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Effects of School-related Factors and Early Learning Experiences on Mathematics Achievement "A Multilevel Analysis to Analyse the TIMSS Data"*

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Abstract

The overall aim of this study is to investigate the effect of school-related factors and early learning experiences on mathematics achievement. In this causal-comparative research, HLM analysis was performed on the data of 6378 students, their parents, and 241 school principals and primary school teachers. As a result of the HLM analysis, at the student level, learning resources at home, parent-child communication on homework/assignments, parent-child activities in early learning years, and the skills acquired during these years were found to have statistically significant effects on the mathematics academic achievement scores of primary school students. At the school level, on the other hand, the socioeconomic structure of the school, the importance that the school attaches to mathematics academic achievement and teachers' perceptions about it, teachers' experiences, and a safe and disciplined school environment have significant effects. These results indicate the importance of early learning experiences especially in the development of the academic performance of primary school students.

Keywords: early learning experiences, school characteristics, TIMSS 2015, mathematics achievement, HLM analysis

1. Introduction

Considering the education system's objectives of raising effective individuals, the quality of educational activities comes to the forefront to raise individuals with prediction skills, curiosity, and an improved ability to reason, analyse, and to solve real-life problems. Increasing the quality of education improves students' knowledge and skills in different areas and enables them to perform better.

The approach to be adopted to carry out the monitoring and evaluation activities in line with this in a healthy manner is important. Reddy (2005) argues that the most realistic approach to such activities is an international comparison. International comparisons help compare different education systems and provide countries with the opportunity to make necessary changes in light of the scientific data.

In this respect, one of the international applications that Turkey has participated is the 'Trends in Mathematics and Science Study- TIMSS', applied to students at grades 4 and 8 in four-year periods by IEA. It aims to evaluate students' mathematics and science knowledge and skills (IEA, 2017). For this purpose, TIMSS examines student, home, school and class factors associated with students' achievement.

Various environmental factors significantly affect students' academic achievement (Eccles & Wigfield, 2002; Scherer & Nilsen, 2016; Lamb & Fullarton, 2002; Marzano, 2003; Hattie, 2009). One of these is, as defined in TIMSS 2015, school-related factors (Hooper, Mullis & Martin, 2013): socioeconomic structures of schools, impacts of schools on academic achievement, safe and disciplined school climate, educational activities at school, and qualifications of teachers.

Also, for the first time in TIMSS 2015, a different factor was put forward that may affect the academic achievement of 4th grade students: "home context". The items in the home survey developed in this direction include factors associated with early learning experiences which are critical in childhood (Teale & Sulzby, 1992).

The fact that the early childhood period has a significant share in the development of academic knowledge and skills in primary school makes the studies on this subject important. Indeed, some studies (Kyriakides, 2006; Blomeke, Suhl & Kaiser, 2011; OECD, 2013) have reported that the interaction between parents and schools affects students' achievement. Scherer and Nilsen (2016) stated that there are a limited number of studies (Seidel & Shavelson, 2007; Wang & Degol, 2015) that address various school-related factors, qualifications of classroom teaching activities, and parental characteristics concerning the international academic achievement.

The present study brings together some family-based factors, early childhood experiences, and some school-related factors with the aim of investigating to what extent these factors affect students' mathematics achievement in primary school.

1.1 The Purpose of the Research

The overall aim of this study is to investigate the effect of school-related factors and early learning experiences on academic achievement (*mathematics achievement*). To this end, answers to the following questions were sought:

1. How much of the differences in students’ mathematics achievements result from the differences between schools?
2. Do students’ mathematics achievement scores differ regarding their early learning experiences? If there are differences, what are the early learning experiences that explain this difference?
3. How much of the variance in mathematics achievement scores is explained by the early learning experiences with significant effects?
4. Do students’ mathematics achievement scores differ regarding school-related factors? If there are differences, which school-related factors explain this difference?
5. How much of the variance in mathematics achievement scores is explained by the school-related factors with significant effects?

2. Method

2.1 Research Model

Since the present study aimed to determine and compare the variables affecting the mathematics achievement scores of the 4th-grade students who participated in TIMSS 2015, it was conducted with the causal-comparative design, one of the quantitative research methods. The causal-comparative design is a research design that seeks to determine the cause or consequences of differences that already exist between or among groups of individuals. In other words, it aims to identify the causal variables that affect the consequence-related variable or the consequences of the cause without any intervention on participants and conditions (Buyukozturk, Cakmak, Akgun, Karadeniz & Demirel, 2011, p. 226; Fraenkel, Wallen & Hyun, 2012). Since the linear relations, as well as strong nonlinear relations, were predicted among the variables, relational screening models were not preferred in order not to fail to notice these relationships (Tabacnick & Fidell, 2001).

2.2 Sample

In the first stage of the implementation of the TIMSS, schools were listed according to their demographic variables. After that, schools were determined from this list using the probability-proportional-to-size sampling method. Then, random branches were selected from the schools (LaRoche, Joncas&Foy, 2016, p. 3.11).

TIMSS 2015 enrolled a total of 6456 Turkish fourth-grade students, the parents of these students (n= 6456), the teachers of these students (n=249), and the principals of schools (n=242)(LaRoche&Foy, 2016). As a result of the preliminary analysis, this study was carried out with data obtained from 6378 parents, 241 primary school teachers, and 241 school principals. Within the scope of the research, average mathematics achievement scores (PV1-5) of 6378 students (3148 girls and 3230 boys) were calculated.

2.3 Data Collection Tools

As indicators of students’ mathematics achievement, the results obtained from the mathematics achievement test in TIMSS (plausible values) were used. A booklet contains an average of 10-15 mathematics questions, half of which is multiple choice and the other half is structured test-item response. The items include the following learning areas: 50% numbers, 35% geometric shapes and measurement, 15% data display. Besides, the cognitive domain distribution of items is as follows: 40% knowledge, 40% practice and 20% reasoning (Martin, Mullis & Foy, 2013).

“Teacher surveys” were used to obtain data on classroom teaching practices and teachers’ characteristics. Of the 21 items, 11 mathematics-related items were filled in by the teachers.

Another part of school-level variables was obtained through the “school survey”. The 22-item survey was filled in by the principals. All the student-level variables were obtained by the “early learning (home) survey”.

This 23-item survey was filled in by parents. The items were on the following topics: home resources that support children's reading and arithmetic skills; literacy in early childhood; children's arithmetic and science skills; parents' educational backgrounds, occupations and attitudes towards science and mathematics (Hooper et al., 2013).

2.4 Data Collection

The data of the study were obtained through the achievement tests and surveys applied to the 4th-grade students in TIMSS 2015 (TIMSS, 2015).

2.5 Data Analysis

2.5.1 Multilevel Analysis

The majority of the data obtained in the studies measuring the qualifications of students are hierarchical (graded) due to the sampling structure or sampling techniques (Atar, 2014). The TIMSS exhibits a hierarchical structure: students are clustered in classes, classes in schools, schools in regions and regions in countries (Hooper et al., 2013). Hox (2002) argues that the application of single-level models for the analysis of data in this structure will cause statistical and conceptual problems.

Multilevel models while working on data with hierarchical structure enables the separation of the variances within groups and between groups. Therefore, more reliable results are obtained since the effects both within and between groups can be analyzed separately. However, since single-level analysis methods require the aggregation of data at a higher level or the disaggregation of data to a lower level (Raudenbush & Bryk, 2002; Heck and Thomas, 2009), group effect is not noticed in the disaggregation model and the individual effect not noticed in the aggregation model. Therefore, the effects of the individual or group cannot be seen (Raudenbush & Bryk, 2002).

One of the basic assumptions of single-level analysis methods is the homoscedasticity. Multilevel models allow the calculation of within-group and between-groups variances associated with dependent variables, enabling an understanding of the effects of the levels (Raudenbush and Bryk, 2002; Hox, 2002; Heck and Thomas, 2009). Another of the basic assumptions of single-level analysis methods is the independence of observations. Osborne (2002) argues that the data obtained for different groups in a hierarchical structure tend to be more similar to each other. In this case, it is impossible to achieve completely independent observations from the students in the same unit. Multilevel models may violate the assumption of independence of observations.

Another statistical problem in the use of single-level models in the analysis of data in a hierarchical structure is that the standard errors of the regression coefficient estimates are underestimated. In this case, the severity of the estimated regression coefficients can be overestimated. In multi-level models, however, this can be eliminated by including a random effect factor (u_{qj}) at each level. Thus, variability in random effects is taken into account, and standard errors can be estimated accurately (Raudenbush and Bryk, 2002).

Due to the statistical advantages mentioned in the analysis of the hierarchical data, the data of this study were analysed by the Hierarchical Linear Modelling (HLM).

2.5.2 HLM Analysis

Level-1 variables in the HLM are student-level variables. Level-2 variables are school-level variables. In the first stage of the analysis, the following steps were applied to the variables included in the home, teacher and school surveys and preliminary analyses were performed. After the data were arranged in line with the purpose of the study, they were included in the HLM analysis.

- *The Arrangement of Data:* "X" refers to Level-1 variables while "W" refers to Level-2 variables. SPSS files were created for student and school-level variables. The category of multi-category variables was reduced to two.

- *Data Cleaning:* By the purpose of the research and relevant literature, some items in the surveys were excluded from the data. Variables with index score were deleted from the data.

- *Correlation between Variables:* Correlation between dependent variables and independent variables was examined, and student and school-level variables not correlated with the dependent variable were checked. Among the independent variables included in the study, there was none that was not correlated with the dependent variable.

- *Multicollinearity:* The correlations of the independent variables in Level-1 were examined to see if there was multicollinearity. Multicollinearity exists whenever there is a correlation value greater than 0.90 (Tabachnick & Fidell, 2001, 88). Among the variables predicted to be included in Level-1, those with a high (> 0.90) relationship were checked. Since no highly correlated variables were found, no variables from the Level-1 file were deleted.

- *Missing Value Analysis*: Firstly, it was checked whether the missing data in Level-1 was systematically distributed. The missing data analysis performed in the SPSS program and the significance of Little's MCAR test showed that the missing data was systematically distributed. If the missing data is below 5%, the listwise method can be applied (Garson, 2008). An alternative to handling missing values for quantitative missing data of over 5% and with systematic distribution in large samples is to make estimations about the missing value *(imputation)* and to use these values in the actual analysis (Cokluk, Olculuoglu & Buyukozturk, 2018, 11). The most common three methods are "the use of past information", "mean substitution", and "regression" (Tabacnick & Fidell, 2001; Mertler &Vannatta, 2005; Cokluk et al., 2018). In this study, the missing data without a random distribution was not deleted (the listwise method was not applied); rather, multiple imputation-MI was conducted by the SPSS regression technique. The advantage of regression over the mean substitution technique is that it is more objective than the prediction made by the researcher and contains more information than simply assigning a mean value (Tabachnick & Fidell, 2001).

➢ *Outlier Removal*: In scientific research, differentiation of any subject from the rest of the sample constitutes an outlier. Especially when working on large samples (n>400), outlier removal procedure is performed to check if there is a value that is left ± 4 points outside after values of continuous variables are converted to Z points (Tabacnick & Fidell, 2001; Mertler & Vannatta, 2005). Once the outliers were removed from the data set, the sample of the study consisted of 6378 students, 6378 parents, 241 schools and 241 teachers.

➢ *Exploratory Analysis*: It was conducted for Level-2 variables. The t-test is one of the best indicators to determine which Level-2 variables will be included in the HLM analysis. The obtained t value shows the approximate result to be achieved when a predictor variable is added to the Level-2 equation. Therefore, if the t value is greater than 1, then the corresponding variable can be included in the analysis (Raudenbush & Bryk, 2002, p. 270). Of the 26 variables associated with mathematics achievement, the t values of 19 variables were significant. All the variables with significant t value were included in the model.

Variables with insignificant t value were excluded from the analysis. Finally, there were 16 student-level variables and 19 school-level variables associated with mathematics achievement.

Variables: The dependent variables were TIMSS 2015 mathematics achievement scores. The independent variables were student-level (Level-1) characteristics (home survey), and school-level (Level-2) characteristics (school and teacher surveys). Table 1 and Table 2 present descriptive statistics of the variables included in the HLM program.

Table 1. Descriptive statistics of Level-1 variables included in the HLM analysis

Variables	N	Mean	SD	Minimum	Maximum
X12	6378	8.42	1.98	0.69	15.03
X13	6378	9.05	2.25	1.52	15.30
X14	6378	9.15	2.39	2.00	15.54
X15	6378	1.05	0.92	0	3
X16	6378	1.54	0.49	1	2
X17	6378	10.65	1.87	3.94	12.45
X18	6378	10.71	1.70	2.47	12.66
X19A	6378	1.25	0.74	1	5
X19B	6378	2.07	1.28	1	5
X19C	6378	1.93	1.27	1	5
PV1	6378	483.174	95.21	114.44	770.91
PV2	6378	482.703	95.58	116.41	766.78
PV3	6378	483.417	95.57	72.05	773.45
PV4	6378	482.573	96.09	84.48	868.08
PV5	6378	483.175	95.87	84.73	784.46

Table 2. Descriptive statistics of Level-2 variables included in the HLM analysis

Variables	N	Mean	SD	Minimum	Maximum
W1	241	9.07	2.01	1.11	16.73
W2	241	8.66	2.23	3.69	12.88
W3	241	2.29	0.80	1.00	3.00
W8	241	15.92	10.43	1.00	42.00
W9	241	10.31	1.75	4.30	12.40
W10	241	0.01	0.99	-1.62	3.17
W12	241	9.29	1.97	2.81	15.82
W13	241	9.67	2.16	3.75	13.41
W14	241	8.95	2.25	3.19	13.57
W15	241	11.48	2.08	5.54	18.41
W16	241	8.77	1.74	3.80	14.51
W17B	241	1.57	0.551	1.00	3.00
W19	241	9.31	2.03	2.81	15.82
W20C	241	2.47	0.76	1.00	4.00
W20D	241	2.88	0.85	1.00	4.00
W20E	241	2.31	0.91	1.00	4.00
W20F	241	1.48	0.74	1.00	4.00
W20G	241	1.59	0.79	1.00	4.00
W20H	241	1.19	0.50	1.00	3.00

“X” is encoded for Level-1 variables and “W” for Level-2 variables. Accordingly, X12 denotes learning resources at home; X13 pre-school learning activities; X14 pre-school skills; X15 level of participation in pre-school education; X16 primary school starting age; X17 parents’ opinions on students’ performance; X18 parents’ attitudes towards science and mathematics; X19A school assignments; X19B parents’ helping with assignment; and X19C parents’ monitoring assignments. For these variables, parents’ responses to the home survey were used. W1 denotes the importance schools attach to academic achievement; W2 a safe and disciplined school environment; and W3 socioeconomic structure of schools. For these variables, principals’ responses to the school survey were used. Furthermore, W8 denotes teachers’ experiences; W9 professional satisfaction; W10 self-confidence in mathematics teaching; W12 teachers’ perceptions about the importance that schools attach to academic achievement (teachers); W13, perceptions of a safe and disciplined school structure (teachers); W14 problems related to school facilities and resources (teachers); W15, difficulties encountered (teachers); W16, limited education due to students’ needs; W17B feedback on mathematics homework; W19 emphasis on research; 20C use of interesting material *s;*20D challenging activities; 20E classroom discussions; 20F connection between new contents-previous contents; 20G deciding on problem-solving durations; and 20H expressing thoughts. For these variables, teachers’ responses to the teacher survey were used.

- *Assumptions of HLM*: Following preliminary analyses, the assumptions were first checked for HLM analysis. Using the data from the residual files created for Level-1 and Level-2, the normal distribution of residues, their homogeneity and their relations with each other were investigated. The results of the Shapiro-Wilk test for the normality of residues at both levels were significant (*p* =0,000); Skewness and Kurtosis values within the range of +1 to -1 (±1) indicate that the residues at both levels did not show large deviation (Cokluk, Sekercioglu & Buyukozturk, 2012). The residues in Level-1 showed a homogeneous distribution close to normal and the variables were independent of " r_{it}", which is the error term at this level, and of random effects at other levels. For Level-2, the slope coefficients of the cut-off point and variables at this level showed a normal distribution. The variables were independent of “u_{0j}”, which is the error term at this level. Also, Level-2 errors show multiple normalities with an average of zero. Therefore, the assumptions of HLM for Level-1 and Level-2 were met.

- *Construction of Multivariate Data Matrix (MDM) Files*: According to the results of the assumptions, MDM files were created in the HLM program, and the models related to answering the research problems were analysed through these files.

- *Centering the variables*: In the study, centering was performed to eliminate the bias caused by the multicollinearity problem (Raudenbush & Bryk, 2002). For the continuous variables in Level-1 and Level-2, grand-mean centering was performed; and for the categorical variables in both levels, un-centering was performed.

- *Random and Fixed Effects:* In the two-level Hierarchical Linear Model, student-level (Level-1) variables were randomly assigned to the second model to test the significance of the error terms of the variables. The variables with significant error terms (*u0j*) were randomly assigned to model 3 where the intersection and slope coefficients were output; the variables with insignificant error terms (*u0j*) were fixed to the model.

- *Effect Size*: To determine whether the interpretations as a result of the data analysis indicated significance about daily life, the effect size calculation was performed by dividing the constant coefficients obtained by the analysis conducted at each level to the standard deviation of the residual value at the corresponding level. An effect size of 0.41 is considered "minimum", an effect size of 1.15 is considered "medium", and an effect size of 2.70 is considered "large" (Ferguson, 2009).

With the completion of preliminary analyzes, HLM models were established. To answer the research problems, SPSS-based HLM 7.01 program developed by Raudenbush and Bryk (2002) was used, and the models were tested.

2.5.3 HLM Models

1) One-Way ANOVA with Random Effects: With this model, the question "How much of the differences in students' mathematics achievements result from the differences between schools?" was answered. Also, it was checked whether the HLM is suitable for the analysis of the data. In this model, there is no explanatory variable for Level-1 or Level-2 (Hox, 2002). Model equations are as follows (Raudenbush & Bryk, 2002).

$$\text{Level 1: } Yij=\beta0j+rij \quad (1)$$

$$\text{Level 2: } \beta0j=\gamma00+u0j \quad (2)$$

Here,

"Yij" denotes the i student's mathematics achievement score at the j school;

"$\beta0j$" denotes the average mathematics achievement score of the j school,

"rij" denotes the error score of the i student at the j school, i.e. the difference between the i student's average mathematics achievement score and the j school's average mathematics achievement score. It is assumed that the error score at each student level is normally distributed with "0" average and fixed *Level-1* ($\sigma2$) variance.

"$\gamma00$" denotes the average mathematics achievement scores of the schools;

"$u0j$" denotes the error score of the j school, i.e. the difference between the average mathematics achievement score of the j school and the general average mathematics achievement score. It is assumed that the error score at each school level is normally distributed with "0" average and "$\tau00$" variance. An u0j value close to zero means that there is very little difference between schools.

2) Random Coefficients: In this model, student variables associated with mathematics scores were assigned to the Level-1 to determine which student-level variable affects mathematics achievement score. Level-2 variables are not included in this model (Raudenbush&Bryk, 2002). Equations of the model are as follows.

$$\text{Level 1: } Yij=\beta0j+\beta1jX_{ij}+rij \quad (3)$$

$$\text{Level 2: } \beta_{0j}=\gamma_{00}+u_{0j} \quad (4)$$

$$\beta_{1j}=\gamma_{10}+u_{1j}$$

Here,

"$\beta1j$" denotes expected change in the average mathematics achievement scores for a one-unit change in the corresponding independent variable at the j school (when other predictive variables are controlled);

"X_{ij}" denotes the value of the independent variable for the I student at the j school;

"$\beta1j$" denotes expected change in the average mathematics achievement scores versus one-unit change in the corresponding independent variable at the j school (when other predictive variables are controlled);

"$\gamma10$" denotes the average school slope for the corresponding variable at the school level (the effect of the corresponding variable on the mathematics achievement score of the *j* class);

"$u1j$" denotes the effect of the j school on the Level-1 slope.

3) Intercepts and Slopes as Outcomes Model: To Level 1 of this model established to answer the questions 4 and 5, student-level variables, and to Level 2, school-level variables were assigned. Then, the HLM analysis was performed. School-level variables associated with mathematics achievement scores were determined. Also, the relationship between school-level variables and student-level variables could be observed. Equations of the model established in this direction are as follows (Raudenbush&Bryk, 2002):

$$\text{Level 1: } Y_{ij}=\beta_{0j}+\beta_{ij}X_{ij}+r_{ij} \quad (5)$$

$$\text{Level 2: } \beta0j=\gamma00+\gamma01(W_j)+u0j \quad (6)$$

$$\beta1j=\gamma01+\gamma11(W_j)+u1j$$

Here,

"$\gamma 00$" denotes Level-1 intercept in the case any school has a value of 0 in the corresponding independent value (W=0);

"$\gamma 01$" denotes the estimated effect of a unit change in the corresponding school-level variable on average mathematics achievement scores when other predictive variables in the model are controlled;

"W_j" denotes the corresponding independent value at school-level;

"$\gamma 10$" denotes the estimated Level-1 slope for a group with W=0;

"u1" denotes the effect of the j school in Level-1 slope when W*j* is kept constant

3. Results

3.1.1 Research Problems

Table 3a. and Table 3b. present the results of the analysis of the One-Way ANOVA with Random Effects conducted to determine whether there is a difference between the mathematics achievement scores of the schools in TIMSS 2015.

Table 3a. One-Way ANOVA Fixed Effects Model Analysis Results

Fixed Effects	Coefficients	Standard Error (SE)	*T*	Approximate *s.d.*	*p*
Cut-off Point, $\gamma 00$	481.49*	3.98	120.97	240	0.000

**p* <0.05

According to Table 3a., the average mathematics achievement score can be estimated as 481.49 with a standard error of 3.98. When the confidence interval is calculated for the estimated overall averages [%95CI($\gamma 00$)=$\gamma 00 \pm$ (1.96)(SH)], the real value of the average mathematics achievement scores is expected to be between 483.45 and 479.53. Furthermore, the reliability coefficient of the overall average of mathematics achievement scores was 0.927. According to these results, fixed parameters were significant ($p < 0.05$). Mathematics achievement varies significantly between schools. In this respect, the data has a nested structure, and therefore it should be analysed with multilevel models.

Table 3b. One-Way ANOVA Random Effects Model Analysis Results

Random Effects	Standard Deviation	Variance Component	s.d.	$\chi 2$
Level -2, (u_0)	59.56*	3547.72	240	4435.79
Level -1, (r_{ij})	74.31	5522.79		

**p* <0.05

In Table 3b, intra-school variability ($\sigma 2$) on average mathematics achievement score was estimated as 5522.79 while the inter-school variability ($\tau 00$) was estimated as 3547.72 ($\chi 2$ =4435.79, s.d.=240). The extent to which the variability between mathematics achievement scores is explained by the levels is calculated using the inter-class correlation (ICC) (Raudenbush & Bryk, 2002).

$$\rho=\sigma 2/(\tau 00 + \sigma 2): 5522.79/ (3547.72+5522.79)=0.60 \tag{7}$$

$$\rho=\tau 00/(\tau 00 + \sigma 2): 3547.72/(3547.72+5522.79)=0.40 \tag{8}$$

Accordingly, 40% of the total variability in the mathematics achievement scores is due to the differences between schools, and 60% is due to the differences between students.

3.2 Research Problems

According to the results of the analyzes of the Random Coefficient-Regression Model established to find answers to the 2nd and 3rd problems, six student-level variables [parents' monitoring children's assignments (X19A), parents' helping children with their assignments (X19B), learning resources at home (X12), pre-school learning activities (X13), pre-school skills (X14), parents' attitudes towards science and mathematics (X18)] have significant effects on mathematics achievement scores ($p < 0.05$) while four variables [parents' control of children's assignments (X19C), parents' views on school performance (X17), level of participation in pre-school education (X15), primary school starting age (X16)]] do not have significant effects ($p > 0.05$).

The variables with insignificant effects on mathematics achievement scores [X19C ($\gamma 80=4.98$, $SH=2.10$, p >0.05), X17 ($\gamma 80=4.98$, $SH=2.10$, p >0.05), X15 ($\gamma 80=0.43$, $SH=1.18$, p >0.05), ve X16 ($\gamma 80=2.21$ $SH=2.24$, p>0.05)] were excluded from the analysis and the Final Random Coefficient Regression Model was established. The results of the fixed effects and variance components of the final model obtained by the final analysis are given below.

Table 4a. Estimation of Fixed Effects of Random Coefficient Regression Model

Fixed Effects	Coefficients	Standar Error	t	Approximate sd	p	Effect Size
Cut-off point1, β_0 Cut-off point2, $\gamma 00$	481.42	3.99	120.64	240	0.000	-----
X19A Slope, β_1 Cut-off point2, $\gamma 10$	-3.96	1.86	-2.12	130	0.035	-0.05
X19B Slope β_2 Cut-off point2, $\gamma 20$	2.91	0.96	3.03	57	0.004	0.03
X12 Slope, β_4 Cut-off point2, $\gamma 40$	11.78	0.76	15.37	240	0.000	0.15
X13, β_5 Cut-off point2, $\gamma 50$	4.79	0.76	15.37	240	0.000	0.06
X14 Slope, β_6 Cut-off point2 $\gamma 60$	4.31	0.54	7.84	240	0.000	0.05
X18 Slope, β_8 Cut-off point2, $\gamma 80$	1.03	0.65	1.58	240	0.114	-----

According to Table 4a., the average mathematics achievement scores of the schools as a result of the variables in the analysis is 481.42. This value reflects a student's score if the student's other variables in the model are equal to the average value of the group.

"Learning resources at home (X12)" variable has the highest effect on the average mathematics achievement of schools. *(β_4)* was estimated to be approximately 11.78 with a standard error of about 0.76. Since the *p*-value of this coefficient was statistically significant ($p<0.05$, sd.=240), when the other variables in the model are controlled, a one-unit increase in learning resources at home may result in an 11.79 unit increase in the students' mathematics achievement scores. Furthermore, the average mathematics achievement score of students with a lot of learning resources at home is 11.79 units more than the students with less learning resources at home. When a 95% confidence interval for (β_4) is generated, its actual value is expected to be in the range of 13.75 to 9.83. Considering its sie (0.15), the effect of this variable is too small to be felt in daily life.

The variable "parents' helping the children with their assignments (X19B)" has the lowest effect on the average mathematics achievement of schools $\gamma 20=2.91$, $SH=0.96$, $p<0.05$). Finally, the variable "parents' attitudes towards Science and Mathematics (X18)" does not significantly affect students' academic achievements ($\gamma 60=1.03$, $SH=0.65$, $p>>0.05$).

Table 4b presents the estimation of the variance components of the Final Random Coefficient-Regression Model to determine how students' mathematics achievement scores differ between schools according to their early learning experiences.

Table 4b. Estimation of the Variance Components of the Final Random Coefficient Regression Model

Random Effect	Standard Deviation	Variance Component	s.d.	$\chi 2$	p
Level-2 Error Term, u_{0i}	59.912	3589.55	209	5120.00955	0.000
X19A Slope, u_1	11.202	125.49	209	125.49005	0.034
X19B Slope, u_2	3.635	13.21	209	204.46677	>.500
X12 Slope, u_3	6.140	37.71	209	265.42784	0.005
X13 Slope, u_4	3.175	10.08	209	218.24732	0.316
X14 Slope, u_5	3.286	10.80	209	240.56226	0.066
X18 Slope, u_6	4.697	22.06	209	247.60361	0.035
Level-1 Error Term, *rij*	67.968	4619.66			

According to Table 4b, *random effects of u1, u3, u6* coefficients are significant ($p<0.05$). The residual variance at student level (4619.66) is smaller than the variance (5522.79) obtained in the ANOVA model. This indicates that the difference between the students in mathematics achievement scores decreases by the addition of early learning experiences.

In line with the "[*(5522.79-4619.70)/5522.79]=* 0.16" *value obtained by the "* [σ2(ANOVA)-σ2(Final Random Coefficient Model)]/σ2(ANOVA)] " operation to explain how the inclusion of determined student-level variables in the model reduces the random error variance at the student level, 16% of the differences between students' mathematics achievement scores (60%) is explained by parents' monitoring their children's assignments, parents' helping with their children's assignments, learning resources at home, pre-school learning activities, and pre-school skills. The remaining 84% of the variance can be explained by other student-level variables not included in this model.

3.3 Findings on the 4th and 5th Research Problems

To answer the 4th and 5th questions, HLM analysis was established in which the intersection and slope coefficients were the dependent variables. According to the analysis of the model, the variables included in the model [the importance the school attaches to academic achievement (W1) *($\gamma01=7.57$, SH=1.96, p* <0.05), a safe and disciplined school environment (W2) *($\gamma02=3.60$, SH=1.46,* p<0.05), socioeconomic *structure of the school (W3) ($\gamma03=-10.54$, SH=4.51, p* <0.05), teachers' *experiences (W8) ($\gamma04=1.47$, SH=0.306, p<0.05), and teachers' perceptions of* the importance *that the school attaches to academic achievement (W12) ($\gamma14=5.73$, SH=2.33, p* <0.05)] significantly affect students' mathematics achievement.

The variables with insignificant effects were excluded from the model, and the analyses were repeated. The final model was established only with the variables with significant effects. Table 5a presents the results of the final analysis.

Table 5a. Estimation of Fixed Effects of the Final Model where the Intersect and Slope Coefficients were Output

Fixed Effects	Coefficients	Standard Error	t	*p*	Effect Size
Average Mathematics Achievement, $\beta0$ Fixed$\gamma00$	481.322	3.00	160.113	0.000	-----
W1, $\gamma01$	8.530	1.88	4.528	0.000	0.14
W2, $\gamma02$	3.482	1.39	2.504	0.013	0.05
W3, $\gamma03$	-10.276	4.37	-2.348	0.020	0.17
W8, $\gamma04$	1.518	0.29	5.517	0.000	0.02
W12, $\gamma014$	5.829	1.72	3.378	0.001	0.09
X19A Model for Slope, $\beta1$ Fixed, $\gamma10$	-4.09	1.88	-2.174	0.031	-----
X19B Model for Slope, $\beta2$ Fixed, $\gamma20$	2.955	0.94	3.126	0.000	-----
X12 Model for Slope, $\beta4$ Fixed, $\gamma40$	11.865	0.76	15.514	0.000	-----
X13 Model for Slope, $\beta5$ Fixed, $\gamma50$	4.830	0.68	7.047	0.000	-----
X14 Model for Slope, $\beta6$ Fixed, $\gamma60$	4.162	0.50	8.316	0.000	-----
X18 Model for Slope, $\beta8$ Fixed, $\gamma80$	0.914	0.66	1.369	0.172	-----

The socioeconomic structure of the school (W3) has the highest impact on the average mathematics achievement of schools. However, this effect is negative. After controlling other variables in the model, the effect of the variable on the average mathematics achievement of schools was estimated as -10.276; the standard error of the estimation is 4.37. A one-unit increase in schools where students with poor economic background are enrolled will cause a decrease of 11 points in mathematics achievement scores. The effect (0.17) of the variable with a statistically significant (*p* <0.05) effect on mathematics achievement is felt at a moderate level in daily life.

The variable "teachers' experiences" (W8) has the lowest impact on the average mathematics achievement of schools. After controlling other variables in the model, the effect of W8 on the average mathematics achievement of schools was estimated to be 1.51. A one-unit increase in teachers' experience variable will produce an increase of approximately 1.50 points in students' mathematics achievement scores. The effect of the variable with a statistically significant effect (*p* <0.05) on mathematics achievement is felt at a moderate level in daily life.

Also, considering the coefficients of the *variables* associated with early learning experiences in this final model, there is no significant change in the gamma (*β*) coefficients *compared to the previous models (($\beta1=-4.09$, $\beta2= 2.95$, $\beta3=11.86$, $\beta4=4.83$, $\beta5=4.16$ and $\beta6=0.91$)* and their significant effects are continuing. Table 5b presents the estimation of the variance components of the final model, where the intersection and slope coefficients are the dependent variables.

Table 5b. Estimation of the variance components of the Final Model, where the intersection and slope coefficients are the dependent variables

Random Effect	Standard deviation	Variance Component	s.d.	$\chi2$	*p*
Level-2 Error Term, u_{0j}	43.93	1930.19	208	2650.240	0.000
X19A, u_1	11.81	139.49	213	288.601	0.001
X12, *u3*	6.11	37.36	213	310.163	0.000
X18, *u6*	5.03	25.32	213	289.095	0.001
Level-1 Error Term, *rij*	68.47	4689.20			

When the variance components of the model were examined, the variance of the average mathematical achievement of schools (residual variance) was determined as 1930.19 after controlling X19A, X12, and X18 at the school level. For average mathematics achievements, the variance ratio index explained by "[$\tau 00$ (Model 2)- $\tau 00$ (Model 3) / $\tau 00$ (Model 2)]" was calculated between the estimated variance values of Random Coefficient Regression Model (Model 2) and the Model where the Intersect and Slope Coefficients are output

This value (46%) shows that about 46% of the differences between schools in mathematics achievement (40%) are explained by school-level variables (W1, W2, W3, W8, and W12) with significant effects. The remaining 54% of the variance can be explained by other school-level variables not included in this model.

Also, 40% of the difference between mathematics achievement scores can be explained by differences between schools according to the results of One-Way ANOVA Random Effects. Accordingly, 18% of the students' mathematics achievement (%40*%46) can be explained by the school-level variables.

4. Discussion and Conclusion

Considering the objectives and theoretical approach of the study, ten variables from the parent survey and 19 variables from the teacher and school survey were included in the HLM analysis.

Firstly, the extent to which the levels explain the differences in mathematics achievement scores was investigated. Recent meta-analysis studies (Sirin, 2005; Hattie, 2009) indicate that the predictions of differences in students' achievement are divided into two. Some studies (Yilmaz & Aztekin, 2012; Mohammadpour & Abdul Ghafar, 2014; Ipekcioglu Onal, 2015) reported that school-level variables explain most of the differences in students' achievement. There are also some studies (Ryoo, 2001; Akyuz&Berberoglu, 2010; Aydin, 2015) suggesting that school-level variables explain a part of the differences in students' achievement. In this study, student-level variables explain a large part of the variance in mathematics achievement scores. It can, therefore, be argued that various student-level factors in Turkey affect academic achievement more.

The second part of the study examines the effects of early learning experiences on mathematics achievement scores. A meta-analysis of the studies on student-level factors associated with students' achievement (Marzano, 2003; Hattie, 2009) indicates that student-level factors have a high impact on the determinants of academic achievement. According to Hox (1995), student-related features forming the basis of measurement activities in education may be students' attitudes, readiness, interests, etc. in a certain subject. The factors associated with students' parents, school and class affect these features. Nilsen, Gustafsson, and Blomeke (2016) state that students' past experiences and characteristics have a significant impact on the student outputs. Schmidt and Cogan (1996) argue that parents' educational backgrounds, learning activities at home, and educational resources also affect students' achievement. Dewald, Meijer, Oort, Kerkhof, and Bogels (2010) stated that educational conditions at home and socio-economic levels of parents affect students' achievement. Bradley and Corwyn (2002) state that students who are advantageous regarding learning resources at home are more successful at school than others. Furthermore, a positive parent-child relationship has a positive effect on academic achievement (Dahl&Lochner, 2005).

Given these studies, it is possible to bring together the variables that affect students' achievement under the heading of early learning experiences (Epstein, 1992; Huira, 1996; Arnold, Zeljo, Doctoroff & Ortiz, 2008). Therefore, learning resources at home, pre-school skills, early learning activities, and healthy parent-child relationships about the child's assignments are examined in studies on early learning experiences (Epstein, 1992). As a result of this study, the variables with significant effects on academic skills are consistent with the literature on the components of early learning experiences.

To determine the extent to which parents support the learning process, Akyuz (2006) examined the relationship of parental involvement with academic achievement. Uninvolved parenting, evaluated as a limitation in the teaching process, has a negative effect on academic achievement. However, according to the results of this research, parents' monitoring their children's assignments has significant negative effects while parents' helping with students' assignments has positive effects on achievement. Therefore, the fact that students' achievement increases as their parents help with their assignments is consistent with the findings of Akyuz (2006). However, another finding of this research is that the academic achievement of students whose parents monitor their assignments is lower than that of those whose parents do not. Students may be displeased with parental monitoring, and their achievements may be negatively affected by this. If the parents who do not monitor their children's assignments are considered as "neglectful", then the findings of the present study are not consistent with those of Akyuz (2006).

Besides, the results of the study indicate that the attitudes of parents toward the courses have no significant effect on academic achievement. Lyons (2006) states that students' attitudes towards science and mathematics and hence their performance in these courses are influenced by their parents' perspectives on these courses. Parents' positive attitudes towards science and mathematics increase students' science and mathematics achievement. Ipekcioglu Onal (2015) found insignificant relationships between parental involvement and students' achievement. The results of this study are partly consistent with previous studies because parents' attitudes towards science and mathematics have insignificant effects on students' achievement.

In the final part of the study, the effects of school-level factors on mathematics achievement scores were examined. The importance that the school attaches to academic achievement (responses of principals), teachers' perceptions about it, and a safe and disciplined school environment have significant effects on academic achievement. The meta-analysis study by Hattie (2012) reported the significant effects of school-related factors on academic achievement. In their study on the determinants of student outputs, Nilsen et al. (2016) stated that the importance attached by schools to academic achievement, perceptions of teachers about it, and a safe and disciplined school environment affect students' achievement.

Some studies (Buluc, 2014; Olculuoglu & Cetin, 2016) stated that the importance of the safe and disciplined school environment and the importance that schools attach to academic achievement significantly affect academic achievement. Furthermore, some studies (Freiberg&Stein, 1999; Stanco, 2012) reported a low academic achievement in schools where incidents of property damage and theft, and threats and verbal abuse among students frequently occur. Nilsen and Gustafsson (2014) argued that a safe and disciplined school environment would also enhance the school's emphasis on academic achievement and make it easier to focus on learning. Therefore, the results of the present study are consistent with those of previous studies.

The socioeconomic structure of the school is also one of the variables with significant effects. Agirdag, Van Houtte and Van Avermaet (2012) stated that students from poor socio-economic backgrounds are more likely to develop apathy towards school, arguing that academic achievement is negatively affected by this situation. One of the variables with significant effects is the experience of teachers. Akyuz (2006) and Atar (2014) stated that teachers' experiences do not have significant effects on students' achievement. However, there are also studies reporting that teachers' experiences have significant effects on students' achievement (Rice, 2003; Leigh, 2010; Harris & Sass, 2011).

According to the results of this research, students' academic performance varies from school to school in Turkey. The most important reason for this variance is socioeconomic factors. Similarly, the academic performance of students varies according to the educational conditions, especially in the early childhood period. International studies such as TIMSS allow countries to compare the academic performance of students at a global level. Another contribution of TIMSS to countries is that it provides policymakers with information on how much of the differences in the performance levels of participating students result from regional differences and how much from socioeconomic differences. This information is essential regarding equal opportunities in education. Therefore, the results of this research can provide some ideas to the relevant institutions and organizations in Turkey on educational practices. The findings of this study support the need for preschool education and the steps to be taken in the education of families in Turkey. Similarly, it can also be inferred from the findings of the research that students' motivation and achievement will increase as a result of efforts by principals and teachers on academic achievement. In this regard, to ensure and maintain a positive climate in schools, all the officials, principals and teachers in particular need to undertake fundamental responsibilities and take beneficial steps. The findings of the study are also of particular concern to parents. Important effects of parent-child communication on students' academic achievements highlight the importance of school-family cooperation and parent-centered activities both in pre-school and primary school periods.

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