DOCUMENT RESUME

ED 389 749 TM 024 382

AUTHOR	van der Linden, Wim J.; Zwarts, Michel A.
TITLE	Robustness of Judgments in Evaluation Research. Research Report 94-10.
INSTITUTION	Twente Univ., Enschede (Netherlands). Faculty of Educational Science and Technology.
PUB DATE	Nov 94
NOTE	39p.; Paper presented at a Vereniging voor Onderwijsresearch Symposium (Arnhem, Netherlands, March 23, 1994).
AVAILABLE FROM	Bibliotheek, Faculty of Educational Science and Technology, University of Twente, P.O. Box 217, 7500 AE Enschede, The Netherlands.
PUB TYPE	Reports - Evaluative/Feasibility (142) -- Speeches/Conference Papers (150)
EDRS PRICE	MF01/PC02 Plus Postage.
DESCRIPTORS	Ability; Case Studies; Criteria; *Decision Making; Difficulty Level; Elementary Secondary Education; Evaluation Methods; *Evaluation Research; Foreign Countries; Program Evaluation; *Research Problems; *Robustness (Statistics); Scaling; *Test Items
IDENTIFIERS	*Missing Data; Netherlands

ABSTRACT

It is argued that judgments in evaluative research are ultimately subjective, but that good criteria are available to assess their quality. One of these criteria is the robustness of the judgments against incompleteness or uncertainty in the data used to describe the educational system. The use of the robustness criterion is demonstrated through the case of a recent evaluation project in which the state of elementary education in The Netherlands was evaluated. To test robustness, four different procedures were simulated for item removal: (1) scaling; (2) removal of easy items; (3) removal of difficult items; and (4) removal of extreme items. The robustness study demonstrated that the qualifications used in the evaluation project were quite stable under the removal of items from the pool by these four methods. Nearly all the qualifications met the rigorous criterion of robustness. An appendix discusses the independence of the mean observed score of covariation between abilities. (Contains 3 tables, 8 figures, and 17 references.) (Author/SLD)

Robustness of Judgments in Evaluation Research

Research Report 94-10

Wim J. van der Linden

Michel A. Zwarts

faculty of
EDUCATIONAL SCIENCE
AND TECHNOLOGY

University of Twente

Department of
Educational Measurement and Data Analysis

Robustness of Judgments in Evaluation Research

Wim J. van der Linden

Michel A. Zwarts

To appear in Tijdschrift voor Onderwijsresearch

Robustness of judgments in evaluation research, Wim J. van der Linden and Michel A. Zwarts - Enschede: University of Twente, Faculty of Educational Science and Technology, November, 1994. - 33 pages

Abstract

The point of view is taken that judgments in evaluative research are ultimately subjective but that good criteria are available to assess their quality. One of these criteria is robustness of the judgments against incompleteness or uncertainty in the data used to describe the educational system. The use of the robustness criterion is demonstrated for the case of a recent evaluation project in which the state of elementary education in The Netherlands was evaluated.

Robustness of Judgments in Evaluation Research

Typically, the first stage of an evaluation project consists of a careful description of the state of an educational object or system. In the next stage, the state of the system is evaluated through a series of evaluative statements or *judgments*. Examples of such judgments are: "The quality of teaching in the system is excellent"; "Too many students in the system do not reach a satisfactory level of proficiency in physics"; and "School management is poor". If the goal of the evaluation project is to serve a reorientation of a policy with respect to the system, the judgments usually result in a series of recommendations to improve the functioning of the system.

For the descriptive stage, the standard methodology of empirical research in the social sciences is available. This methodology includes the use of such methods as survey and observation as well as various techniques of (multivariate) descriptive statistical analysis to summarize the results. Though descriptive statements can be founded on a rigorous methodology, judgments seem to lack this support. The main reason is the use of such qualifications as "excellent", "not satisfactory", and "poor" in the examples above. The choice of such qualifications, as well as their definitions, is a subjective matter. However, subjectivity is not necessarily erratic, and criteria for good qualifications do exist. Judgment does not imply lack of rationality.

One criterion for the quality of judgments is *consistency*. For example, suppose that empirical research has shown time and again that certain instructional measures lead to an increase in the achievements of the students in a given domain, and that a system to be evaluated scores high on the use of these measures. Then, ignoring the role of costs as well as the possibility of interaction between factors in the system, it seems inconsistent to make judgments that provide the former finding with a negative and the latter with a positive qualification. Such evaluations are inconsistent in the sense that they imply a world that can never exist. It should be noted that in this example empirical research was used to show that a set of qualifications is inconsistent. Empirical research can only provide the evaluator with objective information about what worlds are possible and what not. It remains a subjective choice to evaluate one possible world over the other.

Another obvious criterion is *explicitness*. The criterion of explicitness includes the requirement that all judgments be based on explicit definitions of the qualifications and procedures used in the evaluation. If this requirement is not met, the evaluator can never communicate his evaluations to others in a meaningful way. Also, it will never be possible to test these evaluations for consistency in the sense defined above.

It is not the purpose of this paper to give an extensive overview of criteria for the use of qualifications in evaluation research (for a more complete review, see van der Linden, to appear). Rather, the emphasis is on one criterion of a more technical nature than the previous examples. The criterion is necessary because judgments may have to be based on a description of the state of the system which is incomplete, uncertain, or erroneous due to the quality of the data. An example is an evaluation project in which the state of some relevant throughput factor is not precisely known. In such a case, which is certainly not untypical of educational evaluation, the evaluator may have to base his or her judgments on a best guess as to the state of this part of the system. An important criterion for the quality of his or her judgments, then, is *robustness*. Generally, a judgment is robust if minor changes in the description of the state of the system do not lead to changes in the qualifications used in it. The idea underlying this criterion is obvious: Uncertainty about some part of the state of the system is less critical, the less dependent the qualifications are on the precise state the part of the system is in. The robustness of qualifications is usually assessed through a series of analyses in which changes in the values of some of the variables are made to simulate uncertainty about the state of the system, whereafter it is determined to what extent the qualifications would have to change. Obviously, robustness analyses are only possible if both the qualifications and the procedures leading to them are defined explicitly.

In the remainder of this paper, the results from a robustness study in a recent evaluation project in The Netherlands are reported to illustrate the possible contribution of robustness analysis to educational evaluation. The project was run by the Committee for the Evaluation of Elementary Education (CEB). In the next section, the problem addressed in the study is described. Subsequently, the methods of analysis will be given and the results will be discussed. The paper concludes with a discussion of the practical implications of the study.

Introduction to the Problem

The evaluation committee was appointed by the Dutch Secretary of Education in 1991. Its mission was to evaluate the state of elementary education in the Netherlands from 1988-1992. In particular, the interest was in an evaluation of four different aspects of elementary education in this period, its level of achievements being one of them. The results of the evaluation were published recently (Commissie Evaluatie Basisonderwijs, 1994a, 1994b, 1994c, 1994d, 1994e).

A fuller description of the assignment to the committee is given in Janssens (1995).

The committee had to report its findings at a level of aggregation that would suit a possible reorientation of the current policy of the Ministry of Education with respect to elementary education. Another constraint was that resources for data gathering were limited, and that the committee had to use existing sources of empirical data to perform its evaluation.

To present its evaluation of the achievements, the committee used the item material and scales from PPON. In this large-scale program for the assessment of educational progress in The Netherlands, which is run by the National Institute for Educational Measurement (Cito), the level of achievement in elementary education is periodically fathomed. The basic methodology used in PPON to scale the item pools and score the achievements is item response theory (IRT). The use of this methodology restricts the scaling of the items to the level of homogeneous subsets of the pool each measuring the same ability. An overview of the number of scales that were necessary to scale the item pools for the various subjects is given in Table 1.

Table 1 about here

For a complete review of the methodology used in PPON as well as reports of its assessments, the reader should consult van der Schoot (1993), Sijtstra (1992), Vinjé (1993), van Weerden (1993), Wijnstra (1998, 1990), and Zwarts (1990)

Definition of Qualifications

The selection of the qualifications by which the committee evaluated the achievements was guided by various considerations, three of which need to be explained here to be able to define the research problems addressed in this paper:

1. As already mentioned, the evaluation had to be reported at a level of aggregation suitable for recommendations on policy decisions. Therefore, it was necessary to combine sets of separate PPON scales into higher-level measures of achievement. For example, six separate scales for reading (Reading Reports; Reading Persuasive Texts; Reading Arguments; Reading References; and Reading Tables and Graphs) were combined into a single measure for Reading Comprehension. As IRT scales were not possible at this level of aggregation, the simple number of items correct score was used as a measure of achievement. However, this measure can be estimated from the scores on the IRT scales underlying the aggregate (see below). The number of aggregates in the evaluation is given in the last column of Table 1.

2. A second form of data reduction was also necessary to report the evaluations. The achievements of the population of students were in the form of distributions of scores. A usual way of defining qualifications for distinguishing between "good distributions" and "bad distributions" is in terms of their moments. Based on displays of the estimated distributions of the observed scores, the committee opted for qualifications for the first moments or means of the distributions. The main purpose of inspecting the displays was to get familiar with the relation between the location of the means and the shape of the left tails of the distribution. The qualifications were knowingly selected to be conservative; that is, relatively large

proportions of students in the population had to be at the lower ends of the achievement scales before an unfavorable qualification applied.

3. Instead of qualifications in the form of a simple good/bad dichotomy, the committee chose three different qualifications for which the terms "Satisfactory" (Dutch: voldoende), "Moderate" (Dutch: matig) and "Unsatisfactory" (Dutch: onvoldoende) were used. As a compromise between the fact that evaluations in terms of observed scores are dependent on item pool content and the fact that a single set of qualifications is easier to communicate, the committee opted for a common definition of qualifications with adjustments for item pools that were deemed to be too difficult or too easy.

In fact, the definition of the qualifications was a long process in which such factors as familiarity with the curriculum, teaching practices, quality of the learning materials, previous evaluations, and extensive consulting of relevant parties played an important role. The results are given in Table 2.

Table 2 about here

Estimation of Mean Observed Scores

Two typical distributions of observed scores are given in Figure 1. Both distributions were estimated using the assumption of a correlation equal to .80

Figure 1 about here

---

between the abilities on the underlying IRT scales.

The distribution for Calculating was evaluated as "Moderate". Its mean was just higher than the lower bound for this category but some 13% of the examinees solved less than one third of the items correctly. The distribution for Proportions/Percentages was estimated to have a mean in the category "Unsatisfactory". In this distribution, 36% of the examinees had less than one third of the items correct.

The means of the observed-score distributions were calculated from the item parameters estimated in the PPON projects. These estimates were obtained under the one-parameter logistic model with imputed values for the discrimination parameter (Verhelst, Glas & Verstralen, 1994). The ability distributions were scaled to be normal with mean 250 and standard deviation 50. Under the previous assumptions, the mean of an observed-score distribution can simply be calculated from the common marginal ability distribution and the sum of the response functions. This claim is proved in the Appendix.

Research Problems

The decision to use PPON item material and scales entailed two questions both related to the use of IRT in PPON.

First, though there is national agreement that the blueprints for the item pools had high content validity and that the sets of items in the pools covered the blueprints, some of the items were removed from the original pools in the scaling process. For example, for Arithmetic 4% of the items was removed from a pool of 491 items, whereas for Dutch 6% was removed from a pool of 498 items. These numbers are not large but important enough to pay attention to. As these items were removed on the basis of values of psychometric parameters and not of their content, it seems safe to conclude that:

1. The resulting pools still define the same ability variables, and that these variables have therefore not lost their validity; and
2. The removal of some of the items from the pools may nevertheless have had effects on the observed-score distributions, and hence on the judgments by the committee.

An important question is how serious these possible effects are.

Second, only the marginal ability distributions were available from PPON. As already explained, the choice for the mean as the critical moment of the distribution of observed-scores was based on plots of observed-score distributions. However, under the assumption of multivariate normality, to be able to plot observed-score distributions for aggregates of IRT scales, Pearson's correlation between the abilities must be known. (Remember that this requirement does not hold for the mean of the distributions.) As the abilities in each aggregate were "close", and numerous research projects have shown high correlations between subtests covering different aspects of, for example, language and arithmetic, the assumptions of correlations in the neighborhood of .80 seemed realistic. An important question is how serious the consequences of violation of this assumption are.

Both questions were addressed in a robustness study.

Method

Removal of Items

Four different procedures of item removal were simulated. In each procedure, after the removal of an item the mean of the observed-score distribution was calculated, and the correct qualification from Table 2 was selected.

The following procedures were studied:

1. Scaling. The pair of items with the smallest difference between their values for the difficulty parameter was selected, and one item of the pair was chosen at random and removed from the pool. The mean of the observed-score distribution was calculated, and the appropriate qualification was identified The steps were repeated until the pool was empty. This procedure simulates item analysis in which the range of the scale values of the items has to remain maximal but redundancies are removed by eliminating items from subsets that cluster too strongly. The procedure applies when the ideal is a pool of items with uniformly distributed scale values.
2. Easy items. The item with the smallest value for the difficulty parameter was removed from the pool, the mean of the observed-score distribution was calculated, and the appropriate qualification was identified. The steps were repeated until the pool was empty. This procedure simulates the case where the item pool is considered too easy.
3. Difficult items. The previous procedure was repeated, but now at each step the most difficult item was removed.
4. Extreme items. This procedure is a combination of the previous two procedures. Alternately, the easiest and the most difficult item were removed. This procedure

simulates the case where the item pool is considered to be on target but, for example, the distribution of abilities of the examinees is expected to have less spread than the item pool.

Correlation between Abilities

To assess the robustness of the observed-score distributions with respect to the correlation between the abilities, a Monte Carlo method was used to generate observed-score distributions on the sets of items in the aggregates for various values of the correlation coefficient. As a correlation between the abilities lower than .60 was most unlikely, the following values for the correlation coefficient were used: .60, .70, .80, and .90.

In the description of the Monte Carlo procedure below, the notation of the variables is the same as in the Appendix but the indices $j = 1,\ldots,J$ and $i = 1,\ldots,I$ are now used to denote the abilities and the items in a subset for the same ability, respectively:

1. For each simulated examinee, the values of the vector of abilities $(\theta_1,\ldots,\theta_J)$ were drawn from a multivariate normal distribution with the assumed (common) value of the correlation coefficient.
2. The true scores $(t_1,\ldots,t_J)$ were calculated as

$$t_j = \sum_{i=1}^{I} P_i(\theta_j), \qquad j=1,\ldots,J, \tag{1}$$

and normed on [0,1].

3. The conditional distributions of X_j given $T_j=t_j$ are generalized binomial. Their probability functions, Prob(X_j), were calculated using the first term in the expansion of the generalized binomial probability function given in

Lord and Novick (1968, sect. 23.10).

4. The probabilities of the number-correct scores, $\sum_{j=1}^{J} X_j$, were calculated as

$$Prob(T=t) = \sum_{\Sigma X_j = t} \prod_j Prob(X_j). \tag{2}$$

The last step in the procedure made use of the fact that for a fixed examinee the observed scores X_j, $j=1,...,J$, were independent.

The accuracy of the approximation in Step 3 was checked against an algorithm suggested by Lord and Wingersky (1984) which produces the full generalized binomial distribution (see below).

The procedure was repeated for N=10,000 examinees. It should be noted, however, that for each examinee not one realization of X_j given $T_j=t_j$ but its full conditional distribution was generated. The number is thus large enough to guarantee a smooth and stable result.

Results

Graphs are used to present the results for the scaling procedure. In Figure 2, the mean observed relative scores for the five aggregates in Arithmetic are displayed as a function of the proportion of items removed due to scaling.

Figure 2 about here

---

qualifications defined in Table 2. Generally, the curves follow a flat course, indicating extreme robustness of the mean with respect to the removal of items due to scaling. To cross one of the lines, the removal of 91% of the items for Basic Skills and 100% of the items for Proportions/Percentages was needed. For Calculating, the percentage was equal to 62%. The percentages for Fractions and Measurement are lower but still equal an impressive 45% and 33%, respectively. After these values, the two last curves started moving back and forth between the two sides of the upper (Fractions) and lower lines (Measurement). This behavior is typical of mean scores that were close to the borderline between two qualifications, remained there after removal of the items, but showed small fluctuations.

The results for the aggregates in the other subjects are given in Figures 3 through 6.

Figure 3-6 about here

The results are generally the same as for Arithmetic. All curves had a flat course, and, except for Reading English, at least 30-40% of the items had to be removed before the qualifications change. The case of Reading English is an interesting one. The curve was flattest of all curves in Figures 2-6, but the curve coincided with the upper line nearly perfectly. The same phenomenon was observed for Reading Comprehension. Its curve was also flat and uniformly close to the line between "Satisfactory" and "Moderate". Nevertheless, 38% of the items had to be removed from the pool to change the qualification. At a later stage, the curve moved back to the original qualification. In its report, the committee made the provision that important parts of this aggregate were less favorable than the general impression suggested. Also, uncertainty was expressed due to the fact that data from an international comparison of achievements in Reading Comprehension had yielded conflicting information (Commissie Evaluatie Basisonderwijs, 1994a, sect. 5.1).

The results for all four principles of item removal are given in Table 3. The first column gives the percentages of items that had to be removed for the scaling procedure. The next three columns present the results for the other item removal procedures. Obviously, removal of the most difficult or easy items introduced a shift in the observed-score distributions, and generally the qualifications changed

Table 3 about here

earlier than in the previous case. Nevertheless, with the exception of Measurement and Reading Comprehension for the removal of the easiest items and Biology for the most difficult items, the qualifications were remarkably robust for all aggregates. In these exceptional cases of change, again the mean observed scores were already close to the borderline between two classifications for the intact item pool. For example, for Reading Comprehension the mean relative observed score for the intact item pool for the pool was .71, a result close to the cut-off score of .70 separating "Satisfactory" from "Moderate" (see Figure 2). The removal of the items with extreme difficulty values at both ends of the scale had, except for Reading of English, no noticeable effect on the qualifications. In the majority of the cases, nearly all items had to be removed before the qualification changed.

In Figure 7, two typical observed-score distributions for values of the correlation coefficient in the range from .60-.90 are shown. The effect of lowering

Figure 7 about here

the value of the correlation was a small shift of the mode of the distribution to the center of the scale. (However, remember that this phenomenon does not hold for the mean of the distribution. This parameter is independent of the value of the correlation coefficient.) Consequently, the value of the correlation coefficient does have some effect on the left tail of the distribution, but the effect is not dramatic. It seems safe to conclude that the relation between the mean and the left tail of the distributions observed by the committee does not change much in the neighborhood of r=.80.

As already observed, in Step 3 of the procedure for generating the observed-score distributions, an approximation to the generalized binomial distribution of X given T=t was made. The quality of the approximation was checked by comparing its results against those obtained for the exact distributions using the computer program AAPMOMT which implements the algorithm by Lord and Wingersky (1984) referred to earlier. The results were always virtually identical. Figure 8 gives the distributions for the same two aggregates as in Figure 7.

Figure 8 about here

The approximation proved to be excellent; the difference between the results of the two methods is hardly discernible.

Discussion

The main conclusion from the robustness study reported in this paper is that the qualifications used in the evaluation project are quite stable under the removal of items from the pool according to the four procedures defined above. Nearly all of the qualifications thus met a rigorous criterion of robustness.

In this study, the results for the scaling procedure are most important since this procedure comes closest to the procedure actually used in the PPON projects. However, it should be noted that the former is an idealized version of the latter, and that differences between the two may exist. Also, the procedure was applied to the item pools that were the results from PPON item analyses, and not to the original pools. Generalizing the findings to the original pools thus involves an element of extrapolation, albeit that the differences between the sizes of the two kinds of pools were generally small. Also, the fact that, with a few exceptions, remarkably robust results were obtained for procedures that deliberately made the item pools easier or more difficult does lend some support to the claim that this generalization is unlikely to involve serious bias.

It is emphasized that robustness of qualifications is only one necessary criterion which judgments in evaluation projects must meet, and that judgments are not automatically meaningful if they are robust. However, as illustrated in this paper, if uncertainty exists as to the knowledge base on which the judgments have to based, then robustness analysis is an excellent means to assess how serious the consequences of this uncertainty are.

Appendix

Independence of Mean Observed Score of Covariation between Abilities

For ease of exposition, the case of two distinct abilities is addressed. Let θ_1 and θ_2 be these two abilities. The bivariate distribution of the two abilities is represented by probability density function $f(\theta_1,\theta_2)$, whereas the marginal distributions of θ_1 and θ_2 are denoted as $f_1(\theta_1)$ and $f_2(\theta_2)$. Let X_1 and X_2 be the observed scores on the item sets measuring θ_1 and θ_2 and T_1 en T_2 the classical true scores for these observed scores.

In PPON, the marginal distributions of θ_1 and θ_2 are scaled to have common marginal densities:

$$f_1(\theta_1)=f_2(\theta_2)=f(\theta).$$

This feature is used in the proof below. The first step in the derivation follows from classical test theory, whereas the other steps are straightforward. Indices i and j denote items measuring the first and second ability, respectively. The proof runs as follows:

$$
\begin{aligned}
E(X_1+X_2) &= E(T_1+T_2)\\
&= \int\int[\sum_i P_i(\theta_i)+\sum_j P_j(\theta_j)]f(\theta_1,\theta_2)d\theta_1 d\theta_2\\
&= \int\sum_i P_i(\theta_1)[\int f(\theta_1,\theta_2)d\theta_2]d\theta_1 + \int\sum_j P_j(\theta_2)[\int f(\theta_1,\theta_2)d\theta_1]d\theta_2\\
&= \int\sum_i P_i(\theta_1)f_1(\theta_1)d\theta_1 + \int\sum_j P_j(\theta_2)f_2(\theta_2)d\theta_2\\
&= \int[\sum_i P_i(\theta) + \sum_j P_j(\theta)]f(\theta)d\theta.
\end{aligned}
$$

Hence, when calculating the mean observed score, possible covariation between the underlying abilities can be ignored, and the item response function may be summed across abilities.

References

American College Testing (1993). AAPMOMT (computer program). Iowa City, Iowa.

Commissie Evaluatie Basisonderwijs (1994a). Inhoud en opbrengsten van het basisonderwijs (Deelrapport 1). De Meern: Inspectie van het Onderwijs.

Commissie Evaluatie Basisonderwijs (1994b). Onderwijs op maat (Deelrapport 2). De Meern: Inspectie van het Onderwijs.

Commissie Evaluatie Basisonderwijs (1994c). Onderwijs aan jonge kinderen (Deelrapport 3). De Meern: Inspectie van het Onderwijs.

Commissie Evaluatie Basisonderwijs (1994d). Onderwijs gericht op een multiculturele samenleving (Deelrapport 4). De Meern: Inspectie van het Onderwijs.

Commissie Evaluatie Basisonderwijs (1994e). Zicht op kwaliteit (Eindrapport). De Meern: Inspectie van het Onderwijs.

Janssens, F.J.G. (1995). De evaluatie van het basisonderwijs door de CEB: aanpak en werkwijze. Tijdschrift voor Onderwijsresearch, 20,

van der Linden (to apear). Standards for standard setting in large-scale assessments. In Proceedings of the Joint Conference on Large-Scale Assessments. Washington, DC: National Assessment Governing Board & National Center for Education Statistics.

Lord, F.M., & Novick, M.R. (1968) Statistical theories of mental test scores. Reading, MA: Addison-Wesley.

Lord, F.M. & Wingersky, M.S. (1984). Comparison of IRT true-score and equipercentile observed score "equatings". Applied Psychological Measurement, 8, 453-461.

van der Schoot, F. (1993). Verantwoording van de peiling verkeerssituatie einde basisonderwijs (PPON-report no.7). Arnhem: Instituut voor Toetsontwikkeling Cito.

Sijtstra, J. (1992). Balans van het taalonderwijs halverwege de basisschool. Arnhem: Instituut voor Toetsontwikkeling Cito.

Verhelst, N.D., Glas, C.A.W. & Verstralen (H.H.F.M.) (1994). OPLM: The One-Parameter Logistic Model (computerprogramma en manual). Arnhem: Instituut voor Toetsontwikkeling Cito

Vinjé, M. (1993). Balans van het Engels aan het einde van de basisschool. Arnhem: Instituut voor Toetsontwikkeling Cito.

Wijnstra (1988). Balans van het rekenonderwijs in het basisonderwijs. Arnhem: Instituut voor Toetsontwikkeling Cito.

Wijnstra, J. (1990). Verantwoording van de rekenpeiling medio en einde basisonderwijs 1987. Arnhem: Instituut voor Toetsontwikkeling Cito.

Zwarts, (M.). (1990). Balans van het taalonderwijs aan het einde van het basisonderwijs. Arnhem: Instituut voor Toetsontwikkeling Cito.

Table 1.

Aggregation of PPON scales in evaluation project

Subject	# Original Scales	# Aggregates
Dutch Language	13	7
Arithmetic	27	5
World Orientation	30	8
English	5	5
Traffic	2	1

Note. World Orientation is a combination of subjects. See Table 3.

Table 2.

Definition of qualifications used in evaluation

Qualification	Mean of Score Distribution
Satisfactory	> 70%
Moderate	55% - 70%
Unsatisfactory	< 55%

Note. For item pools judged to be too difficult a downward adjustment of 10% and 5% was made for the lower bounds of Satisfactory and Moderate, respectively.

Table 3

Percentages of items needed to change the qualifications for the four methods

Subject	Scaling	Easy	Difficult	Extreme
Arithmetic				
Basic Skills	91	14	27	100
Calculating	62	29	16	100
Fractions	45	17	9	100
Proportions/Percentages	100	100	14	100
Measurement	33	3	25	27
Dutch				
Reading Comprehension	37	3	100	100
Listening	94	32	100	91
Composition	71	21	100	100
Spelling	39	34	100	100
Grammar	79	54	100	100
Parsing	71	37	13	100
Language Reflection	100	32	100	100
World Orientation				
Biology	41	28	4	26
Physics	66	13	17	100
Regional Geography	88	26	12	100
Physical Geography	91	16	17	100
Topography	100	100	17	100
History	40	47	100	100
Spiritual & Religious Movements	78	30	100	39
Social Relations	97	20	100	100
English				
Reading	3	3	100	6
Listening	96	41	100	100
Speaking	97	27	14	100
Vocabulary	59	24	13	100
Use of Dictionary	100	75	100	55
Traffic				
Practical Skills	91	42	100	100

Authors' Note

Both authors are equally responsible for the contents of this paper; the order of their names is alphabetical. Michel A. Zwarts is at the Inspectorale of Education, De Meern, Netherlands. The empirical results in this paper were presented earlier at a Vereniging voor Onderwijsresearch, Divisie Methodologie en Evaluatie, symposium, Arnhem, March 23, 1994.

Figure Captions

Figure 1. Estimated observed-score distributions for: (a) Calculating; and (b) Proportions/Percentages.

Figure 2. Mean observed score as a function of the proportions of items removed due to scaling for Arithmetic.

Figure 3. Mean observed score as a function of the proportions of items removed due to scaling for Dutch.

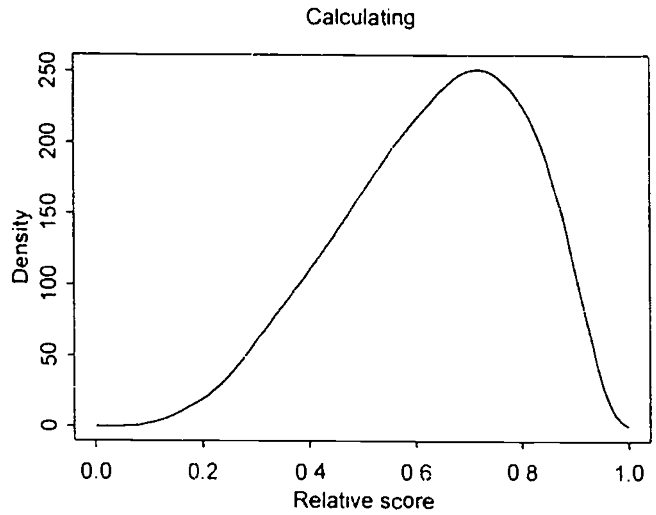
Figure 4. Mean observed score as a function of the proportions of items removed due to scaling for World Orientation.

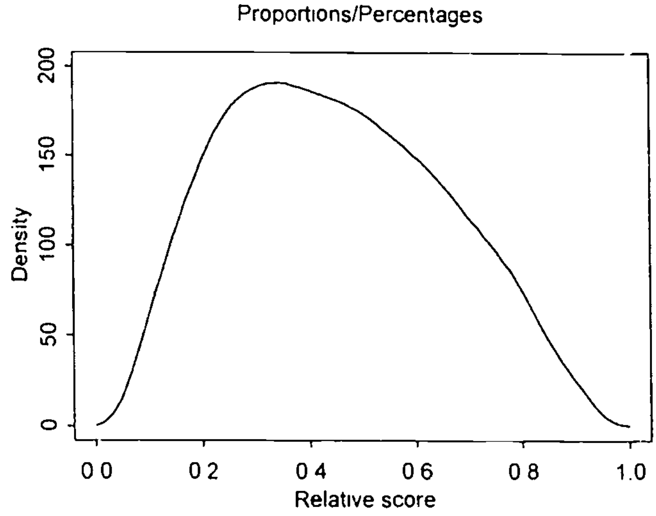
Figure 5. Mean observed score as a function of the proportions of items removed due to scaling for English.

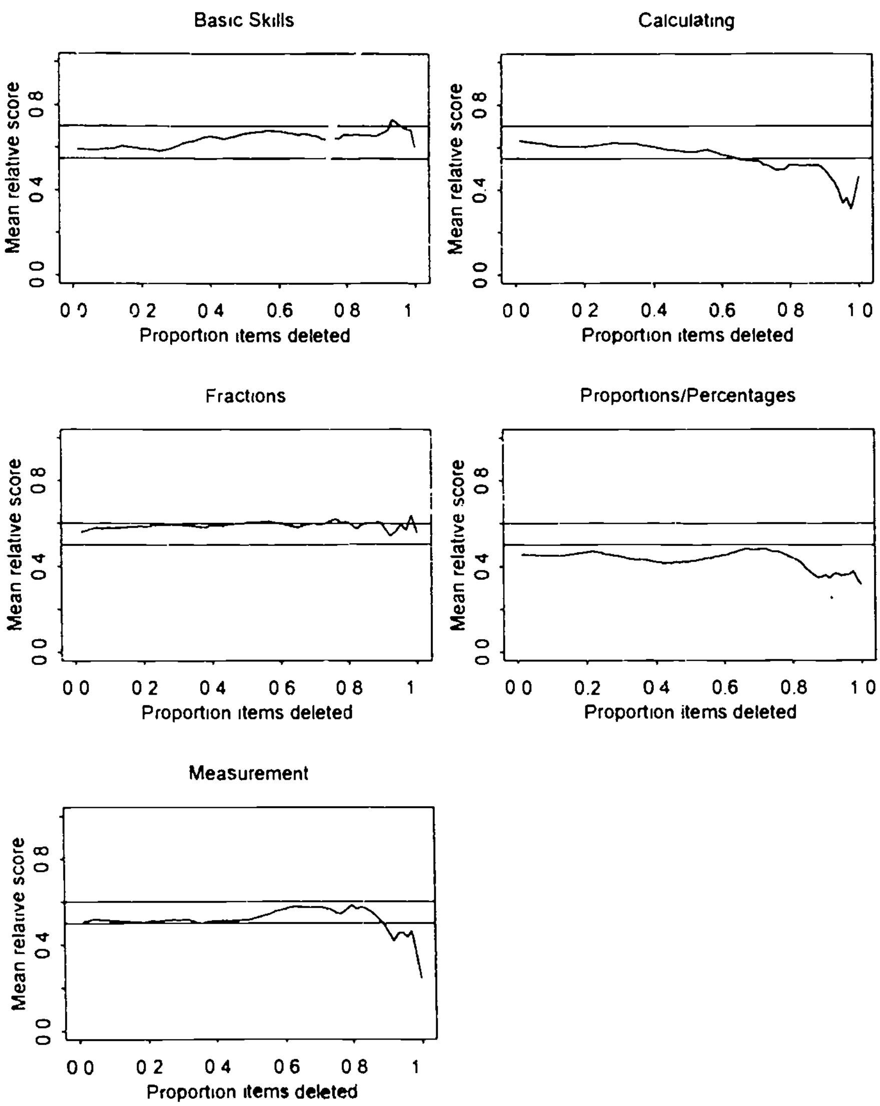
Figure 6. Mean observed score as a function of the proportions of items removed due to scaling for Traffic.

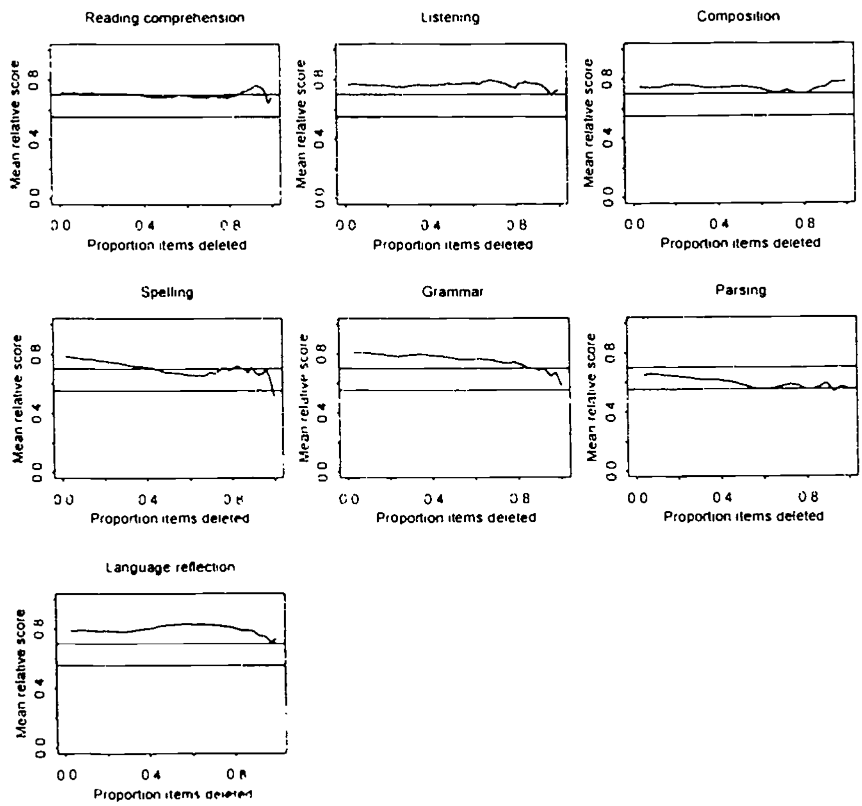
Figure 7. Estimated observed-score distributions for: (a) Calculating; and (b) Proportions/Percentages (different correlation between abilities).

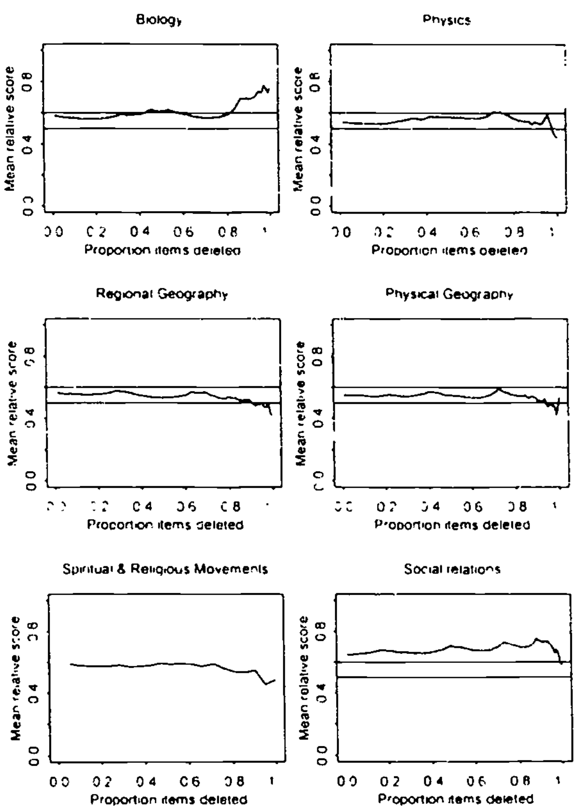
Figure 8. Observed-score distributions estimated by: (a) Taylor approximation to generalized binomial; and (b) exact distribution function.

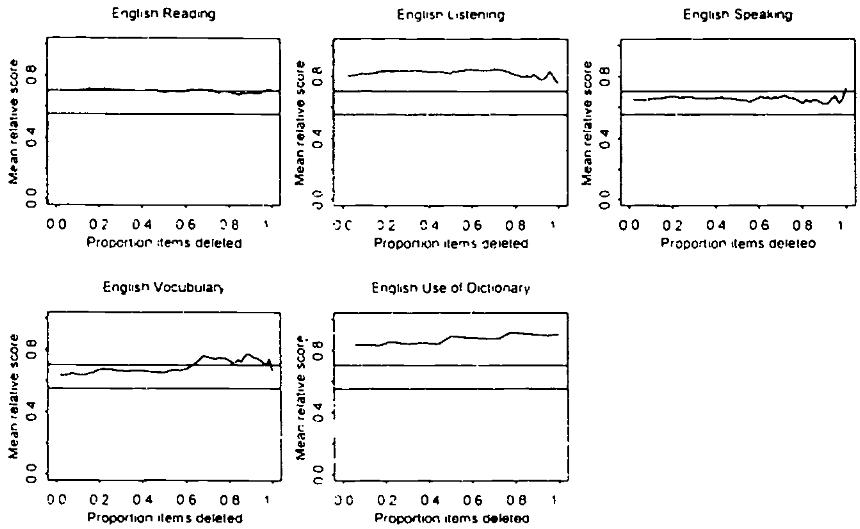

Calculating
Density
0
50
100
150
200
250
0.0
0.2
0 4
0 6
0 8
1.0
Relative score


Proportions/Percentages
Density
0
50
100
150
200
0 0
0 2
0 4
0 6
0 8
1.0
Relative score

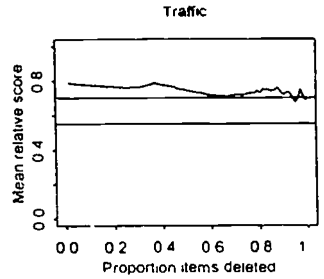

Basic Skills
Calculating
Fractions
Proportions/Percentages
Measurement
Mean relative score
0.0
0.4
0.8
0.0 0.2 0.4 0.6 0.8 1
0.0 0.2 0.4 0.6 0.8 1.0
Proportion items deleted


Reading comprehension
Listening
Composition
Spelling
Grammar
Parsing
Language reflection
Mean relative score
0.0
0.4
0.8
Proportion items deleted

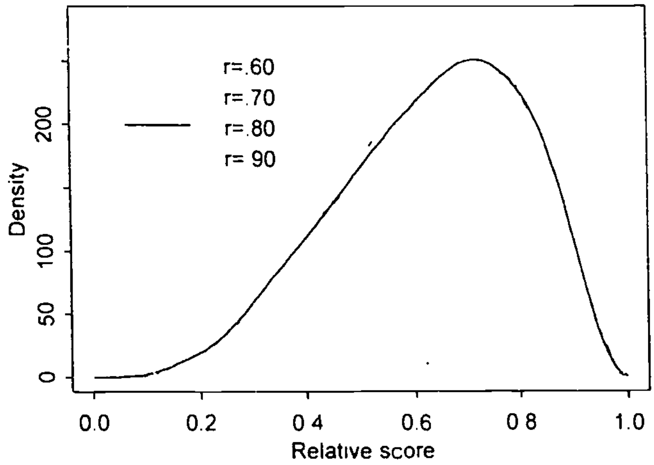

Biology
Physics
History
Regional Geography
Physical Geography
Topography
Spiritual & Religious Movements
Social relations
Mean relative score
0.0 0.4 0.8
0.0 0.2 0.4 0.6 0.8 1
Proportion items deleted



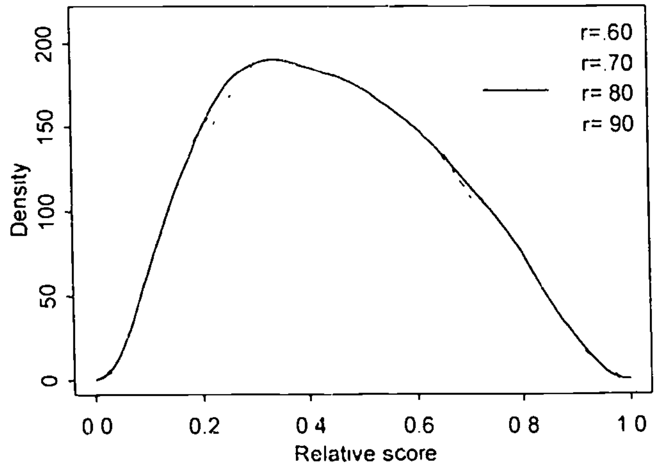
BEST COPY AVAILABLE


Traffic
Mean relative score
0 0
0 4
0 8
0 0
0 2
0 4
0 6
0 8
1
Proportion items deleted

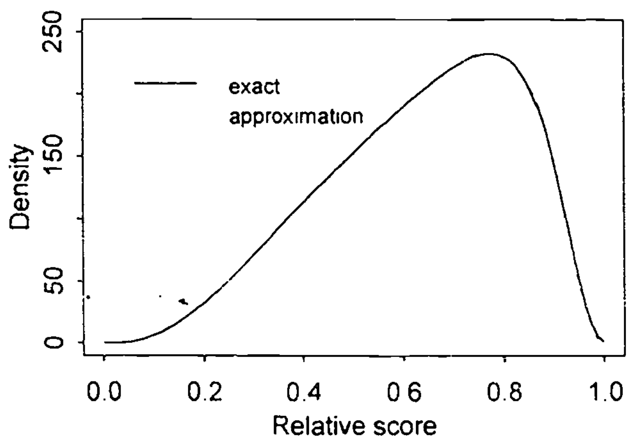
Calculating



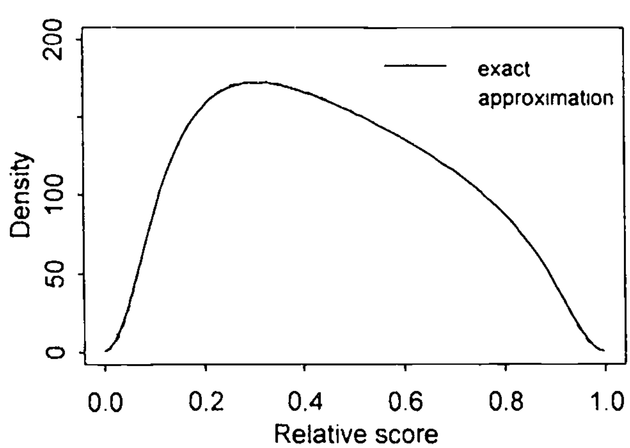
Proportions/Percentages



Calculating



Proportions/Percentages



Titles of recent Research Reports from the Department of Educational Measurement and Data Analysis. University of Twente, Enschede, The Netherlands.

RR-94-10 W.J. van der Linden & M.A. Zwarts, *Robustness of judgments in evaluation research*

RR-94-9 L.M.W. Akkermans, *Monte Carlo estimation of the conditional Rasch model*

RR-94-8 R.R. Meijer & K. Sijtsma, *Detection of aberrant item score patterns: A review of recent developments*

RR-94-7 W.J. van der Linden & R.M. Luecht, *An optimization model for test assembly to match observed-score distributions*

RR-94-6 W.J.J. Veerkamp & M.P.F. Berger, *Some new item selection criteria for adaptive testing*

RR-94-5 R.R. Meijer, K. Sijtsma & I.W. Molenaar, *Reliability estimation for single dichotomous items*

RR-94-4 M.P.F. Berger & W.J.J. Veerkamp, *A review of selection methods for optimal design*

RR-94-3 W.J. van der Linden, *A conceptual analysis of standard setting in large-scale assessments*

RR-94-2 W.J. van der Linden & H.J. Vos, *A compensatory approach to optimal selection with mastery scores*

RR-94-1 R.R. Meijer, *The influence of the presence of deviant item score patterns on the power of a person-fit statistic*

RR-93-1 P. Westers & H. Kelderman, *Generalizations of the Solution-Error Response-Error Model*

RR-91-1 H. Kelderman, *Computing Maximum Likelihood Estimates of Loglinear Models from Marginal Sums with Special Attention to Loglinear Item Response Theory*

RR-90-8 M.P.F. Berger & D.L. Knol, *On the Assessment of Dimensionality in Multidimensional Item Response Theory Models*

RR-90-7 E. Boekkooi-Timminga, *A Method for Designing IRT-based Item Banks*

RR-90-6 J.J. Adema, *The Construction of Weakly Parallel Tests by Mathematical Programming*

RR-90-5 J.J. Adema, *A Revised Simplex Method for Test Construction Problems*

RR-90-4 J.J. Adema, *Methods and Models for the Construction of Weakly Parallel Tests*

RR-90-2 H. Tobi, *Item Response Theory at subject- and group-level*

RR-90-1 P. Westers & H. Kelderman, *Differential item functioning in multiple choice items*

Research Reports can be obtained at costs from Bibliotheek, Faculty of Educational Science and Technology, University of Twente, P.O. Box 217, 7500 AE Enschede, The Netherlands.

faculty of
EDUCATIONAL SCIENCE
AND TECHNOLOGY

A publication by
The Faculty of Educational Science and Technology of the University of Twente
P.O. Box 217
7500 AE Enschede
The Netherlands