INTEGRATING COGNITIVE AND PSYCHOMETRIC MODELS TO MEASURE DOCUMENT LITERACY

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Abstract

The Survey of Young Adult Literacy conducted in 1985 by the National Assessment of Educational Progress included sixty-three items that elicited skills in acquiring and using information from written documents. These items were analyzed in two distinct ways: (1) with an item response theory (IRT) model, which characterized items' difficulties and respondents' proficiencies as revealed simply by tendencies toward correct responses; (2) a qualitative cognitive model, which characterized the processing tasks they required. This paper describes how a generalization of Fischer and Scheiblechner's linear Logistic Test Model can be used to integrate information from the cognitive analysis into the IRT analysis.

Subject Terms: Bayesian estimation; cognitive processing models; Item Response Theory; Linear Logistic Test Model; literacy assessment; National Assessment of Educational Progress
1.0 Introduction

Perhaps the most important thrust in educational measurement today is, in Burstein's (1983) words, "... linking achievement testing to the cognitive processes employed in giving test responses and to the instructional experiences of students." Standard item-response theory and classical true-score psychometric models, while often providing practically useful summaries of the overall proficiencies of examinees and of the relative difficulties of items, do not do this. Cognitive-processing models, on the other hand, are typically qualitative, descriptive, and poorly suited to the broadly cast decision-making problems often encountered in educational practice. A recent line of development, therefore, has been to study the characteristics of psychometric items as cognitive tasks, using psychometric theory to summarize test data for action but cognitive theory to construct and analyze the test (Embretson, 1985).

This paper describes the implementation of such an approach in the construction and analysis of the Document Literacy scale in the Survey of Adult Literacy (Kirsch and Jungeblut, 1986), a study carried out under the auspices of the National Assessment of Educational Progress. After a brief overview of the Adult Literacy project, we outline (i) a cognitive-processing model proposed for solving the exercises, (ii) a psychometric model for the test, and (iii) a structure relating item parameters in the psychometric model to item features that are salient in the cognitive model, based on Mislevy's (1988) extension of
Scheiblechner (1972) and Fischer's (1973) linear logistic test model (LLTM).

2.0 An Overview of the NAEP Literacy Assessment

In 1984, the U.S. Department of Education provided funding for a nationwide assessment of the literacy skills of America’s young adults, ages 21 through 25. The assessment was designed and carried out by the National Assessment of Educational Progress (NAEP) over the three year period from 1984 to 1986. A major innovation of the NAEP design was to call for a set of literacy tasks that simulate the diverse literacy demands of adult interactions in occupational, social, and educational settings. Implementation of this design led to a definition of literacy that encompassed three distinct skill areas:

- **Document literacy** -- the skills needed to locate and use information contained in non-prose formats such as forms, tables, charts, signs/labels, indexes, schematics, and catalogues;

- **Prose literacy** -- the skills needed to understand and use information from texts such as editorials, news stories, and poems;

and

- **Quantitative literacy** -- the skills needed to perform arithmetic operations that are embedded in printed materials such as checkbook registers, order forms, and loan advertisements.

NAEP developed a total of ninety-three literacy tasks, sixty-three of which were classified as measuring document literacy, fifteen as measuring prose literacy, and fifteen as
measuring quantitative literacy. Most involved open-ended responses. For example, respondents were directed to: fill in a deposit slip; determine eligibility from a table of employee benefits; fill out an order form taken from a catalogue; and follow a set of directions to travel from one location to another using a map.

Trained interviewers administered the literacy tasks to a nationally representative household sample of approximately 3,600 young adults living in the 48 contiguous United States, using an item sampling design under which each task was administered to approximately 1,500 respondents. The procedures and the results of the assessment are detailed in Kirsch & Jungeblut (1986). In this paper, we describe a secondary analysis that was conducted to investigate correlates of task difficulty. Due to the small numbers of tasks available for measuring prose literacy and quantitative literacy, our analysis is restricted to the sixty-three tasks which comprise the document literacy scale.

3.0 A Cognitive Model for Document Literacy

A cognitive processing model for performance on document literacy tasks has been proposed by Kirsch and Mosenthal (1988). The model posits a solution process that can be summarized in the following four steps: (1) Identify the information given and requested in the task directive; (2) search the document until the requested information has been located; (3) make a match between the information identified in the document and the information
As part of an earlier study of the factors influencing document task difficulty, Kirsch and Mosenthal developed a system to describe the complexity and organizational structure of documents and of the directives associated with document literacy tasks. This system, based on a significant revision of Mosenthal's (1985) taxonomic grammar of the expository continuum, characterizes the information contained in documents and document task directives according to three basic levels of organization: (1) the organizing category or OC, (2) the specific category or SPE, and (3) the semantic feature. These three levels of organization constitute three nested categories: semantic features are properties of pieces of information that belong to specific categories, which are nested within distinct organizing categories. Specific categories can also be nested within other specific categories. In fact, the more complex the document, the more likely it will be to find several levels of nesting of SPEs.

To illustrate these levels, consider the medicine label given in Figure 1. This document has three organizing categories: (1) the purpose for taking the medicine, (2) the recommended dosage levels, and (3) the list of cautions. Within the "Purpose" OC are two SPEs, one specifying that the medicine can be taken for "stuffed noses" and one specifying that it can also be taken for "running noses". The "Dosage" OC also contains two SPEs, one containing information specific to adult dosages and one...
containing information specific to children's dosages. The "Caution" OC, which is the most complex, contains four level-one SPE's and three level-two SPEs. These levels are illustrated in Figure 2, which provides a full linguistic representation, or parsing, of the medicine label. The reader should see Kirsch and Mosenthal (1988) for more information about this new grammar.

Based on this grammar, Kirsch and Mosenthal defined a number of variables, which, according to the processing model, would be expected to correlate with task difficulty. These variables have been classified into three distinct types: (1) Materials variables, which characterize the length and organizational complexity of the document to which a task refers; (2) Directive variables, which characterize the length and organizational complexity of the task directive; and (3) Process variables, which characterize the difficulty of the task solution process.

The Materials variables are

(1) the number of OCs in the document;
(2) the number of OCs in the document that are embedded;
(3) the deepest level of embedding for an OC;
(4) the number of SPEs in the document;
(5) the number of SPEs in the document that are embedded; and
(6) the deepest level of embedding for an SPE.

The Directive variables are

(1) the number of OCs in the directive;
(2) the number of OCs in the directive that are embedded;
(3) the deepest level of embedding for an OC;
(4) the number of SPEs in the Directive;
(5) the number of SPEs in the Directive that are embedded; and
(6) the deepest level of embedding for an SPE.

The process variables are defined as follows:

(1) Degree of Correspondence (DECCORR). This variable refers to the explicitness of the match between the information requested in the directive or question and the corresponding information in the text. It is scored on an integer scale ranging from one to five with higher values indicating less explicit correspondence and therefore, more difficulty. For example, tasks requiring a single literal match are scored one, tasks requiring an inferential text-based match are scored three, and tasks requiring matches based on specialized prior knowledge are scored five.

(2) Type of Information (TYPINFO). This variable concerns the type and number of restrictive conditions that must be held in mind in identifying and matching features. It too is scored on a one to five scale with lower values indicating less restrictive conditions.

(3) Plausibility of Distractors (DEGPLAUS). Document tasks typically require the examinee to skim an entire document in order to locate a piece of requested information. Since any piece of information embedded in the document could be interpreted as the requested information, the typical interpretation of the term "distractor", that is, the incorrect alternatives given with a
multiple-choice item, is not appropriate for document tasks. Instead, document task “distractors” include all pieces of information embedded in the document. The degree of plausibility of a distractor is measured by the extent to which the information embedded in the document shares semantic information with the correct answer to the question or directive, but does not satisfy all conditions specified. This variable is scored on a one to five scale with lower numbers indicating more shared semantic information and higher numbers indicating less.

The relationship between these three sets of variables and the four-step processing model can be stated as follows: The Directive variables characterize the difficulty of Step 1, identifying the information given and requested in the task directive; the Materials variables characterize the difficulty of Step 2, searching the document for requested information; and the Process variables characterize the difficulty of Steps 3 and 4, matching information and determining whether the criterion of the task has been satisfied.

Kirsch and Mosenthal (1988) succeeded in parsing sixty-one of the sixty-three document tasks, then scored the sixty-one in terms of the Materials, Directives, and Process variables using the scoring instructions in the appendices of their report. The results appear in Table 1; correlations among the variables appear in Table 2. (Because the level of OC and SPE embeddings for the document literacy task directives were almost entirely at the first level, not all of the directive embedding variables were
Task 46 is based on the Medicine Label. The reliability of the scoring was checked by training a third scorer and observing the proportion of exact agreement in rescores of one-third of the documents; the (very satisfactory) results are given in Table 3.

Kirsch and Mosenthal regressed task proportions-correct on these task features in the total survey sample and in selected subpopulations. An adjusted $R^2$ of .87 resulted, with the strongest predictors being numbers and embedding of OCs, and the plausibility of distractors. This result provided empirical confirmation that the task attributes identified by the processing model did indeed largely account for task difficulty. The analysis addresses only average difficulty within populations, however, and provides no link between individuals' overall performance on the set of tasks and their expected success with documents and tasks with varying structures—the type of information required to target instruction to individual students and to design documents for specified types of users.

4.0 A Psychometric Model for Measuring Task Difficulty

In contrast, the expected outcomes of the confrontations between particular examinees and tasks are addressed by the response scaling methodology called item response theory (IRT; Lord, 1980). Unidimensional IRT models express the probability that an examinee will respond correctly to a particular test item
as a function of a single parameter that characterizes the proficiency of the examinee, and one or more additional parameters for each item that characterize measurement properties such as its difficulty. An important feature of IRT scaling is that the proficiency levels of all respondents can be reported on the same scale even when different individuals have been administered different subsets of tasks, as in the NAEP literacy assessment.

In this paper, we use the Rasch IRT model (Rasch, 1960) to exemplify the process of measuring task difficulty with a psychometric model. Let $x_{ij}$ denote the response of examinee $i$ to task $j$. Assume that responses are dichotomously scored, with 1 indicating a correct response and 0 indicating an incorrect response. The standard Rasch model gives the probability of a correct response as

$$P_j(\theta_i) = P(x_{ij} = 1|\theta_i, \beta_j)$$

$$= \frac{\exp(\theta_i - \beta_j)}{1 + \exp(-\beta_j)}$$

(1)

where $\beta_j$ characterizes the difficulty of task $j$ and $\theta_i$ characterizes the proficiency of examinee $i$. Under the usual assumption of conditional independence, the probability of a respondent's pattern $x_i = (x_{i1}, \ldots, x_{in})'$ of responses to $n$ tasks is obtained as

$$P(x_i|\theta_i, \beta) = \prod_j P_j(\theta_i) x_{ij} Q_j(\theta_i) (1 - x_{ij})$$

(2)
where $Q_i(\theta) = 1 - P_i(\theta)$ and $\beta = (\beta_1, ..., \beta_p)'$. The probability of a data matrix $X = (x_1, ..., x_N)'$ of responses from $N$ examinees responding independently can be obtained as

$$P(X|\theta, \beta) = \prod_i P(x_i|\theta_i, \beta).$$

(3)

where $\theta = (\theta_1, ..., \theta_N)'$. Once $X$ has been observed, Equation 3 can be interpreted as a likelihood function, and provides a basis for estimating the parameters $\theta$ and $\beta$.

Table 4 gives Rasch item parameter estimates obtained with Mislevy and Bock's (1984) BILOG computer program for the sixty-one literacy tasks that were parsed, on a scale in which the distribution of $\theta$ has a mean of zero and a standard deviation of one. Shown with estimates of the difficulty parameters are their (approximated) standard errors of estimation, or $\sigma$. Item 46 is the Medicine Label item, which with a difficulty parameter estimate of -2 is one of the easier items. A value of $\theta$ could be estimated for any respondent, and, via (i), the expectation of a correct response from that respondent to this item or any other could be calculated.

Table 4 about here

IRT models such as the Rasch model are widely accepted as useful tools for creating and analysing tests, adding precision and flexibility to the ways that examinees' proficiencies can be measured and compared. Note, however, that these models make no reference to the cognitive processes which an examinee must employ.
in order to have a high probability of making a correct response; nor do they address the features of tasks that make them difficult. The model parameters merely indicate the relative proficiencies of respondents ($\theta$) and the relative difficulties of tasks ($\beta$) in the skill area considered.

5.0 An Integrated Approach

In a pioneering step toward integrating cognitive and psychometric models, Scheiblechner (1972) and Fischer (1973) posited a constrained Rasch model for item responses, the Linear Logistic Test Model (LLTM). In this model, task difficulty parameters are estimated as linear combinations of a smaller number of more elementary components. The elementary components are defined to reflect differences in the cognitive processing demands of the tasks. This approach represents a significant advance beyond standard IRT procedures, because it exploits auxiliary information about the cognitive processing demands of tasks to address why some tasks are more difficult than others.

To apply the LLTM to a set of test data, the usual response matrix $X$ must be augmented with information pertaining to the processing demands of each test item. This information is expressed in terms of a set of $K$ variables characterizing features of the items which are salient in the cognitive processing model. Examples include (i) Fischer's (1973) calculus example, in which items are characterized in terms of the number and type of operations a pupil must carry out in order to solve a differentiation problem, and (ii) the document literacy variables.
which were defined in the previous section. Let $q_1, \ldots, q_K$ denote the item feature variables defined for the $j$th item. The LLTM assumes a Rasch model for task difficulty, but constrains the difficulty parameters $\beta_j$ as follows:

$$
\beta_j = \sum_{k=1}^{K} q_{kj} \eta_k \quad \text{for } j = 1, \ldots, n,
$$

or, in matrix notation $\beta = Q' \eta$, where $Q'$ is an $n \times K$ matrix of item feature data and $\eta = (\eta_1, \ldots, \eta_K)'$.

The original goal of explaining all of the reliable variation in item parameters by item features was not realized (Fischer and Formann, 1982), as rigorous tests of the sufficiency of the LLTM against the unconstrained model failed with few exceptions. It was often possible, however, to account for large portions of variation among item difficulties in terms of substantively meaningful item features, thus providing insights into the effects of educational treatments and helping to identify flawed items as unexpectedly easy or hard in light of the features that were expected to determine their operating characteristics.

A less restrictive method for incorporating cognitive processing information into a psychometric model has been proposed by Mislevy (1988). This alternative approach combines key aspects of the LLTM with the exchangeability concept of Bayesian inference (Lindley & Novick, 1981). As in the LLTM, differences in the cognitive processing demands of tasks are accounted for by regressing task difficulty on a smaller set of more elementary
components. Unlike the LLTM, however, parameter estimates obtained from the fitted regression model are not expected to account for all of the variation in true task difficulties. Instead, the expectation that true task difficulties will be distributed about the central values predicted by the fitted regression model is accounted for by (i) positing that the difficulty parameters of tasks with similar values of the item feature variables are exchangeable members of a common population; and (ii) imposing this task-population structure on the task difficulties, by means of Bayesian prior distributions.

In Mislevy's (1988) implementation of the approach, the prior distribution for individual task difficulties was assumed to be multivariate normal with mean $Q'n$ and variance $\phi^2 I$, where the mean structure is defined as in the LLTM. This model was fitted as a two-stage empirical Bayes (EB) regression model: unconstrained difficulty parameters for individual tasks (as in Table 4), estimated in the first stage, provide data from which to estimate the unknown parameters $\eta$ and $\phi^2$ of the assumed item-parameter distribution in the second stage. Computational details are provided in that reference. Final task difficulty estimates $\hat{\beta}_j$ are precision-weighted combinations of the unrestricted Rasch estimates $\hat{\beta}_j$ and the regression estimates $q_j' \eta$:

$$\hat{\beta}_j = (w_1 q_j' \eta + w_2 \hat{\beta}_j)/(w_1 + w_2)$$
where $w_{1j} = 1/\hat{\beta}_j^2$ and $w_{2j} = 1/\hat{\theta}_j^2$. The final task difficulty estimates can be viewed as a compromise between LLTM estimates, where items with identical features are constrained to have identical difficulty estimates, and standard Rasch difficulty estimates, where information about item features is ignored.

Like the LLTM, this approach provides a link between the cognitive processing model assumed to be influencing task responses and the tasks' resulting difficulties. To the extent that the structural model for item parameters fits, it provides a basis for understanding just what makes items difficult. It is a powerful argument for the construct validity of a test if it can be shown that item difficulties are determined predominantly by manipulable features in a cognitive model built around the skills intended to be measured (Embretson, 1985). To the extent that the model does not fit, it identifies unexpectedly hard or easy items, information that should prove useful for item construction.

6.0 Application to the Document Literacy Scale

As described above, both the cognitive processing analysis and the psychometric analysis were first applied to the Document Literacy data separately. The variables in Table 1, resulting from parsing the tasks, signify salient features of the items as indicated by the cognitive processing model, and provide insights into their processing requirements. The unrestricted Rasch difficulty estimates ($\hat{\beta}$) in Table 4 indicate the difficulty of tasks from a purely empirical point of view. We now apply the integrated model described in the preceding section.
In considering variables to include in the augmented data matrix, Kirsch and Mosenthal's (1988) results were used to eliminate three of the parsing variables: (i) the deepest level of OC embedding in the Materials, (ii) the deepest level of SPE embedding in the Materials, and (iii) the deepest level of OC embedding in the Directives. Univariate distributions were tabulated for the nine remaining item feature variables, and transformations were applied to eliminate extreme asymmetries: a square root transformation for the "Number of OC's" variable, a logarithmic transformation for "Number of SPE's", and logit transformations for "Number of Embedded OC's" and "Number of Embedded SPE's" after expressing them as proportions of total OC's and SPE's respectively. In addition, both the Materials variables and the Directive variables were centered and scaled to have a mean of zero and variance 1. Because the Process variables represent ordered categories, rather than counts, these variables were centered by recoding the original values of 1 to 5 as -1 to 3. These rescaled variables were used in all subsequent analyses.

The parameter estimates obtained from fitting a two-stage Empirical Bayes regression model to these data are given in Table 5. They include the estimated coefficients for the intercept term and the nine item feature variables (\(\eta_0, \eta_1, \ldots, \eta_9\)), and the estimated standard deviation \(\hat{\sigma}\) for the normal distribution of residuals of the task difficulty parameters from their expected values. Because the model was estimated from standardized data.
the magnitude of the coefficients provide an indication of the relative contribution of each variable to expected difficulty.

To further investigate the contribution of each item feature variable to variation in predicted task difficulty, three alternative models were estimated: (1) a model that excluded the Materials variables; (2) a model that excluded the Directive variables; and (3) a model that excluded the Process variables. The estimated coefficients for these three alternative models are also shown in Table 5. Note the similarity of the coefficients listed for the Materials variables in the Full model and in the model which excluded the Directive variables (Model 2), and the similarity of the coefficients listed for the Directive variables in the Full model and in the model which excluded the Materials variables (Model 1). These similarities are a result of the low correlation between the Materials variables and the Directive variables. By contrast, the coefficients of both the Materials variables and the Directive variables changed from the Full model to the model which excluded the Process variables (Model 3). These changes are a result of the higher correlations between the Process variables and the Materials variables and between the Process variables and the Directive variables. Because Model 3 is not contaminated by Process variable correlation, its coefficients provide the most accurate picture of the relative contributions to predicted task difficulty provided by the
Materials variables and the Directive variables. In particular, when the process variables are excluded, task difficulty increases most rapidly with the No. of SPEs in the Materials and the No. of SPEs in the Directive. Increasing the No. of OC's in the Directive and in the Materials also increases task difficulty, but not by as much. By far, the smallest contribution to task difficulty is provided by the OC and SPE embedding variables.

Table 5 also lists approximate $R^2$ values for each model. In the standard regression setting, the $R^2$ statistic is calculated as the ratio of explained variation to total variation. In this application, true task difficulties are unobservable so total variation is approximated using the variation observed in the EB estimates $\hat{\beta}$. Several conclusions can be drawn from the $R^2$ values. First, differences in the cognitive processing demands of document literacy tasks, as measured by the cognitive processing variables proposed by Kirsch and Mosenthal, account for approximately 80% of the observed variation in task difficulty. Second, the largest contribution to explained variation is provided by the Process variables. When these variables were excluded from the model, the $R^2$ statistic dropped by more than 20 points. This indicates that the Process variables are tapping an aspect of task difficulty that is not well predicted by either the Materials variables or the Directive variables. Third, the five point decreases in the $R^2$ values listed for Alternative Models m1 and m2 indicate that both the Materials variables and the Directive variables are also measuring unique aspects of task difficulty. Thus, although the
Process variables appear to be the most important, neither the Materials variables nor the Directive variables, can be excluded without diminishing predictive capability.

Figure 3 plots the residuals obtained from fitting the full model against percent correct. Negative residuals indicate that the task was easier than predicted, that is, easier than other tasks with similar values of the item feature variables. The plot shows a scatter of low positive and negative residuals among tasks with percent correct values below 90 percent. This suggests that the item feature variables have been successful at predicting task difficulty among tasks with low percent correct values. However, several high negative residuals occur among the tasks with percent correct values above 90 percent. This suggests that the item feature variables have not provided useful information pertaining to gradations of difficulty among extremely easy tasks.\footnote{This explains why the $R^2$ is slightly lower in this analysis than in Kirsch and Mosenthal's regression analysis of percents-correct: task features account poorly for differences among easy items, which are minimized in the percent-correct metric but expanded in the Rasch difficulty (logit) metric.}

7.0 Discussion

The two-stage Empirical Bayes regression model provides a link between Kirsch and Mosenthal's cognitive model for solving document literacy tasks and the psychometric IRT model for task difficulty. The integrated approach led to the following findings: (i) document literacy task difficulty was highly related...
to the Process variables and somewhat less related to the
Materials variables and the Directive variables; and (ii) the
cognitive model for explaining task difficulty was deficient at
explaining gradations of difficulty among extremely easy tasks
Of course these results are based on only the present data, which
effectively fit a regression model with nine independent variables
to sixty-one observations. Extensions of the literacy survey
currently in progress, however, should yield response data on as
many as a hundred new document literacy tasks written to similar
specifications. If these subsequent assessments reveal similar
findings, an examination of tasks with high negative residuals
will be conducted in order to determine factors associated with
extremely easy document literacy tasks. Knowledge of such factors
should prove useful for document design and construction

It is increasingly becoming recognized that merely high
reliability coefficients do not guarantee a "good" test, nor do
high predictive relationships guarantee a "valid" one. The onus
has been placed (appropriately!) upon the tester to demonstrate
that the skills tapped in an educational test are in fact those
deemed important to measure. The two-stage approach exemplified
in this paper capitalizes upon advances in the psychometric and
cognitive disciplines to address this need. IRT models, which
provide measures of overall proficiency for making decisions about
individual examinees, also define implicitly the variable being
measured through implications of correct response at the various
levels of proficiency. A demonstration that this empirical
characterization of proficiency can be largely accounted for by the key features of items from the perspective of a cognitive model argues strongly for the construct validity of the measure. constitutes a theoretical foundation for further item development. and provides an additional means of detecting items that tap irrelevant skills.
References


Table 1
Cognitive Processing Variables
for 61 Document Literacy Tasks

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Table 2

Intercorrelations among Item Features

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<tr>
<td>(11) Type of</td>
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<tr>
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<td><strong>Information</strong></td>
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<tr>
<td><strong>Distractors</strong></td>
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26
### Table 3
Proportions of Exact Agreement Among Raters

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<td>100 %</td>
</tr>
<tr>
<td>Number of Embedded OCs</td>
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<tr>
<td>Level of OC Embedding</td>
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</tr>
<tr>
<td>Number of SPEs</td>
<td>96 %</td>
</tr>
<tr>
<td>Number of Embedded SPEs</td>
<td>93 %</td>
</tr>
<tr>
<td>Level of SPE Embedding</td>
<td>88 %</td>
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<tr>
<td><strong>Directive Variables</strong></td>
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<td>Number of OCs</td>
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<tr>
<td>Number of SPEs</td>
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<tr>
<td><strong>Process Variables</strong></td>
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<tr>
<td>Degrees of Correspondence</td>
<td>95 %</td>
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<tr>
<td>Type of Information</td>
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<td>Plausibility of Distractors</td>
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Table 4

Results of Fitting an Unrestricted Rasch Model

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<td>0.060</td>
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<td>0.053</td>
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Note: Rasch difficulty estimates are not strictly monotonically related to proportions correct in this analysis because of the matrix-sampling data collection design; the percents-correct reflect performance in different randomly equivalent samples of respondents.
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*e-variable was intentionally excluded from the model*
For Stuffed and Running Noses:

Dosage:
Adults - 2 teaspoons every 4 hours;
Children over 6 years - 1 teaspoon every 4 hours.

Caution:
Unless directed by physician, do not exceed recommended dosage. If drowsiness occurs, do not drive or operate dangerous machinery. Individuals with high blood pressure, heart disease, diabetes, or thyroid disease should use only as directed by a physician.

Figure 1. The Medicine Label document.
*I\OC purpose
*\SPE For Stuffed Noses
*\SPE For Running Noses
*\OC Dosage
*\SPE *take
*\AG Adults
*\OBJ teaspoons
*\ATT 2
*\TEMP hours
*\ATT 4
*\ATT every
*\ATT over six
*\ATT teaspoon
*\ATT 1
*\ATT every
*\ATT do exceed
*\AG you
*\OBJ dosage
*\ATT recommended
*\NEG not
unless \COND \SPE directed
*\AG by physician
*\OBJ you
*\SPE do drive
*\SPE do operate
*\AG you
*\OBJ machinery
*\ATT dangerous
*\NEG not
If \COND \SPE occurs
\AG drowsiness
*\AG should use
\AG individuals with
*\OR \ATT blood pressure
\ATT high
*\OR \ATT heart disease
*\ATT high
*\OR \ATT diabetes
*\ATT high
*\OR \ATT thyroid disease
*\ATT high
as \COND \SPE directed
*\MAN only
*\AG by physician

Figure 2. A parsing of the Medicine Label document.
Figure 3. The full model residuals plotted against percent correct for 61 document literacy tasks.
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