To compare the linear and curvilinear model, we performed the Satorra-Bentler corrected Likelihood-ratio test (Satorra & Bentler, 2010) and evaluated differences in information criteria (i.e., Akaike's Information Criterion [AIC], Bayesian Information Criterion [BIC], and sample-size adjusted BIC [aBIC]) for each plausible-value dataset (Enders & Mansolf, 2016).

We applied the latent moderated structural (LMS) equations approach to create the squared variable of inquiry-based science teaching and to analyse the latent interaction terms using the XWITH command in the software Mplus (Muthén & Muthén, 1998–2015). We chose the LMS approach in our analyses to overcome the non-normality of the product term (Klein & Moosbrugger, 2000).

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To determine the strength of the relationships

between two dependent constructs (training and resources and facilitating conditions)

in the model, bootstrap method was implemented. The positive coefficient values for all

constructs indicate that participants in this particular study had different difficulties to

develop didactic activities for fostering digital reading competence of students.

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As used in the previous study (Luu & Freeman, 2011), step-be-step exploratory model building strategy (Hox, 2010) was employed to build models with the variables of interest for each subject. All the models had the same meaning and structure for mathematics, reading, and science, and the data analysis procedure was reported altogether.

First, a one-way ANOVA model with random effects (null model) was built to test if the variances were significant at each level:

Yijk=γ000 + eijk + r0jk + u00k

Where

Yijk is the mathematics/reading/science scores for the student i in school j in country k

γ000 is the grand mean mathematics/reading/science scores for all countries included in the sample

eijk is the residues for student i in school j of country k

r0jk is the residues for school j in country k

u00k is the residues for country k.

Second, explanatory predictors were included in sequential sets: the first set was U student-level variables (GENDER, SES, ICTHOME, ICTSCH, HOMESCH, ENTUSE, USESCH, INTICT, COMPICT, AUTICT, SOIAICT). Each student-level predictor was included separately in the null model to test its absolute effect; predictors with significant effects (p < .05) were then added together to test their effects in the presence of other predictors (Luu & Freeman, 2011; Ma et al., 2008). If any predictor became no longer statistically significant in the model, the predictor with the largest p-value was removed. This step was repeated until all included predictors were statistically significant with the dependent variable.

Then, each of the V school-level variables (SCHSIZE, SCHLOCA, RATCMP1, RATCMP2, M\_ICTSCH, M\_USESCH, M\_INTICT, M\_COMPICT, M\_AUTICT, M\_SOIAIC) was added to the model built above, followed by the inclusion of all statistically significant variables. One variable with the largest p-value at one time was still excluded until all remaining variables were statistically significant. Last, the procedure for V was employed for W country-level variables (ACCUSE and

SKILLS) to produce the final model.

Yijk=γ000 + πujk Studentijk + β0vk School0jk + γ00w Country00k + eijk + r0jk + u00k

Where

πujk is the slope of U student-level variables for student u in school j of country k

β0vk is the slope of V school-level variables for school v in country k

γ00w is the slope of W country-level variables for country w.

To build a model with the predictors of interest, an exploratory strategy described by Hox (cited in Tabachnick & Fidell, 2007) was used.

First, the simplest intercept model (null model) was generated to examine the intraclass correlation (ICC). Student-level predictors were assessed for statistical significance, and then school-level predictors were added to the model. The variance explained by the model was determined through a calculation of effect size. A background model, comprised of student demographic characteristics (ESCS, gender, and immigrant status) and school characteristics (school mean ESCS4, school size, and community in which school is located), was generated to account for variables that were not measures of ICT.

2.3.1. The null model

Variance in scientific literacy was partitioned into (a) variance in scientific literacy scores that lies between students within one school (pooled over schools), and (b) variance that lies systematically between schools. The proportion of variance in the dependent variable may be modeled as a function of school characteristics, and the ICC is the proportion of the total variance that lies systematically between schools; if ICC\_ 10% of the total variance in the outcome, it is an indication that HLM techniques would be appropriate in a school-effects study (Lee, 2000). The null model tests the hypothesis that all schools have the same mean scientific literacy (i.e., whether or not mean differences exist between schools), since no student or school characteristics are considered (Lee, 2000; Tabachnick & Fidell, 2007), and provides an estimated scientific literacy score for each country (Heck & Thomas, 1999).

To examine the absolute effect, each student-level variable was added separately to the null model to determine whether or not its relationship varied significantly across schools, independent of other variables (Ma & Klinger, 2000). Variables with statistically significant effects (i.e., a critical value of jtj ¼ 1.96, p < .05) were then introduced together to examine their effects in the presence of other variables. Thus the relative effect of the variable was adjusted for the shared effects of other variables (Ma & Klinger, 2000). Variables that were no

longer statistically significant were removed one at a time, starting with the variable with the largest p-value in the model, until all remaining variables in the model were statistically significant. When the variance of the relative effects model is compared to the null model, the proportional reduction in the within-group variance can be determined.

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Direct effects on the endogenous variables were calculated as standardized beta-weight (path coefficients or bs). The path models were estimated using AMOS (Arbuckle, 2003). Different parameters will be tested to assess the fit between the hypothesized model and the data. Cut-off criteria for fit indexes recommended by Hu and Bentler (1999) were used: 1) the χ² statistic and corresponding *p*-value; the *p*-value should not be significant; 2) the Adjusted Goodness of Fit Index (AGFI) should be at least 0.9; 3) the Comparative Fit Index (CFI) should be close to 0.95; and, 4) the Root Mean Square Error of Approximation (RMSEA) should have a value of 0.05 or less.

In the model selection, the simplest model (which has minimum latent class and the least predictive parameter) is preferred (Vermunt, 2003; Vermunt & Magidson, 2004). Fitting measures such as log-likelihood (LL) and Bayesian information criterion (BIC) are used in order to define the best number of clusters. However, related literature (Lukočienė,

Varriale, and Vermunt, 2010) recommends only using of BIC value. Thus, this research was used BIC value as criteria regarding model selection. Secondly, three-step analysis is employed in order to determine chosen independent variables’ ability to predict emerged latent classes (Vermunt, 2010). Latent Gold 5.1 package programme is used in analyses (Vermunt & Magidson, 2013a, 2013b). Furthermore, country level weightings are employed while analyzing.

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The goodness-of-fit of the structural equation models was assessed with

the values of the Root-Mean-Square Error of Approximation (RMSEA), the

Comparative Fit Index (CFI), and the Tucker Lewis Index (TLI). It has been

showed that the value of RMSEA should be less than 0.06 and the CFI and

the TLI should be more than 0.95 (Hu & Bentler, 1999). Additionally, lower

values of the χ2 test of absolute model fit suggest better model fit to the data

(Schreiber et al., 2006).