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Relationship between Networked Readiness and Mathematics Literacy in PISA

Yuan-Horng Lin[1,*] *and Jeng-Ming Yih*[2]

[1] Department of Mathematics Education, National Taichung University of Education, Taiwan
[2] Center of General Education, Min-Hwei College of Health Care Management, Taiwan

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Abstract: The relationship between technology and education should be an important issue. NRI (networked readiness index) is a national index to measure the readiness of network ready for the national development. PISA2006 is an important international assessment to measure mathematics literacy. As to this point, investigation on the multilevel relationship for national NRI to influence the personal mathematics literacy is prospective. Therefore, the purpose of this study is to analyze the multilevel relationship between mathematics literacy and NRI. The two-level and stepwise Hierarchical Linear Model (HLM) is to discover the multilevel relationship. The unit in level-1 is students and the level-2 is nations. Mathematics literacy and out-of school-time lessons measured from PISA2006 are dependent variable and independent variable of level-1 respectively. NRI measured from the World Economy Forum is the level-2 variable to explain mathematics literacy directly and the influence between out-of school-time and mathematics literacy indirectly. Five sub-models with one full model are discussed so that the multilevel information between students and nations is clearly understood. The major findings show that out-of school-time will influence mathematics literacy positively and NRI can explain its variance among nations. In addition, it needs more national variables to explain the process for out-of school-time lessons to influence mathematics literacy. Finally, according to the findings, some suggestions and recommendations are discussed.

Keywords: Hierarchical Linear Model, Mathematics Literacy, Networked Readiness Index, PISA2006

1 Introduction

Technology and education are two important dimensions to construct the competiveness of nations. Technology usually influences the learning, environment, assessment of the education. Many researchers also indicate the reciprocal causation between technology and education [1,2]. However, most of them only limit its scope owing to the database resource. Therefore, investigation on the multilevel relationship between technology and education based on international assessment database should be prospective.

One direct influence on education from technology is the achievement or literacy of students. As to this point, the major motivation of the international assessment is to investigate the influential factors on students achievement so that it can improve educational progress. Two well-known international assessments are TIMSS (Trends in International Mathematics and Science Study) and PISA (Programme for International Student Assessment). TIMSS is an international assessment of the mathematics and science of fourth- and eighth-grade students. TIMSS focuses on the knowledge of mathematics and science curriculum [3]. PISA is developed by OECD (Organization for Economic Co-operation and Development) and it is to assess the literacy of 15-year-olds and the literacy includes reading, mathematics and science. As to this point, some literatures indicate technology usage will influence the performance of TIMSS [26,27]. It is because technology can improve the learning environment so that students could easily understand important concepts and construct knowledge well. However, the purpose of PISA is to assess literacy and little is known about the relationship between technology and mathematics literacy [28]. Therefore, it is prospective to investigate the influence of technology on mathematics literacy in this study.

One intension of PISA is to build the longitudinal database and the trace of international assessment is a distinguishing feature [4,5]. The PISA2000 was held in

* Corresponding author e-mail: lyh@mail.ntcu.edu.tw

2000 and it was the first series of triennial assessments. The PISA has been held every three years. The major feature of PISA which differs from TIMSS is the content of assessment. PISA emphasizes the dynamic model of lifelong learning in which new knowledge and skills necessary for successful adaptation throughout life. Assessment of PISA2006 focuses on required daily and life knowledge to be citizen. Therefore, mathematics items of PISA2006 are almost related to non-routine questions. PISA database establishes important resource of international assessment to detect and compare the educational development among nations [6,8].

One popular consensus related to technology is ICT (Information and communication technologies). Besides, one well-known index to evaluate national ICT is NRI (networked readiness index) developed by The World Economic Forum (WEF), which is a non-profit foundation. There is WEF annual meeting which brings together top leaders, including business, international politics, and journalists, to discuss the most important issues of the world. These issues include economics, health, environment, and so on. The WEF also produces a series of research reports which evaluate the international development. The NRI measures the propensity for nations to exploit the opportunities offered by information and communications technology. The NRI consists of three components. They are the environment for ICT offered by a given country or community, the readiness of the communitys key stakeholders (individuals, businesses, and governments) to use ICT, and finally the usage of ICT for these stakeholders. The NRI is used to better comprehend the impact of ICT on the competitiveness of nations. NRI is the national index to express the technology development of learning environment. However, little literatures investigate its influence on educational achievement with the multilevel relationship. For that reason, the issue of this paper is to discuss the nested relationship between NRI and mathematics literacy.

Issue of technology on education outcome is important [9,10,11,12]. High NRI means it may provide good environment for students to learn mathematics. In addition, learning time of mathematics will also influence mathematics achievement. Some literatures reveal that much learning time does not improve mathematics achievement necessarily [29]. The questionnaire of PISA contains the information of out-of school-time lessons. As to mathematics literacy, how the direct influence comes from out-of school-time lessons is unknown. As to NRI, it is essential to explore its intermediary influence on the relationship between school-time lessons in mathematics and mathematics literacy. Therefore, it is meaningful to investigate the relationship of NRI and mathematics literacy with out-of school-time lessons in mathematics based on PISA2006. However, little is known about their multilevel relationship owing to the nested structure of students and nations [13]. Hierarchical Linear Model (HLM) could provide nested variance to reveal the structural relationships. Hence, this study will adopt HLM to investigate multilevel structure between personal students with variables of mathematics literacy and out-of school-time lessons and nations with variable of NRI.

2 Literature Review

PISA2006 and Its Variables. PISA2006 is not the test on specific knowledge in the textbooks. Mathematics domain of PISA2006 includes quantity, space and shape, change and relationships, and uncertainly. Item response theory (IRT) is the psychometric model to calibrate latent trait. The latent trait of mathematics literacy is called plausible values (PV)[14]. Plausible values of students are imputed values that are similar to test scores and approximate to the distribution of latent trait being measured. Most researches indicate there are possible variables needed to clarify the casual relationships in the international assessment database of mathematics literacy. Besides, there exist two hierarchies of nested structure in PISA2006. One is nations and the other is students. Statistical analyses of multilevel model could provide advanced information for casual relationships.

Based on the discussion related to PISA2006 variables above, the plausible values of mathematics literacy are calibrated according to item response theory. The variable out-of school-time lessons comes from the questionnaire of Likert scale. It means the average hours to learn mathematics in out-of school-time lessons per week. The author download the PISA2006 database from the official website of PISA.

ICT and NRI. As to the ICT issue, NRI is an import index to measure the development and readiness for nations to use resource of computers and construction of internet [15]. It is considered better NRI of nations will help teachers proceed with instruction in the classroom. Teachers can adopt computers or digital vehicles to promote pedagogy [16]. On the other hand, students can employ technological equipments to learn and improve their comprehension [17,18]. Most researches also indicate NRI has positive influence on mathematics learning. It is because nations of high NRI could provide diverse learning resources with technological materials. These resources will represent knowledge in the meaningful to help students construct concepts. It also help teachers organize teaching materials well. On the other hand, some literatures also reveal good technological equipments will not help achievement necessarily [30]. The reason is that technology equipments may intervene the information construction and quick change of technology will hinder the usage of equipments.

Hierarchical Linear Model. When data are collected by cluster sampling method, as is the case in PISA2006, the residuals will violate assumption of independence. Therefore, one limitation of ordinal least square (OLS) regression is that the standard error will be too small when it is adopted to estimate relationships on nested data. To overcome the shortcoming, multilevel model consider the nested structure of measured units and their associated variables [19].

Multilevel model is also called hierarchical linear model, nested model or mixed model. This model assumes that statistical parameters vary at more than one level [20]. The model owns quite a few utilities to analyze database logically [21,22,23]. There have been much more popular and availability of software for this model. The common multilevel model is HLM. Suppose there be ( ) nations and students within nation . Nation is the level-2 unit and student is the level-1 unit. A simple expression of the two levels is exemplified in Eq. (1) and Eq. (2). Level-1 is

$$Y_{ij} = \beta_{0j} + \beta_{1j}X_{ij} + r_{ij} \tag{1}$$

Y_{ij} is the level-1 outcome variable (e.g. students' mathematics literacy) and X_{ij} is the level-1 predictor (e.g. students' out-of school-time lessons in mathematics per week). β_{0j} and β_{1j} are level-1 coefficients and r_{ij} is the level-1 random effects. It is assumed $r_{ij} \sim N(0,\ \sigma^2)$ and σ^2 is the level-1 variance.

Each of the level-1 coefficients becomes an outcome variable in the levele-2 model. It is

$$\beta_{0j} = \gamma_{00} + \gamma_{01}W_j + u_{0j} \text{ and } \beta_{1j} = \gamma_{10} + \gamma_{11}W_j + u_{1j} \tag{2}$$

W_j is the level-2 predictor (e.g. national NRI). γ_{00}, γ_{01}, γ_{10} and γ_{11} are level-2 coefficients. u_{0j} and u_{1j} are level-2 random effects. It is assumed $(u_{0j},\ u_{1j})'$ be distributed as multivariate normal.

When it is to combine Eq. (1) and Eq. (2) together, the variance will show its source and explanation according to nested structure. Therefore, regression coefficients will indicate the influence between two levels [24]. All the above is the simple example of two-level HLM. A general description of two-level HLM is shown as Eq. (3) and Eq. (4) [25]

$$Y_{ij} = \beta_{0j} + \sum_{q=1}^{Q} \beta_{qj}X_{qij} + r_{ij} \tag{3}$$

$$\beta_{qj} = \gamma_{q0} + \sum_{s=1}^{S_q} \gamma_{qs}W_{sj} + u_{qj} \tag{4}$$

The related assumption is the same as mentioned in Eq. (1) and Eq. (2). Three kinds of parameter estimates are available in HLM. They are empirical Bayes estimates of randomly level-1 coefficients, generalized least square estimates of the level-2 coefficients and maximum-likelihood estimates of variance and covariance. There will be several sub-models when it is to restrict random error or eliminate predictors in the general model. Therefore, the nested sub-models could classify the source of variance.

Table 1: Mean of variables for all nations

Nations (Areas)	NRI	mean		Nations (Areas)	NRI	mean	
		PV	Time			PV	Time
Argentina	3.59	388.269	1.59	Kyrgyzstan	2.90	315.963	2.12
Australia	5.24	516.233	1.55	Latvia	4.13	491.120	1.91
Austria	5.17	509.340	1.38	Liechtenstein	-	524.967	1.47
Azerbaijan	3.53	476.561	2.17	Lithuania	4.18	485.268	1.61
Belgium	4.93	526.872	1.4	Luxembourg	4.90	490.511	1.63
Brazil	3.84	365.847	1.94	Macao	-	523.456	1.85
Bulgaria	3.53	417.206	1.83	Mexico	3.91	420.840	1.81
Canada	5.35	517.446	1.7	Montenegro	-	395.184	1.67
Chile	4.36	417.458	1.77	Netherlands	5.54	537.228	1.55
Chinese Taipei	5.28	563.333	2.08	New Zealand	5.01	523.043	1.53
Colombia	3.59	373.452	1.89	Norway	5.42	489.925	1.84
Croatia	4.00	467.345	1.58	Poland	3.69	500.273	1.64
Czech Republic	4.28	536.017	1.56	Portugal	4.48	470.190	1.64
Denmark	5.71	512.402	2.03	Qatar	4.21	317.934	2.27
Estonia	5.02	517.202	1.76	Romania	3.80	414.972	2.02
Finland	5.59	549.934	1.31	Russian Federation	3.54	478.596	1.89
France	4.99	496.956	1.73	Serbia	-	436.133	1.72
Germany	5.22	503.734	1.61	Slovak Republic	4.15	494.652	1.71
Greece	3.98	461.885	2.5	Slovenia	4.41	482.335	1.83
Hong Kong	5.35	551.624	2.01	Spain	4.35	501.435	1.78
Hungary	4.33	496.746	1.98	Sweden	5.66	503.349	1.51
Iceland	5.50	505.151	1.55	Switzerland	5.58	527.781	1.54
Indonesia	3.59	380.726	2.07	Thailand	4.21	425.218	1.75
Ireland	5.01	502.151	1.55	Tunisia	4.24	363.548	2.6
Israel	5.14	443.023	2.48	Turkey	3.86	428.021	2.41
Italy	4.19	473.759	1.59	United Kingdom	5.45	497.461	1.52
Japan	5.27	525.819	1.54	United State	5.54	475.177	1.85
Jordan	3.74	388.894	2.24	Uruguay	3.67	435.204	1.64
Korea	5.14	546.807	2.51				

3 Methodology and Data Description

Mathematics literacy is from PISA2006 and NRI is from 2006 World Economy Forum (WEF). There are 57 nations or areas participating in the PISA2006. In Table 1, the mean of plausible value (PV) for mathematics literacy and out-of school-time lessons in mathematics per week (Time) are depicted. The NRI for each nation is also displayed in Table 1. Among these nations, one is OECD member and there are 30 nations. The other is non-OECD member and there are 27 nations. There are about 398 thousands of students in PISA2006 database.

The units and variables of two levels in this study are depicted in Figure 1. It shows the unit of level-1 is students and its variables are mathematics literacy and out-of school-time lessons in mathematics per week. Furthermore, it is assumed that out-of school-time lessons in mathematics per week will influence mathematics literacy. The unit of level-2 is nations and its variable is NRI. It is considered that NRI intervene in the casual relationship between out-of school-time lessons in mathematics per week and mathematics literacy.

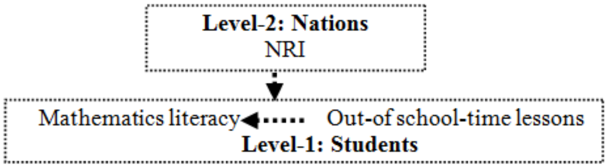

Fig. 1: The units and variables of two levels

4 Results and Discussions

In level-1, Y_{ij} is mathematics literacy and X_{ij} is out-of school-time lessons in mathematics per week. As to level-2, W_j is the national NRI. In this study, HLM 6.02 software is used to analyze data. These models could explain the multilevel information step-by-step. The structural relations with equations and variables are depicted in Figure 2 .

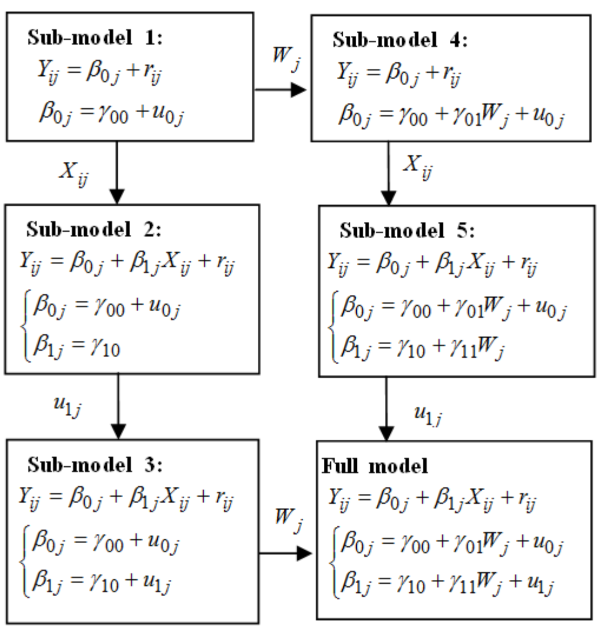

Fig. 2: Structural relations among sub-models and the full model

The five sub-models with one full model are to clarify the casual relationship and their results are depicted in Table 2. In Table 2, the name of models and their equations are shown. In addition, the main results of coefficients and variance as to each model also reveal the multilevel relationship. One is concluded that all the important coefficients are statistically significant.

From sub-model 1 to sub-model 5, their structural relationship is nested. The sub-model 1 is to compare the mean difference among units of level-2. The sub-model 2 is to realize the influence of covariates and compare the conditional mean difference among units of level-2 without random error. The sub-model 3 is to explore the regression model in units of level-1 and compare the mean difference on regression coefficient in level-1. The sub-model 4 suppose the mean difference in level-1 could be explained by predictive variables of level-2. The sub-model 5 explore regression model in units of level-1 and suppose regression coefficients in level-1 could be explained by independent variables of level-2 without random error as to coefficients of slope. Finally, the full model is established in the form of regression model with independent variables in level-1 and level-2. There are no restrictions on random errors.

Owing to the structural and nested relationship among the above sub-models and full model, the step-by-step statistical analysis from sub-model 1 to sub-model 5 could reveal the source of variance so that the multilevel relationship will be easily understood. In this study, all the sub-models and the full model will be adopted to explore the multilevel relationship between students and nations.

Table 2: The nested models with equations and results

Equations of sub-models	Results
Sub-model 1 $Y_{ij} = \beta_{0j} + r_{ij}$ $\beta_{0j} = \gamma_{00} + u_{0j}$	γ_{00}=488.657 (p<.001) $Var(u_{0j})$=1657.121 (p<.001)
Sub-model 2 $Y_{ij} = \beta_{0j} + \beta_{1j}X_{ij} + r_{ij}$ $\begin{cases} \beta_{0j} = \gamma_{00} + u_{0j} \\ \beta_{1j} = \gamma_{10} \end{cases}$	γ_{00}=510.973 (p<.001) γ_{10}= -11.139 (p<.001) $Var(u_{0j})$=1553.278 (p<.001)
Sub-model 3 $Y_{ij} = \beta_{0j} + \beta_{1j}X_{ij} + r_{ij}$ $\begin{cases} \beta_{0j} = \gamma_{00} + u_{0j} \\ \beta_{1j} = \gamma_{10} + u_{1j} \end{cases}$	γ_{00}=510.738 (p<.001) γ_{10}= -12.963 (p<.001) $Var(u_{0j})$=3198.856 (p<.001) $Var(u_{1j})$=237.363 (p<.001)
Sub-model 4 $Y_{ij} = \beta_{0j} + r_{ij}$ $\beta_{0j} = \gamma_{00} + \gamma_{01}W_j + u_{0j}$	γ_{00}=326.696 (p<.001) γ_{01}=34.287 (p<.01) $Var(u_{0j})$=1197.263 (p<.001)
Sub-model 5 $Y_{ij} = \beta_{0j} + \beta_{1j}X_{ij} + r_{ij}$ $\begin{cases} \beta_{0j} = \gamma_{00} + \gamma_{01}W_j + u_{0j} \\ \beta_{1j} = \gamma_{10} + \gamma_{11}W_j \end{cases}$	γ_{00}=278.625 (p<.001) γ_{01}=49.649 (p<.01) γ_{10}=30.422 (p=.07) γ_{11}= -9.111 (p<.05) $Var(u_{0j})$=1136.591 (p<.001)
Full model $Y_{ij} = \beta_{0j} + \beta_{1j}X_{ij} + r_{ij}$ $\begin{cases} \beta_{0j} = \gamma_{00} + \gamma_{01}W_j + u_{0j} \\ \beta_{1j} = \gamma_{10} + \gamma_{11}W_j + u_{1j} \end{cases}$	γ_{00}=254.886 (p<.01) γ_{01}=54.165 (p<.001) γ_{10}=41. 229 (p<.05) γ_{11}= -11.471 (p<.01) $Var(u_{0j})$=2017.651 (p<.001) $Var(u_{1j})$=187.861 (p<.001)

According to the representation in Figure 2 and the results in Table 2, the explanations and findings could be concluded in Table 3. As shown in Table 3, one is concluded that the comparison among nested sub-models will reveal the influence from multilevel relationship.

Table 3: Findings and results of sub-models and the full model

Names of Sub-models	Results
Sub-model 1: One-way ANOVA model with random effects	1. Mean of mathematics literacy for all nations is γ_{00}=488.657 and $Var(u_{0j})$=1657.121 (p<.001) is significant. 2. There is difference on mean of mathematics literacy among nations.
Sub-model 2: One-way ANCOVA model with random effects	γ_{10}= -11.139 (p<.001) means out-of school-time lessons in mathematics per week influences mathematics literacy with negative effect significantly.
Sub-model 3 : Random coefficients regression model	1. out-of school-time lessons in mathematics per week influence mathematics literacy with negative effect significantly. 2. $Var(u_{0j})$=3198.856 (p<.001) indicates there exists another predictive variables to explain variance of mathematics literacy.
Sub-model 4: Means-as-Outcomes regression model	1. γ_{01}=34.287 (p<.01) means NRI influence mathematics literacy with positive effect significantly. 2. $Var(u_{0j})$=1197.263 (p<.001) also shows there are another national variables to explain mathematics literacy.
Sub-model 5: Model with nonrandomly varying slopes	1. γ_{11}= -9.111 (p<.05) shows that NRI will negatively affect the process when out-of school-time lessons in mathematics per week influences mathematics literacy. 2. $Var(u_{0j})$=1136.591 (p<.001) indicates there exist possible variables to explain variance of mathematics literacy in addition to NRI and out-of school-time lessons in mathematics per week.
Full model	In addition to the same results of sub-model 5, it indicates there are another national variables to explain the process for out-of school-time lessons in mathematics per week to influence mathematics literacy because it is $Var(u_{1j})$=187.861 (p<.001).

5 Conclusions

According to the findings above, mathematics literacy among nations differs and out-of school-time lessons in mathematics per week will negatively influence mathematics literacy. In addition to out-of school-time lessons in mathematics per week, there exist another predictive variables to explain variance of mathematics literacy. NRI is a positive predictor for mathematics literacy but it will negatively intervene the relationship between mathematics literacy and out-of school-time lessons in mathematics per week. Moreover, there exist another intervening variables which may explain the influential process for mathematics literacy on out-of school-time lessons in mathematics per week. The step-by-step procedures in this study show the structural relationship of students and nations. Advanced research could aim at the possible level-2 variables to explain the causal relationship. Besides, multivariate multilevel model could be an important methodology to be applied in the issue. On the other hand, future investigation of science literacy or reading literacy for PISA 2006 and PISA2009 are also prospective.

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Yuan-Horng Lin received his Ph. D degree from National Chengchi University, Taiwan. He is currently a professor and chairman in Department of Mathematics Education, National Taichung University of Education, Taiwan. His current research interests include applied statistics, mathematics assessment, psychometric methodology, fuzzy theory, cognition diagnosis in mathematics learning, and mathematics education.

Jeng-Ming Yih received his Ph. D degree from National Taichung University of Education, Taiwan. He is currently a professor and director in Center of General Education, Min-Hwei College of Health Care Management, Taiwan. His current research interests include linear algebra, fuzzy theory, applied statistics, mathematics assessment, and mathematics education. of pure and applied mathematics, applied economics. His main research interests are: dynamical systems, patterns of growth and sustainable development, mathematical economics, game theory, optimization theory, applied economics, differential geometry and applications, geometric dynamics and applications.