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ABSTRACT

The latent structure of the reading test of the International Association for the Evaluation of Educational Achievement (IEA) Reading Literacy study was investigated. The use of latent class modeling for investigating the measurement properties of a large-scale reading assessment database is demonstrated. The study focused on response data from the United States, Canada, Hong Kong, and Denmark, for a total sample of 15,304 nine-year-olds. One of the main research questions was whether the type of text (narrative, expository, and documents) elicits different types of reading comprehension. Findings indicate that there is no empirical evidence of three separate text types for any of the four countries, but there is empirical evidence of two separate reading domains. One latent variable represents a general reading domain associated with all three text types, and the other represents a prose reading domain associated only with expository and narrative text types. The latent class modeling approach provides a way to examine the latent structure of the IEA reading test that avoids many problems that may occur when applying factor-analytic methodology. (Contains 3 figures, 12 tables, and 30 references.) (SLD)

Domain Structure of Reading Literacy: Latent Class Modeling of IEA Data

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Purpose

The purpose of this study was to investigate the latent structure of the reading test of the IEA Reading Literacy Study (Elley, 1992) and to demonstrate the use of latent class modeling for investigating the measurement properties of a large scale reading assessment database. The psychometric properties of reading are a hotly debated issue within the reading research community. Should reading comprehension be conceptualized as a unitary or a domain specific ability? This study demonstrates a new psychometric approach to establishing the domain structure of the IEA reading test using Latent Class Analysis (LCA). The study consists of two phases. In Phase I, the main research question addressed was whether three distinctive domains of reading text types can be identified and whether they can be distinguished from each other. In Phase II, the homogeneity of the latent structure identified in Phase I was examined across countries.

Theoretical framework

The International Association for the Evaluation of Educational Achievement (IEA) Reading Literacy study is summarized in Elley (1992). About 30 countries participated in the study in which reading achievement data were collected. The data collection was performed in 1990-1991 from representative samples of two age groups: nine-year-old and 14-year-old. The present analyses focused on test results from the nine-year-old cohort in four selected countries: Canada, Denmark, Hong Kong, and United States. One basis of test construction stemming from the reading research literature was that reading comprehension should be diversified enough to include three text types: Narrative, Expository, and Documents (Elley, 1992). Thus, the tests used were a composition of different material each representing one of these three domains. Reading comprehension is postulated, to certain degree, to be dependent on the reading domain. Such a division of reading domains, however, is regarded as more pragmatic than conceptual (Weaver & Kintsch, 1991) and sometimes has provoked controversy. Some researchers find that it is impossible to draw absolute boundaries between narrative and expository texts due to similarities of the cognitive processing involved in performing each tasks (Spiro & Taylor 1980); others argued that document search and prose reading involved relatively distinctive cognitive processes (Guthrie & Kirsh, 1987).

A Rasch scaling (Rasch, 1960) performed separately for each domain provided some justification that items from each of the three domains reflects a single construct (Elley,1992). It is an empirical question whether such an assumption is indeed valid. A few studies have suggested that there is no evidence for three separate reading comprehension factors (Balke, 1995; Atash 1996).

Distinction Among Three Text Types

An important implication for reading assessment as a result of the separation of text type is that it becomes very difficult to compare a student's performance across domains. Literature suggests that many children have difficulty understanding expository materials after spending most of their study time with narratives (Spiro & Taylor, 1980) (Berkowitz & Taylor, 1981). Some researchers suggest that students perceive expository materials to be more difficult than narratives (Alvermann & Boothby, 1982). Others found that students are less able to recall expository text (Zabrucky & Ratner, 1992). It had been suggested that the text-specific hierarchical structure of expository text is difficult for students to discern and retain. Another often cited reason is that the vocabulary or content of expository material is unfamiliar to the children. However, there is very little empirical evidence to support this claim. Spiro et al. [1980] conclude that most studies comparing the text difficulty result in ambiguous interpretations.

Researchers in adult literacy have argued that the cognitive processes involved in locating information in text do not appear to be identical to those involved in reading comprehension (Guthrie & Kirsch, 1987; Guthrie & Mosenthal, 1987). They contented that since reading comprehension had been generally defined as recalling of text, a separate operational definition is needed for tasks such as searching information in documents or locating a particular number in the tables. Since the processing requirement for these two types of tasks is different, competencies of reading comprehension and locating information would be relatively independent. It was concluded that reading tasks that required understanding and remembering lengthy sections of text were independent, statistically, from tasks that required locating specific details in manuals, schematics, and periodicals (Guthrie & Kirsch, 1987).

Hierarchical Models for Reading Comprehension

Carroll (1993) identified some primary factors in the language domain and many of the primary factors are associated with the reading tests. In a re-analysis of 148 datasets, a Verbal or Printed Language Comprehension factor measured by vocabulary, information and reading comprehension tests was identified. Carroll concluded that there is evidence for a unitary language ability, even though some specific subskills were identified in different area of verbal domain. It was also demonstrated that the primary factors in the verbal domain are dominated by the second-order 'G' factor, so there is some evidence that general verbal ability is a central component of crystallized intelligence. Carroll also found evidence for special reading comprehension factors separate from other factors in the verbal domain in a re-analysis of 10 datasets. However, he cautioned that factor loaded with reading comprehension tests often have high loadings on various kinds of reasoning tests. Therefore, the common element in this factor is probably not reading comprehension per se, but reasoning ability.

Balke (1995) investigated the domain structure of the IEA reading literacy test for five Nordic countries on both the 9-and 11-year old populations. The main research question was whether three different reading factors (narrative, expository, and document) could be identified from the data. The analysis suggested that three text type factors could not be differentiated because items from expository and narrative texts form one factor that is clearly distinct from the document items. Several attempts to separate narrative and expository text types had proven to be impossible. The model was not identified once such restrictions were imposed on the model. The final analysis shows that there are two structural equation models that best explain the variations in the data. One model (Model 1) contains a general ability factor, the passage factor, and expository-narrative text type factor; the other model (Model 2) contains a general ability factor, the passage factor, and document text type factor. It was concluded that both models were equally representative of the data because the differences in fit statistics are ignorable. However, Model 2 is chosen as the preferred model because it shows more consistencies across countries.

There are some drawbacks in the analytical approaches presented in Balke's study. First, the product moment correlations instead of the tetrachoric correlations were used. Analysis based on the product moment correlations of dichotomous variables may distort the correlations and hence to the factor-analytic results derived from them (Comrey, 1978). Furthermore, neither of the models provided acceptable fit to the data according to the chi-square statistics. Therefore, there is a lack of statistical and empirical justifications for choosing either model as the preferred model.

Past researches in examining the internal structure of reading tests rely on factor-analytic models (Carroll, 1993; Balke, 1993; Atash, 1996). Most of these work are predicated on the assumption that the data followed multivariate normality: an assumption that is left unchecked and often invalid. In contrast, latent class models do not impose distributional assumption on the data.

Method

The basic premise of latent class analysis (LCA) is that the observed dependency among manifest variable is due to each variable's relationship to the latent variables (Lazarsfeld & Henry, 1968; McCutchen, 1987). If a given latent class model holds, then one can say that the relationship among the manifest variables is explained by the latent variables (Aitken, Anderson, & Hinde, 1981; Goodman, 1974). The basic approach of LCA is to identify a set of mutually exclusive latent classes based on the observed item responses. In this study, a series of latent class models corresponding to different structural relationship among the domains were formulated and tested starting at the passage level and then proceeds by aggregating variables across passages. This strategy makes it possible to identify general and specific components of reading domains.

Data

The current study focused on response data from four countries: U.S.A., Canada, Hong Kong, and Denmark. The selection of these countries provides a broad range of variations in terms of the distributions of test scores across reading domains. The sample size is 2,565 for Canada, 3,327 for Denmark, 3,186 for Hong Kong, and 6,390 for the United States, resulting a total sample size of 15,304. The analyses in this study were conducted using LCAG, version 2.10a (Hagenaars & Luijkx, 1987) and Lem, version 0.11 (Vermunt, 1993).

Fifteen reading passages were administered to the nine-year-old population in the IEA study. Each passage was followed by three to six questions. The items were given in multiple-choice format except for the four items in the passage "Buses,", where the examinees had to write the answers consisting of a number or a name. Due to the large number of non-response or non-reached items for some countries, response data for some passages are not reliable. Nine passages were selected in this study: three document passages ("Buses", "Maria", and "Temperature"), three expository passages ("Marmot", "Quick Sand", and "Walrus"), and three narrative passages ("Bird", "No Dog", and "Shark"), with a total of 41 items.

Since an efficient estimation method for a large number of items for restricted Latent Class Models (LCM) is not yet available, passage scores created at an earlier study (Yen, 1997) were used to assess the domain structure. The latent structure for each passage within each country was first identified, the parameter estimates were inspected to identify a dominating mastery class in the population. Examinees belonging to the mastery class were assigned a passage score of '1' and those belonging to other classes were assigned a passage score of '0'. Across nine passages, there are $(2^9)=512$ response vectors consisting of the classification decisions for each respondents.

Phase I: Domain Structure Within Each Country

The first research question examined was the domain structure across the nine passages within each country. The basic modeling framework is the domain structure analysis based on log-linear path model with latent variables proposed by Goodman (1974), Hagenaars, (1990) and Vermunt (1993). The log-linear path model may be conceptualized as consisting of two parts: a measurement part and a structural part. The structural part of a log-linear path model specifies the relationship between the latent variables. The measurement part of the model specifies the relationship between the latent construct and their indicators. Latent class models can be considered as the measurement part of a log-linear path model where the relationship between the latent construct and their indicators is specified.

A basic latent class model may be represented in terms of Lazarsfelds's original parameterization (Goodman, 1973) or in terms of log-linear modeling (Haberman, 1979). Starting with the former and following Goodman's notation, the basic equation of a latent class model with three manifest variables *A* through *C* with indices *a*, *b* , and *c* and one latent variable *X* with index *x* may be stated as follows:

$$m_{xabc} = N\pi_x \pi_{a|x} \pi_{b|x} \pi_{c|x} \qquad (1)$$

Where *m* denotes the expected frequency, *N* denotes the total sample size. Latent class proportion is denoted as π_X and the conditional probability of being in level *a* of latent class *x* is denoted as $\pi_{a|x}$. All parameters in equation (5) are probabilities and subject to the standard restrictions. Secondly, the same latent class model can be expressed in terms of a log-linear model:

$$\log m_{xabc} = \eta_x^X + \lambda_a^A + \lambda_b^B + \lambda_c^C + \lambda_{xa}^{XA} + \lambda_{xb}^{XB} + \lambda_{xc}^{XC} \qquad (2)$$

In Equation (2), m_{xabc} denotes the expected frequencies of marginal table XABC, η_x^X refers to the fixed margin and the λ's are ordinary log-linear parameters. All parameters in equation (2) are subject to the standard restrictions of log-linear models. From the log-linear path model perspective, Equation (2) specifies a logit model with *A*, *B*, and *C* as independent variables and *X* as dependent variable.

It can be verified that both parameterizations of the latent class model implement the assumption of local independence. Haberman (1979) also demonstrated that the relation between the conditional probabilities of equation (1) and the λ parameters of equation (2) is

$$\pi_{a|x} = \frac{\exp(\lambda_a^A + \lambda_{xa}^{XA})}{\sum_a \exp(\lambda_a^A + \lambda_{xa}^{XA})} \tag{3}$$

Conversely, it can be verified that the log-linear parameters in equation (3) can be expressed in terms of the conditional probabilities in equation (2) with some algebraic manipulations. For the rest of this paper, the measurement part of each model was presented using Goodman's parameterization in order to demonstrate the constraints imposed on the model. The structural part of the model in this paper was specified as a long-linear model in order to demonstrate the structural relationship among the latent variables.

Latent Class Models in investigating Domain Structure

To investigate the latent structure of three reading domains, seven types of latent class models were tested for adequate absolute fit and relative fit to the data :

Unconstrained one latent-variable model (Model 1): This model is equivalent to a latent class model that assumes one latent variable with three levels or latent classes. The measurement part of the model can be obtained by expanding the number of manifest variable to nine in Equation (1) and let x=3.

Three-independent domain Model (Model 2): This model assumes that the relationship among the manifest variables can be explained by introducing three latent variables, each representing a text domain. Each latent variable has three classes. It further specifies that the latent variables are independent of one another. Thus, the model states that each text domain explains the relationships among the passages underlying the domain and three reading domains are independent of one another. Model 2 specifies that Y, Z, and U are three latent variable representing document, expository, and narrative domain, respectively. Manifest variables A through C are assumed to be explained by latent variable Y, D through F explained by Z, and G through I explained by U. Furthermore, there is no direct relationships among X, Y, and Z. The measurement part of Model 2 can be stated as:

$$m_{yzuabcdefghi} = N\pi_y\pi_z\pi_u\pi_{a|y}\pi_{b|y}\pi_{c|y}\pi_{d|z}\pi_{e|z}\pi_{f|z}\pi_{g|u}\pi_{h|u}\pi_{i|u} \tag{5}$$

The structural part Model 2 may be stated as:

$$\log m_{xzu} = \eta_{yzu}^{YZU} + \lambda_y^Y + \lambda_z^Z + \lambda_u^U \tag{6}$$

<u>*Three-related reading domain Model*</u> (Model 3): In contrast to Model 2, this model relaxes the assumption that three latent variables are independent of one another. Therefore, the measurement part of the model is the same as specified in equation (5). However, the structural part of the model now includes two-way and three-way interactions among *Y*, *Z* and *U*:

$$\log m_{xzu} = \eta_{yzu}^{YZU} + \lambda_y^Y + \lambda_z^Z + \lambda_u^U + \lambda_{yz}^{YZ} + \lambda_{yu}^{YU} + \lambda_{zu}^{ZU} + \lambda_{yzu}^{YZU} \tag{7}$$

For the following models, the restrictions imposed on the models can be derived by following the algorithm presented above. Details of the derivation are not presented here.

<u>*One general reading domain and one specific text domain*</u> (Model 4-6): This model postulates one latent variable has direct effect on all nine passages and the other has direct effect only on the reading passages underlying a specific text type. The general reading domain has three classes and the text domain has two classes. Furthermore, the latent variables are independent of each other. For example, Model 4 (Table 1) assumes that in addition to a general reading domain, document texts could be identified as a separate reading domain. This also means that the general reading domain is more influenced by the expository and narrative passages.

<u>*One general reading domain and a composite of two text types*</u> (Model 7-9): In contrast to the previous model, this model assumes that the text domain is a composite of two text types. The general reading domain has three classes and the composite text domain has two classes. For example, Model 7 (Table 1) assumes that there exist two independent latent variables: one being the general reading domain and the other being the combination of document and expository text type. That is, the general reading domain is more influenced by the narrative texts.

<u>*One general reading domain, a composite of two text types, and a specific text domain*</u> (Model 10-12): In contrast to the previous model, this model includes an additional text type as a separate latent variable with two classes. For example, Model 10 (Table 1) assumes that there exist one general reading domain, one document-expository text domain, and one narrative text domain.

<u>*One general reading domain and three independent text domains*</u> (Model 13): In contrast to the three-independent text domain model (Model 2), this model postulated an additional

reading domain that has direct effect on all reading passages. This model is equivalent to a bi-factor model. It is the most complex structure examined in this phase.

Model No.	*Descriptions*	
1	One Reading Domain	
2	Three-Independent Text Domains	
3	Three-Related Text Domains	
4	General and Document Domain	
5	General and Expository Domain	
6	General and Narrative Domain	
7	General and Composite of Document, Narrative	
8	General and Composite of Document, Expository	
9	General and Composite of Expository, Narrative	
10	General, Composite of Nar. and Exp., and Document	
11	General. Composite of Nar. and Doc., and Expository	
12	General. Composite of Exp. and Doc., and Narrative	
13	General. Document, Expository, and Narrative	

Table 1: Descriptions of Domain Structure Models in Phase I

For each country, a total of 13 latent class models were compared to determine the model that best represents the domain structure of that country. Table 1 presents the descriptions of all the models being compared for this phase. For model 1, 2, and 3, each latent variable has three levels. For the rest of the models, the General reading domain has three classes whereas the text specific reading domain has two classes. Models with different number of levels for the latent classes were considered in an earlier study (Yen, 1997). The absolute fit of each hypothesized model was examined using the likelihood ratio chi-square statistic. Competing models that provided acceptable fit were compared with respect to their parsimony using ***AIC*** criterion (Akaike, 1973) and model with minimum ***AIC*** was chosen as the preferred model to represent the domain structure for that country.

Phase II: Domain Structure Across Countries

The purpose of this phase was to examine whether the domain structure identified in Phase I was homogeneous across the four nations. Under the framework of the multiple-group LCAs (Clogg & Goodman, 1985), one may test the hypothesis with respect to a heterogeneous or a homogeneous latent structure across groups. Heterogeneous latent structure applies when there is no across-group restrictions imposed on the parameters. When across-group equality restrictions are imposed on the parameters, then the model is said to have a homogeneous latent structure across groups. To test the hypothesis that a given latent structure is adequate in explaining the relationship among the manifest variables across groups is equivalent to testing whether the groups are homogeneous with respect to the item structure. This can be achieved by imposing equality restrictions on the latent proportions and/or the conditional probabilities across groups (Clogg & Goodman, 1985).

Results

Domain Structure Within Country

Likelihood ratio chi-square statistics (G^2), degrees of freedom, and ***AIC*** information criterion (Akaike, 1973) for each model are reported in Tables 2 to 5. Model 9 had the smallest ***AIC*** among all 13 models for all four countries. This model provides support for existing theory about the domain structure of the IEA reading test in that a two-independent latent variable structure is necessary to explain the relationship among the manifest variables. One latent variable represents a general reading ability with three classes; the other latent variable represents expository/narrative reading with two classes.

Model	G^2	df	AIC
1	390.719	482	-573.281
2	1460.550*	478	504.550
3	363.515	458	-552.485
4	375.726	475	-574.274
5	389.141	475	-560.859
6	371.365	475	-578.635
7	366.775	469	-571.225
8	362.184	469	-575.816
9	**357.269**	**469**	**-580.731****
10	354.172	462	-569.828
11	361.710	462	-562.290
12	364.026	462	-559.843
13	360.397	461	-561.603

$p < 0.05$. **: Minimum *AIC*

Table 2: Model Comparisons of Domain Structure for Canada

Model	G^2	df	AIC
1	416.999	482	-547.001
2	1823.202*	478	867.202
3	397.620	458	-518.380
4	400.226	475	-549.774
5	413.645	475	-536.355
6	413.547	475	-536.453
7	394.836	469	-543.164
8	395.937	469	-542.063
9	**379.249**	**469**	**-558.751****
10	374.325	462	-549.675
11	389.731	462	-534.269
12	389.006	462	-534.994
13	393.923	461	-528.077

*:$p < 0.05$. **: Minimum *AIC*.

Table 3: Model Comparisons of Domain Structure for Denmark

Model	G^2	df	AIC
1	423.533	482	-540.467
2	1837.462*	478	881.462
3	389.810	458	-526.190
4	387.969	475	-562.031
5	421.630	475	-528.370
6	416.630	475	-533.370
7	383.052	475	-554.948
8	380.809	475	-569.191
9	**367.455**	**475**	**-570.545****
10	362.700	462	-561.300
11	380.680	462	-543.322
12	379.592	462	-544.408
13	379.891	461	-542.109

$p < 0.05$. **: Minimum *AIC*.

Table 4: Model Comparisons of Domain Structure for Hong Kong

Model	G^2	df	AIC
1	484.243	482	-479.757
2	4265.945*	478	3309.945
3	428.363	458	-487.637
4	448.614	475	-501.139
5	472.570	475	-477.430
6	451.154	475	-498.846
7	441.104	469	-496.896
8	409.935	469	-528.065
9	**405.709**	**469**	**-532.291****
10	401.352	462	-522.647
11	429.538	462	-494.462
12	403.070	462	-520.930
13	418.821	461	-503.179

*: $p < 0.05$. **: Minimum *AIC*.

Table 5: Model Comparisons of Domain Structure for U.S.A.

Estimates of latent class parameters for each country are presented in a two by three contingency table with six cells in Tables 6 to 9. The row margins and the column margins contain the latent class proportions for the Exp/Nar reading domain and the General reading domain, respectively. It is apparent from the row and column margins that the two latent domains are independent. Overall, there is a relatively even split between the row margins whereas more variation is noted among the column margins. Wide variations were found for the General reading domain where the majorities of the respondents belonging to the intermediate class and very few were nonmasters. The distribution of latent class proportions for the Exp/Nar domain was fairly evenly split between two classes. Canada and Denmark have slightly more masters than nonmasters while the opposite is true for Hong Kong and U.S.A.

Exp/Nar Domain	General Reading Domain				
		Nonmaster	Intermediate	Master	Total
	Nonmaster	0.078	0.233	0.130	.441
	Master	0.099	0.295	0.165	.559
	Total	0.177	0.528	0.295	1

Table 6: Latent Class Parameters for Canada

Exp/Nar Domain	General Reading Domain				
		Nonmaster	Intermediate	Master	Total
	Nonmaster	0.050	0.194	0.182	.426
	Master	0.067	0.261	0.245	.573
	Total	0.117	0.455	0.427	1

Table 7: Latent Class Parameters for Denmark

Exp/Nar Domain	General Reading Domain				
		Nonmaster	Intermediate	Master	Total
	Nonmaster	0.066	0.237	0.245	.548
	Master	0.055	0.195	0.202	.452
	Total	0.121	0.432	0.447	1

Table 8: Latent Class Parameters for Hong Kong

Exp/Nar Domain	General Reading Domain				
		Nonmaster	Intermediate	Master	Total
	Nonmaster	0.100	0.266	0.171	0.537
	Master	0.086	0.230	0.147	0.463
	Total	0.186	0.496	0.318	1

Table 9: Latent Class Parameters for U.S.A

Model	General	Nar/Exp	G^2	*df*	*AIC*
H_1	θ free, α free	θ free, α free	1509.682	1876	-2142.318
H_2	θ free, α free	θ free, α equal	**1535.366**	**1912**	**-2288.634****
H_3	θ free, α free	θ equal, α equal	1546.061	1915	-2283.939
H_4	θ free, α equal	θ free, α free	2112.475	1957	-1801.525
H_5	θ equal, α equal	θ free, α free	2775.203	1963	-1250.797
H_6	θ free, α equal	θ equal, α equal	6178.972*	1996	2286.972
H_7	θ equal, β equal	θ free, α equal	5715.697*	1999	1717.697
H_8	θ free, α equal	θ equal, α equal	4813.249*	1993	817.249
H_9	θ equal, α equal	θ equal, α equal	8971.427*	2001	4969.427

1: θ denotes latent class proportion

2: α denotes conditional probability

*: $p<0.05$. **: Minimum *AIC*.

Table 10: Cross-country Latent Structure Analysis

Domain Structure Across Countries

The research question examined at Phrase II was whether the domain structure is the same across four countries. Nine simultaneous latent structure models were tested using country as the grouping variable. For ease of discussion, these models are grouped into three major categories:

1. Heterogeneous Model (H_1): This model tested the assumption that the latent structure based on Model 9 holds simultaneous across countries, however, conditional probabilities and latent class proportions are unconstrained.

2. Homogeneous Models (H_8 and H_9): Model H_8 specified that conditional probabilities are the same for the four countries. Under the framework of simultaneous latent structure analysis, if conditional probabilities were the same across groups, then latent structure is considered to be homogeneous. By comparing Models H_1 and H_8, the assumption of homogeneity across group is tested. Since they are nested models, comparisons between them may be made using the likelihood ratio chi-square difference test (Hagenaars, 1990). Model H_9 is the more restrictive model than Model H_8 in which latent class proportions are constrained to be equal across countries.

3. Partial Homogeneous Models (Models H_2 to H_7): Models H_2 to H_7 are a series of models in which the latent structure for one reading domain is homogeneous but the latent structure for the other domain is heterogeneous across groups.

	Nonmastery	Intermediate	Mastery	Total
Canada	0.086	0.039	0.039	0.163
Denmark	0.067	0.018	0.069	0.154
Hong Kong	0.019	0.091	0.099	0.209
U.S.A.	0.073	0.229	0.171	0.473
Total	0.245	0.377	0.378	1.000

Table 11. Latent Class Parameters Across Country: General Reading

	Nonmastery	Mastery	Total
Canada	0.122	0.042	0.164
Denmark	0.064	0.091	0.155
Hong Kong	0.109	0.100	0.209
U.S.A.	0.216	0.257	0.473
Total	0.511	0.490	1.000

Table 12. Latent Class Parameters Across Country: Nar/Exp Reading

As shown in Table 10, the heterogeneous model, H_1, fits the data well. When cross-country restrictions were imposed on the conditional probabilities for both latent domains (Model H_8), the fit to the data deteriorated drastically. Three of the six partial homogeneous models fit the data. Among the five models that fit the data, Model H_2 yielded the smallest ***AIC*** and therefore, was chosen as the preferred model. Model H_2 specifies a heterogeneous structure for the General reading domain and a homogeneous structure for the Exp/Nar reading domain across country. In other words, the conditional probabilities for the Exp/Nar reading may be constrained to be equal across countries, while the conditional probabilities associated with the General reading can not be constrained. Furthermore, the latent class proportions for both reading domains are different across countries. Line graphs of average conditional probability of correct response are represented by country in Figure 1 to Figure 3 for each latent class. There were relatively small country differences for the mastery class while larger country differences were found in the nonmastery class. Overall, nonmasters in Hong Kong have a distinctly higher probabilities of getting most of the passages ("Maria," "Temperature," "Marmot," and "Shark") correct than other classes. In contrast, nonmasters in Canada have lower probability of getting the passages correct than other countries. Latent class parameter estimates by country are presented in Tables 11 and 12 for each reading domain.

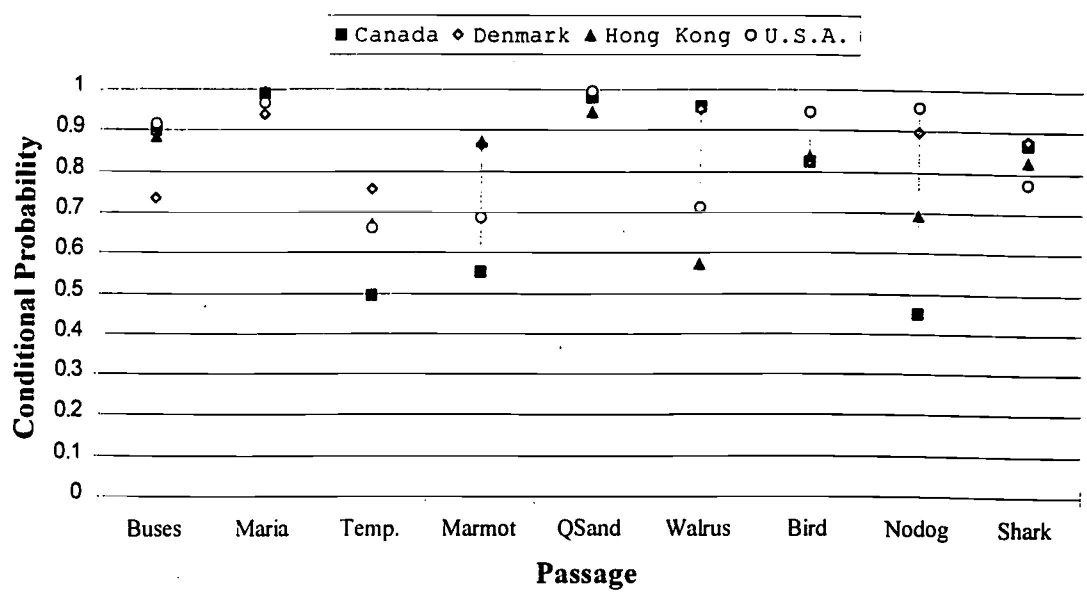

Figure 1: Average Conditional Probability Across Country-Mastery Class

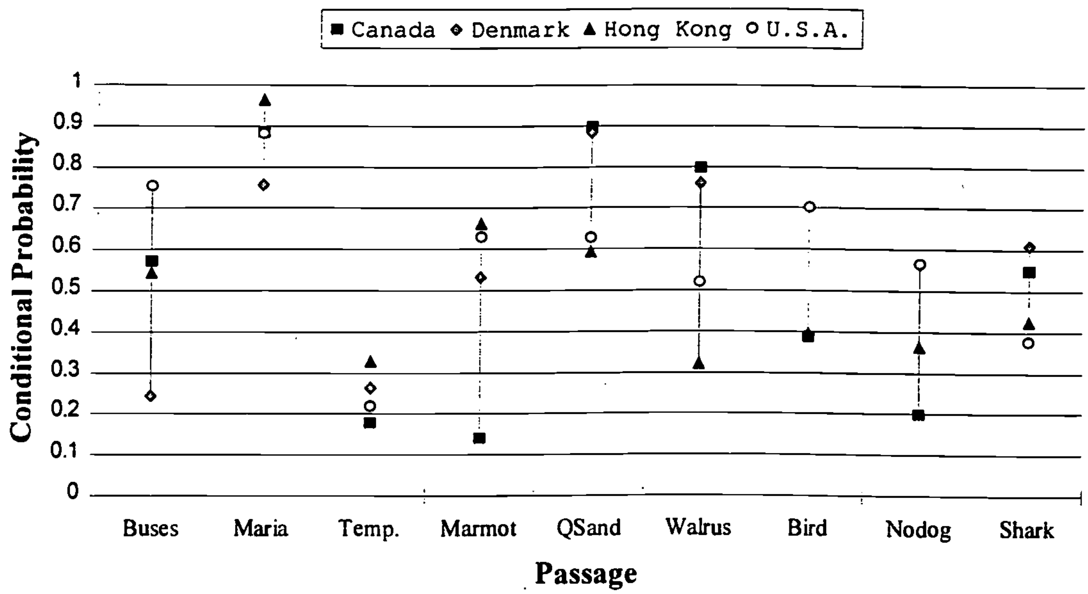

Figure 2: Average Conditional Probability Across Country-Intermediate Class

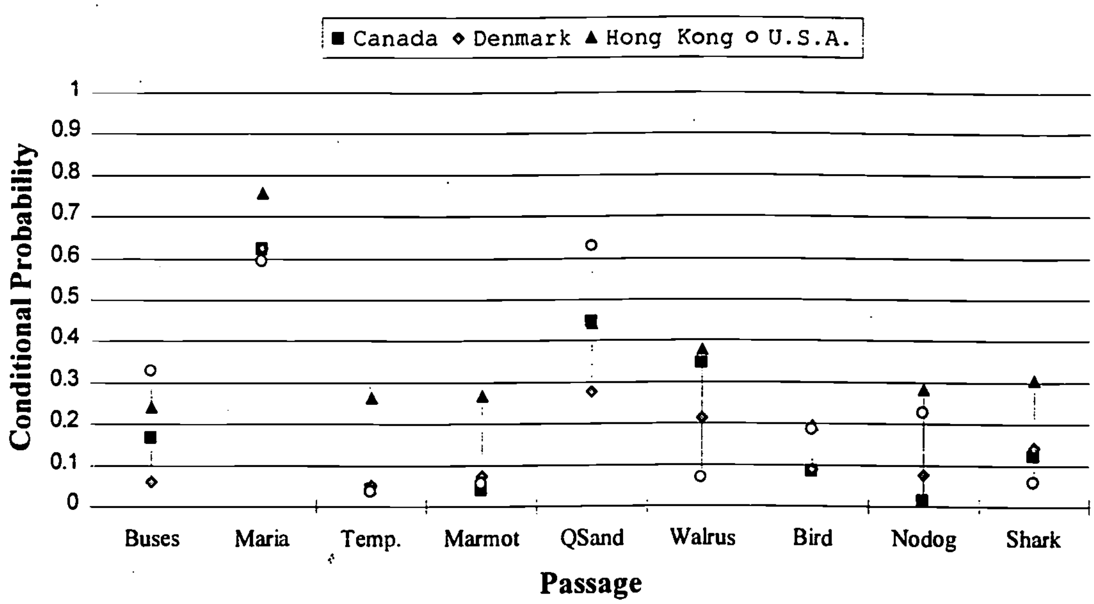

Figure 3: Average Conditional Probability Across Country-Nonmastery Class

Discussion

One of the main research questions examined in the study was whether the type of text elicits different type of reading comprehension. The results indicate that there is no empirical evidence of three separate text types for any of the four countries examined. However, there is empirical evidence of two separate reading domains. One latent variable represents a General reading domain associated with all three text types, the other represents a Prose reading domain associated only with the Expository and Narrative text types. Passages with documentary information do not form a specific text domain. In other words, not three, but only two reading types were identified.

The General reading domain is to be regarded as a complex latent variable. Psychometrically, it accounts for the general cognitive differences among individuals in responding to all reading passages examined. At the most general level, this latent variable may include variations depending on test format, test administration, and an individual's test proficiency. Specifically, this latent variable is associated with some analytical ability to deal with reasoning, making inferences and contrasts, and integrating or synthesizing the information in the content of reading passages in general. Since items from the passages with documentary information do not form a specific text domain, the General reading domain is to be regarded as highly influenced by individual differences in locating information in texts where general intellectual ability is emphasized. Thus, the General reading domain represents the set of cognitive skills common to the respondents in dealing with the reading passages in general. This set of skills consists of both the verbal component and the quantitative component of the reading skills the individuals possess.

In contrast to the General reading domain, the Prose reading domain seems to reflect specific linguistic abilities that are associated with recalling and understanding written prose. This set of skills reflect the individual differences in word meaning or vocabulary, language processing, and world knowledge held in verbal form. Since this latent variable would be freed from the variations from the general cognitive differences among individuals. It may be regarded as more reflective of the individual differences in reading comprehension. In the context of this model, reading comprehension of written prose is therefore regarded as a rather specific ability.

This latent structure helps to explicate the relationship between Document and Narrative-Expository text type. The document items require reading some amount of continuous text, but the major source of the difficulty seems to come from locating information in the tables, graphs, and maps, and processing the information in the passages. Therefore, poor reading skills certainly would affect the performances, but good reading skills are not sufficient in explaining the successful performances on these passages. Instead, the analytic abilities to deal with reasoning and processing information are more important in explaining the performances in these items. Therefore, Document items did not form a distinct text type once the individual differences of performance on these items has been accounted for by the General reading domain. These interpretations by no means suggest that the Document items can be interpreted as a pure measure of reasoning ability. Instead, Document items to some extent capture the same type of reading ability as is measured by the Narrative and Expository items.

Many of the Expository and Narrative passages also require inferences and complex reasoning. However, once the individual differences in making inferences and logic reasoning had been accounted for by the General reading domain, a separate Prose reading domain remains in the model. Therefore, there is evidence of a separate Prose reading domain that is distinct from the General reading domain. Since the major difference between the Narrative-Expository passages and Document passages is the amount of continuous text to process, the Prose reading domain could be regarded as a text-processing domain that reflects certain linguistic ability.

In essence, the results show that there is some evidence for a general reading domain, and the Expository and Narrative text types measure the same text processing skills. These results conform to the finding from previous factor analytic studies by Carroll in 1993. The findings from the current study can also be compared with the analysis conducted by Balke (1996) in which the domain structure of the IEA reading test was analyzed using structural equation modeling. While the domain structure identified in this study bears some similarities to the models proposed by Balke (1996), there are some fundamental differences in the methodology. The significant chi-square statistics in Balke's study indicate that neither of the proposed models fit the response data for any of the five countries. Furthermore, the Goodness of Fit Statistics were far from ideal for both models for any countries. Although these problems may be reflective of the limitations of the fitting statistics, the interpretability of the models was still questionable. In contrast, the domain structure identified in this study fit the response data for all four countries and offer unambiguous interpretations about the nature of the relationship among the reading domains.

The cross-country similarity in the domain structure provided some evidence for the stability of this domain structure. Since the same domain structure hold simultaneously across four countries, it can be concluded that the domain structure is consistent across countries. The simultaneous latent structure analysis across countries provided some further insight with regard to the nature of the latent variables. The cross-country heterogeneity in the conditional probabilities associated with the General reading domain indicates that the individuals in four countries differ in their general reading skills. However, the conditional probabilities may be constrained to be equal across countries in terms of the Prose reading domain. Therefore, the item difficulties do not seem to differ across country with respect to the Prose reading domain.

Conclusions

The internal structure of tests is a critical issue of both classical and modern test theory. Factor-analytic methodology continues to be an active area of research. Most of this work is predicated on the assumption that examinee ability can be represented by one or more continuous latent variables. Under the framework of latent class models, examinees are assumed not to conform to a continuous latent attribute, but to exactly one of some small number of discrete latent classes. Unlike the factor-analytic method and latent trait models, latent class models involves minimum assumption about the data. The only assumption in the formulation of the latent class model is the assumption of local independence. In fact, what all these different methods have in common is their reliance on the axiom of local independence (Mooijaart, 1982). For factor-analytic and latent trait analysis, however, models are derived from this axiom by making further assumptions about the data.

The latent class modeling approach provides a way to examine the latent structure of the IEA reading test that avoids many problems that may occur when applying factor-analytic methodology. Current practice in structural modeling is limited to representing the covariance structure when the first and second moments are assumed and to the distribution theory based on multivariate normality. However, the assumption of marginal multivariate normality is generally ignored in a factor-analytic approach. Several studies have shown that statistics based on normal theory can be seriously in error when the distribution is in fact non-normal (Bentler, 1983) (Browne, 1984). In particular, simulation studies showed that excessive kurtosis usually eliminates asymptotic efficiency and makes that estimated asymptotic covariance matrix and chi-square estimators incorrect (Browne, 1984). Therefore, the tests of fit of a model and standard errors for parameter estimates derived under the assumption of multivariate normality, such as those obtained by LISREL (Joreskog & Sorbom, 1988) should be not employed if the distribution is not normal (Browne, 1984).

Balke's study (1995) analyzed the dimensionality of the IEA reading test using the correlation matrices generated from dichotomous item responses. Severe distortion can be introduced into the correlation matrix which either imposes artificial limits on the size of the correlation or inflate correlation values as compared with what probably would have occurred with continuously measured, normally distributed variables. Furthermore, the assumption of multivariate normality is usually violated when analyzing dichotomous response variables as if they were continuous response variables (Bollen, 1989) (Comrey, 1978). Researchers demonstrated that the covariance structure hypothesis does not hold for categorical indicators (Bollen, 1989). Moreover, the distribution of the categorical variables generally differs from that of the continuous indicators. Therefore, the asymptotic covariance matrix is not likely to equal those of the continuous indicators. Furthermore, the distribution of the categorical variables is likely to be non-normal. Therefore, the parameter estimates and tests of goodness of fit may be incorrect. Consequently, the interpretations one may derive from the models may be in error.

The current study demonstrates the usefulness of latent class modeling in addressing some measurement issues, including the domain structure and skill compositions of the reading tests. Latent class modeling approach provides a way to study the cognitive structure of the IEA reading test without making strong assumptions about the data. Under the framework of log-linear path models, latent class models can be used to distinguish cognitive skills and skill level reflecting item characteristics. Under the framework of multiple group latent structure analysis, the nature of the latent parameters can be studied simultaneously across groups. The study also demonstrates the usefulness of latent class modeling in large scale, cross-country reading assessment. Although reading achievement has been commonly modeled in a continuous latent variable framework, this study shows the applicability of latent class models to reading achievement. Therefore, it demonstrated that the application of latent class modeling is wider than otherwise suggested in the literature.

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