.29	.9	0	1.0	0	.17	861	P_861
66	42	1.6	1.541	2.18	.35	.8	0	.7	-1	.27	862	P_862
36	28	1.3	1.131	.58	.38	1.4	1	1.3	0	.21	863	P_863
33	42	.8	.961	.00	.29	.9	0	.9	0	.27	864	P_864
40	28	1.4	1.441	1.74	.40	2.2	3	2.2	2	.22	865	P_865
37	42	.9	.811	-.87	.29	1.0	0	1.0	0	.12	866	P_866
37	28	1.3	1.351	1.42	.38	1.4	1	1.5	1	.12	868	P_868
39	37	1.1	1.101	.52	.31	.8	0	.8	0	.33	869	P_869
20	25	.8	.901	-.20	.38	.9	0	.9	0	.23	870	P_870
53	41	1.3	1.391	1.88	.31	.7	-1	.7	-1	.24	871	P_871
48	28	1.0	1.751	2.28	.35	.9	0	.8	0	.32	872	P_872
38	28	1.4	1.501	2.01	.38	.9	0	.8	0	.40	873	P_873
47	42	1.1	1.181	.78	.30	1.2	1	1.3	1	.20	874	P_874
40	28	1.4	1.411	1.64	.40	1.2	0	1.3	0	.06	875	P_875
47	42	1.1	1.261	1.08	.30	.5	-2	.5	-2	.31	876	P_876
71	56	1.3	1.271	1.12	.27	1.0	0	.9	0	.14	877	P_877
39	28	1.4	1.401	1.59	.39	.9	0	.8	0	.26	878	P_878
22	42	.5	.401	-2.13	.32	.8	0	.8	0	.43	879	P_879
60	42	1.4	1.471	1.89	.32	.6	-1	.5	-2	.14	881	P_881
28	28	1.0	1.211	.87	.36	.8	0	.7	-1	.30	882	P_882
51	40	1.3	.981	-.06	.32	1.1	0	1.0	0	.32	885	P_885
27	28	1.0	.771	-.69	.36	1.2	0	1.0	0	.21	886	P_886
46	42	1.1	1.061	.35	.29	1.7	2	1.7	2	.17	887	P_887
62	42	1.5	1.351	1.42	.34	1.2	0	1.3	0	.17	889	P_889
11	28	.4	.431	-1.99	.41	1.0	0	1.0	0	.16	890	P_890
37	42	.9	.931	-.12	.29	1.0	0	1.0	0	.32	891	P_891
56	42	1.3	1.271	1.31	.31	.8	0	.9	0	.30	892	P_892
23	28	.9	.571	-1.44	.36	.8	0	.8	0	.15	894	P_894
36	28	1.3	1.241	.99	.38	1.2	0	1.2	0	.26	895	P_895
8	28	.3	.261	-2.82	.45	1.3	1	1.1	0	.10	896	P_896
50	53	.9	.821	-.17	.26	.8	-1	.8	0	.24	898	P_898
24	28	.9	.931	-.14	.36	.8	0	.8	0	.18	901	P_901
54	28	1.0	1.051	1.85	.31	1.0	0	.8	0	.27	903	P_903
31	28	1.1	1.051	.31	.37	1.0	0	.8	0	.15	904	P_904
38	53	.7	.951	-.09	.26	.7	-1	.8	-1	.20	905	P_905
31	28	1.1	1.271	.76	.36	.8	-1	.7	-1	.39	907	P_907
39	42	.9	.951	-.05	.29	1.1	0	1.1	0	.35	908	P_908
16	27	.6	.431	-1.98	.38	1.4	1	1.3	1	.30	910	P_910
29	28	1.0	1.091	.45	.36	.6	-2	.6	-1	.03	911	P_911
22	28	.8	.711	-.92	.36	1.5	1	1.3	1	.21	912	P_912
34	42	.8	.911	-.18	.29	1.1	0	1.2	1	.14	913	P_913
37	28	1.3	1.251	1.02	.38	1.8	1	1.3	1	.32	914	P_914
54	41	1.3	1.301	1.22	.31	1.0	0	1.0	0	.12	916	P_916

Tab. A4 - Estimates of criteria difficulties (δ_i = measure)
(ordered according to the difficulty)

Obsvd Score	Obevd Count	Obevd Average	Fair-H Avrage	Model Measure	S.E.	Infit MnSq	ZStd	Outfit MnSq	ZStd	PtBis	Nu	CRITERI
202	229	.9	.90	.91	.15	.8	-1	.8	-1	.39	4	v14
177	222	.8	.75	.87	.11	1.1	1	1.1	0	.39	14	v43
207	227	.9	.92	.76	.15	.9	0	.9	0	.41	3	v13
211	215	1.0	.99	.43	.16	1.0	0	1.1	0	.30	5	v15
223	228	1.0	.96	.43	.15	1.1	0	1.0	0	.32	1	v11
218	229	1.0	.93	.42	.11	1.0	0	1.0	0	.37	7	v22
227	225	1.0	1.00	.27	.12	1.0	0	1.0	0	.35	6	v21
247	229	1.1	1.07	.00	.13	1.1	1	1.1	1	.21	13	v42
252	225	1.1	1.14	-.01	.11	.9	-1	.9	-1	.45	8	v23
249	228	1.1	1.07	-.17	.15	.9	0	.9	-1	.33	2	v12
278	229	1.2	1.24	-.31	.11	1.0	0	1.0	0	.33	12	v41
152	224	.7	.71	-.64	.16	1.0	0	1.1	0	.29	9	v31
325	228	1.4	1.44	-1.35	.13	1.1	0	1.1	1	.29	10	v32
335	225	1.5	1.51	-1.60	.14	1.0	0	1.0	0	.37	11	v33
235.9	225.9	1.0	1.05	.00	.13	1.0	.0	1.0	.0	.34	Mean (Count: 14)	
49.1	3.7	.2	.22	.74	.02	.1	1.0	.1	1.0	.06	S.D.	
RMSE (Model) .14 Adj S.D. .73 Separation 5.35 Reliability .97												
Fixed (all same) chi-square: 416.9 d.f.: 13 significance: .00												

Tab. A5 - Thresholds estimates (τ_{ik} = step) for the scales of the groups of criteria

Criteria from 1 a 4 (v11, v12, v13, v14)

DATA		QUALITY CONTROL			STEP		EXPECTATION		MOST		5 Cumul.		Cat Response	
Category	Counts	Avg	Exp.	OUTFIT	CALIBRATIONS	Measure	S.E.	Category	-0.5	from	at	Probabil.	PEAK	Category
Score	Used	%	%	Meas	Meas	MnSq	Measure	S.E.	Category	-0.5	from	at	Prob	Name
0	133	15%	15%	-1.49	-1.29	.9	(-3.42)		low	low	100%	0	(0+1+2+3+4+5)	
1	677	74%	89%	-1.12	-1.15	.9	-2.36	.10	.00	-2.36	-2.36	-2.36	94%	1 (6+7+8)
2	102	11%	100%	1.15	1.09	1.0	2.36	.11	(3.44)	2.37	2.36	2.35	100%	2 (9+10)
						(Mean)				(Modal)		(Median)		

Criteria 5 (v15)

DATA		QUALITY CONTROL			STEP		EXPECTATION		MOST		5 Cumul.		Cat Response	
Category	Counts	Avg	Exp.	OUTFIT	CALIBRATIONS	Measure	S.E.	Category	-0.5	from	at	Probabil.	PEAK	Category
Score	Used	%	%	Meas	Meas	MnSq	Measure	S.E.	Category	-0.5	from	at	Prob	Name
0	25	12%	12%	-1.11	-1.21	1.1	(-3.64)		low	low	100%	0	(0+1+2+3)	
1	169	79%	90%	-1.11	-1.09	1.0	-2.57	.23	.00	-2.57	-2.57	-2.57	87%	1 (4+5+6)
2	21	10%	100%	1.09	1.08	1.0	2.57	.25	(3.65)	2.57	2.57	2.56	100%	2 (7+8+9+10)
						(Mean)				(Modal)		(Median)		

Criteria 6 (v21)

DATA		QUALITY CONTROL			STEP		EXPECTATION		MOST		5 Cumul.		Cat Response	
Category	Counts	Avg	Exp.	OUTFIT	CALIBRATIONS	Measure	S.E.	Category	-0.5	from	at	Probabil.	PEAK	Category
Score	Used	%	%	Meas	Meas	MnSq	Measure	S.E.	Category	-0.5	from	at	Prob	Name
0	47	21%	21%	-1.01	-.94	1.1	(-2.58)		low	low	100%	0	(0+1+2+3+4)	
1	129	57%	78%	.06	.01	.9	-1.48	.18	.00	-1.58	-1.48	-1.52	69%	1 (5+6+7)
2	49	22%	100%	.97	1.02	1.0	1.48	.18	(2.59)	1.60	1.48	1.51	100%	2 (8+9+10)
						(Mean)				(Modal)		(Median)		

Criteria from 7 to 8 (v22, v23)

DATA		QUALITY CONTROL			STEP		EXPECTATION		MOST		5 Cumul.		Cat Response	
Category	Counts	Avg	Exp.	OUTFIT	CALIBRATIONS	Measure	S.E.	Category	-0.5	from	at	Probabil.	PEAK	Category
Score	Used	%	%	Meas	Meas	MnSq	Measure	S.E.	Category	-0.5	from	at	Prob	Name
0	127	28%	28%	-.89	-.84	.9	(-1.97)		low	low	100%	0	(0+1+2+3+4+5)	
1	184	41%	69%	.04	.05	.9	-.77	.12	.00	-1.12	-.77	-.93	52%	1 (6+7)
2	143	31%	100%	1.05	1.00	.9	.77	.12	(1.98)	1.13	.77	.92	100%	2 (8+9+10)
						(Mean)				(Modal)		(Median)		

Criteria 9 (v31)

DATA		QUALITY CONTROL			Response		
Category	Counts	Avg	Exp.	OUTFIT	Category	Name	
Score	Used	%	%	Meas	Meas	MnSq	
0	72	32%	32%	.25	.20	1.1	0 (0+1+2+3+4+5+6+7+8+9)
1	152	68%	100%	1.29	1.31	1.0	1 (10)

Criteria 10, 11 and 13 (v32, v33, v42)

DATA		QUALITY CONTROL			STEP		EXPECTATION		MOST		5 Cumul.		Cat Response	
Category	Counts	Avg	Exp.	OUTFIT	CALIBRATIONS	Measure	S.E.	Category	-0.5	from	at	Probabil.	PEAK	Category
Score	Used	%	%	Meas	Meas	MnSq	Measure	S.E.	Category	-0.5	from	at	Prob	Name
0	49	7%	7%	-.20	-.41	1.1	(-2.86)		low	low	100%	0	(0+1+2+3+4+5)	
1	359	53%	60%	.88	.86	1.1	-1.77	.161	.00	-3.83	-1.77	-1.80	75%	1 (6+7+8)
2	274	40%	100%	2.09	2.15	1.1	1.77	.091	(2.87)	1.84	1.77	1.79	100%	2 (9+10)
						(Mean)				(Modal)		(Median)		

Criteria 12 and 14 (v41, v43)

DATA		QUALITY CONTROL			STEP		EXPECTATION		MOST		5 Cumul.		Cat Response	
Category	Counts	Avg	Exp.	OUTFIT	CALIBRATIONS	Measure	S.E.	Category	-0.5	from	at	Probabil.	PEAK	Category
Score	Used	%	%	Meas	Meas	MnSq	Measure	S.E.	Category	-0.5	from	at	Prob	Name
0	124	27%	27%	-1.03	-1.05	1.1	(-2.15)		low	low	100%	0	(0+1+2+3+4+5)	
1	199	44%	72%	.03	.01	.9	-.99	.12	.00	-1.25	-.99	-1.11	57%	1 (6+7)
2	128	28%	100%	1.06	1.11	1.1	.99	.12	(2.16)	1.26	.99	1.10	100%	2 (8+9+10)
						(Mean)				(Modal)		(Median)		

NOTES

- 1.- Latent trait can be defined as every characteristic of individuals or things which has not a measurement instrument. Note that even the height would be a latent trait if there exists no balances.
- 2.- <http://www.rasch.org/memo18.htm>.
- 3.- The content validity assure that only tests able to measure the latent trait are included in set B. This aspect is partially related with the weights associated to the different test, as a weight equal to zero implies that such test is not in set B.
- 4.- Like the ability of an athlete, the goodness of a project, the risk of a company, etc.
- 5.- According to Linacre (<http://www.rasch.org/memo61.htm>), a study aimed to evaluate the degree of concordance of judges in the optimal setting (expert evaluators, well structured evaluation criteria, and registration of behaviour of individuals with clearly different level) it reached only the 80% and the evaluations expressed by the judges resulted quite imperfect on the basis of the established criteria (Gruenfeld, 1981 p.12). Then, instead of believe that training strategies can remove such differences or pretend such differences do not exist, it would be much better try to account for them measuring their magnitude.
- 6.- A Mathematics test can not include latin questions, etc.
- 7.- An analogous property holds for the difference between two item parameters: $\ln \frac{P(X_{+}=1)}{P(X_{+}=0)} - \ln \frac{P(X_{-}=1)}{P(X_{-}=0)} = (\theta_{+} - \delta_{+}) - (\theta_{-} - \delta_{-}) = \delta - \delta$
- 8.- <http://www.rasch.org/memo61.htm>.
- 9.- <http://www.rasch.org/rmt/rmt133m.htm>.
- 10.- See also <http://www.rasch.org/rmt/rmt82a.htm>.
- 11.- <http://ehlt.flinders.edu.au/education/iej/articles/v5n2/curtis/paper.pdf>.

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PALABRAS CLAVE

Jueces, medición objetiva, evaluación de proyectos, modelo de Rasch.

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