Learning and Individual Differences 88 (2021) 102005

Contents lists available at ScienceDirect

Learning and Individual Differences

journal homepage: www.elsevier.com/locate/lindif

Overlearning is as ineffective as underlearning? A cross-culture study from PISA 2015☆

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A R T I C L E I N F O

Keywords:
Learning time
Science achievement
Culture
PISA 2015
Quadratic relation

A B S T R A C T

To better describe the previous findings of inconsistency in the relationship between learning time and academic achievement, we tested new models with different shape and pattern to find what might be the optimal describing pattern between the two concepts. Selected from a large-scale international database – the Program for International Student Assessment (PISA) 2015, science learning time and its corresponding achievement was chosen as an empirical illustration. We further tested if culture could moderate this relationship. Using a multilevel model, it was found that (i) there was a quadratic relationship between learning time and science achievement: science achievement rose with an increase in learning time before an optimal point, and fell when the learning time extended beyond that point; (ii) there was a difference between eastern and western leaners on the quadratic relationship, as eastern learners' performance increased and decreased more sharply with the change of time than that of the western counterparts.

1. Introduction

Academic achievement has always been one of the hottest topics of pedagogy and educational psychology. It is associated with various factors, including but not limited to students' intelligence, gender, personality, learning motivation, socioeconomic status (SES), class and school environment, and not least by learning time (Zhu, 2011). As the social competition is increasingly fierce, it seems necessary for students to be competitive in academic achievements to achieve a bright future, such as getting into a top university, obtaining an estimable job, and so on (Tang & Fu, 2008).

Among various methods of improving academic achievements, extending learning time is regarded as one of the efficient and direct facilitators. However, the relationship between learning time and academic achievement might not be a simple linear one (Plant, Ericsson, Hill, & Asberg, 2005), yet the different composition of learning time, such as engaged time, provided learning time, realized learning time, and so on, might lead to divergent conclusions (Dolton, Gutiérrez, & Navarro, 2003; OECD, 2017). The present study aims to explore the relationship between *engaged* science learning time and science achievement by using a large-scale international database (the Program for International Student Assessment, PISA, OECD, 2017). We proposed a new model to provide an alternative description for the previous inconsistent findings. Besides, we compared the cultural difference in such a description.

1.2. *The relationship between learning and academic achievement*

It could be traced back to the early 20th century when researchers started exploring the relationship between learning time and academic achievement, which then flourished in the 1970s (e.g., Fisher et al., 1978). A general consensus has been reached: learning time is indeed an important facilitating factor of academic achievement (e.g., Gándara, Rumberger, Maxwell-Jolly, & Callahan, 2003; Patall, Cooper, & Allen, 2010; Scheerens & Bosker, 1997; Seidel & Shavelson, 2007). Many studies have repeatedly confirmed that learning time is positively

☆ This work was supported by the National Natural Science Foundation of China under Grant 31800950; Beijing Key Lab of Applied Experimental Psychology Opening Foundation; and Chongqing Social Science Planning Fund (2019QNJY44).The data are from the official website of PISA. Data can be retrieved from http://www.oecd.org/pisa/data/2015database/.

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https://doi.org/10.1016/j.lindif.2021.102005
Received 8 March 2020; Received in revised form 8 April 2021; Accepted 13 April 2021
Available online 28 April 2021
1041-6080/

related to academic achievement. For example, after analyzing 15 major empirical studies on related topics in the past 24 years in the United States, it was found that extending curriculum time could effectively improve students' academic achievements in various subjects, especially for students with a low SES or academic level (Patall et al., 2010). Another example is from the International Association for the Evaluation of Educational Achievement (IEA) who organized the Trends in International Mathematics and Science Study (TIMSS) and found that the instruction time in mathematics was positively correlated with participants' academic achievements in mathematics which was stable across countries and cultures (Martin, Mullis, Foy, & Stanco, 2012). Moreover, in PISA 2015 published by Organization for Economic Cooperation and Development (OECD) (2016), for most education systems in OECD countries, the more time students spent on science class, the higher science scores they got, even when controlling the socioeconomic conditions of students and schools. In OECD countries, every extra hour spent on science class by students could induce an increase of 5 points in marks ($M = 500$, $SD = 100$).

However, the promotional principle of learning time is not always supported: some research found that learning time was negatively related to academic achievement. For example, Kember, Jamieson, and Wong (1995) found that although the average weekly learning time of students (including class and independent study) was as high as 65 h, they would still get low Grade Point Average (GPA) when they blindly followed instructions without meaningful understanding. Plant et al.'s (2005) study recorded students' learning time in- and off-campus (e.g., at home, library, and so on) and found that the total learning time was negatively related to students' GPA and Scholastic Assessment Test (SAT) scores.

More complicated relationships were found to be neither positive nor negative. Some studies found no relationship between learning time and academic achievement (Masui, Broeckmans, Doumen, Groenen, & Molenberghs, 2014). For example, although the average daily total learning time of out-of-US-born students was 50 min longer than that of US-born students, no significant difference observed between their average grades (Eliasson, Eliasson, & Lettieri, 2016). Other researchers found a nonlinear relationship between learning time and achievement. This is evidenced by Tang and Fu (2008) who suggested an inverted U-shape relationship between the time used to finish homework and test scores of Chinese, math, English, and science. Moreover, Grade 4 and Grade 7 students could achieve their best performance by completing homework in 1 or 2 h per day, but their performance would drop if the time went either below or above that period.

The above inconsistency of the relationship between learning time and the performance is influenced by the types of learning time, types of achievements, sampling of studies, among others (Baker, Fabrega, Galindo, & Mishook, 2004; Ghuman & Lloyd, 2010). Though the contexts of studies varied, time boundary mighty play a universal role among them, and the difference on time boundary might be the reason of inconsistent results. For example, in the research conducted by Dolton et al. (2003), they tracked the learning time of students in a Spanish university and found that the formal learning time ($M = 4.03$ h per day, $SD = 1.19$) could positively predict the test scores. Another study using a similar way to measure the learning time based on Chinese university students found that there was no correlation between class time ($M = 4.59$ h per day, $SD = 2.26$) and science achievement (Wang, 2008). The mean and standard deviation of learning time in Dolton et al.'s (2003) research was smaller than that in Wang's (2008) research, which might partially imply the important role of the time boundaries.

1.3. The cultural difference on the relationship between learning time and achievement

There usually exists difference in terms of learning time in different culture, which is usually a fascinating topic among educational settings (e.g., Li, 2012; Liu, Hau, & Zheng, 2020; Tweed & Lehman, 2002). Among the theories distinguishing different kinds of culture, the Confucian-Socratic framework is widely used (Tweed & Lehman, 2002). It classifies the East Asian regions, such as China, Japan, and South Korea, which are widely affected by Confucianism, as eastern cultures (Huntington, 1996; Watkins & Biggs, 1999); in contrast, the British Commonwealth and North America are part of western cultures (Huntington, 1996; Li, 2012). The eastern learners have longer learning time than western learners as congruently showed in the previous literatures (e.g., OECD, 2016; Stevenson & Stigler, 1992; Watkins & Biggs, 1999). For example, the relevant report of PISA 2015 also showed that students in eastern countries such as China, South Korea, and Thailand spent at least 30 h per week on regular courses, which was in the top of the time cost of learning among OECD countries, but students in western countries like Finland spent less than 25 h per week on regular courses (OECD, 2016). As for science class, the learning time of 15-year-old students in China or Singapore spent in school per week was at least twice than that in Iceland, Ireland, or Norway (OECD, 2016).

Although eastern students seem to have longer learning time compared to the westerners, they often do not suffer from it. Researchers have proved that East Asian learners emphasized the virtue of diligence, including diligent learning. Li (2003) used the prototype method to compare eastern and western learners' different understandings about learning. In the study, Li found that Chinese students mentioned a great number of hard-working concepts when asked to recall Chinese words related to learning virtue; this seldom happens from western learners. In another study, Li, Fung, Liang, Resch, and Lou (2008) compared the dialogues of Taiwanese mothers and European mothers with their children and found that Taiwanese mothers were more inclined to help their children develop a studious attitude.

Nevertheless, excessive learning time makes learning like a burden for students (Tang & Fu, 2008). Through a sample survey of junior high schools in seven cities in China, researchers found that 64.2% of students learned too long or attended cram schools, and up to 97.7% of students lacked sleep or exercise. Won (1989) also found that Korean eighth and eleventh graders were occupied with schoolwork for 47% of the random time samples. However, comparable rates of schoolwork for studies employing the same methodology were only 25% to 29% for U.S. adolescents (Csikszentmihalyi, Rathunde, & Whalen, 1993). Such high-intensity academic pressure is likely to cause psychological problems, such as depression, anxiety, and other negative affect. (Li, Tang, Zhang, Weng, & Wang, 2009).

1.4. The present study

Given the inconsistent findings on the relationship between learning time and academic achievement, the current study aims to provide a new perspective on that relationship. As science is the major domain in PISA 2015 (OECD, 2017), we pay more attention to this domain. First, we propose a descriptive model that would inclusively illustrate the inconsistent findings on the relationship between science learning time and science achievement. We believe that the relationship between science learning time and science achievement may not be a simple linear one. Instead, there is probably a most appropriate learning time, called the *optimal point*, before which learning time and science achievement have a positive correlation and the relationship turns negative thereafter. Particularly, we pay more attention to *time boundary* that helps build different sub-models to understand the nuances.

Second, we propose an interactive cultural model to test if there are some cultural differences in such an influence between learning time and science achievement. As mentioned above, since eastern learners respect diligence, they would probably more quickly reach to the optimal learning time compared to the western learners. However, after reaching the optimal learning time, science achievement will decline dramatically with the increase in time because of the negative impact of academic burden.

2. Method

2.1. Participants and data

Organized by the OECD, the purpose of the PISA is to establish and use unified international criteria to collect the personal, family, and school information of 15-year-old students from participating countries jointly. In the international arena, students usually end their compulsory education around the age of 15. Thus, for the sake of investigating academic achievement, monitor the educational results of various countries, and provide practical suggestions for educational policies, 15-year-old students are chosen for the PISA (OECD, 2017).

In the present study, 75,404 valid participants were selected from 8 countries or regions. According to Huntington's (1996) research, we chose four East Asian countries and regions – Japan, South Korea, Singapore and Chinese Taipei – as representations of Eastern culture. The other four countries were counterbalanced as Western cultural ones, consisting of Canada, Britain, Australia, the United States (see Table 2 for the sample size of each country or region).

2.2. Measures

2.2.1. Learning time

The science learning time, named *smins* in PISA 2015, refers to the engaged learning time of students was obtained on science courses since it excluded the wasted time caused by non-teaching activities (OECD, 2017). The averaged *smins* of OECD countries and regions in PISA 2015 was 223.42 min per week, and the standard deviation was 158.13 min. According to this mean and standard deviation, science learning time was standardized. The squared standardized time ($ztime^2$) was used in the quadratic model.

2.2.2. Science achievement

We chose the science score in PISA 2015 as the indicator of science achievement. PISA 2015 defined scientific literacy as "the ability to engage with science-related issues, and with the ideas of science, as a reflective citizen" (OECD, 2017). This score is measured according to the following three specific science-related capabilities: (a) the ability to explain phenomena scientifically through understanding, providing and evaluating explanations for a series of natural phenomena and technological products; (b) the ability to evaluate and design scientific inquiry through scientifically describing and appraising scientific research and providing methods to solve problems; and (c) the ability to interpret data and evidence scientifically by analyzing and evaluating the data, claims, and arguments in various ways of representations and drawing appropriate scientific conclusions (OECD, 2017). The score had a mean of 469.49 and a standard deviation of 102.37 among the selected participants.

2.2.3. Culture

Culture was a moderator coded as a binary variable where 0 indicated western culture and 1 indicated eastern culture. We classified Canada, United Kingdom, Australia, and the United States as western cultures and Japan, South Korea, Singapore, and Chinese Taipei as eastern cultures (Liu et al., 2020; Marsh, Hau, Artelt, Baumert, & Peschar, 2006). The interactive model included the multiplied term between the cultural variable and the squared term of the standardized time ($ztime^2$) and the standardized time (*ztime*): $cul * ztime^2$ and $cul * ztime$.

2.2.4. Controlling variables

Many researchers have found that SES and gender also have significant effects on science achievement (Cheryan, Master, & Meltzoff, 2015; Liu et al., 2020; Marsh & Yeung, 1998; Perry & McConney, 2010; Sánchez, Miguélañez, & Abad, 2019). Therefore, in this study, we chose the *index of economic, social and cultural status*, and *student gender* of PISA 2015 as the control variables.

2.3. Analytical methods

In order to control the group difference, we used the multilevel model (MLM) to explore the relationship between learning time and science achievement. In Model 1, the *intraclass correlations* (ICC) in the null model were large in the corresponding countries, indicating considerable between school differences (see Table 1). The values of In Model 2, to control the difference science achievement, we put schools in Level 2 and put countries in Level 3. The value of ICC was 0.195 for school level and 0.328 for country level. Mplus 8.0 was used to conduct the subsequent analyses.

2.4. Model 1

2.4.1. Model 1a: linear model

In the two-level model, learning time was taken as an individual level as follows:

$$Score_{ij} = \beta_{00} + \beta_{10}\, ztime + u_{0j} + r_{ij}, \tag{1}$$

where $Score_{ij}$ denotes the science achievement for individual *i* in school *j* and *ztime* denotes the standardized science learning time. The random intercept model was used, where the school level residual was u_{0j} and individual level residual was r_{ij}.

2.4.2. Model 1b: quadratic model

Similar to the method established in Model 1a, we added the variable of the time squared term to establish the following quadratic model:

$$Score_{ij} = \beta_{00} + \beta_{10}\, ztime + \beta_{20}\, ztime^2 + u_{0j} + r_{ij}, \tag{2}$$

where $ztime^2$ represents the quadratic term. The influences of time variables were set as fixed effects. Particularly, since there were many students learning for extremely long time, we compared the whole sample with full time and a subsample with time between ±3 *SDs*. Additionally, the alternative cubic model is provided in appendices. The cubic model resembles that of the quadratic model so as not to be selected for succinctness.

2.5. Model 2: cultural interactive model

Similar to Model 1, school was put into level 2, and the difference between countries was further controlled in Level 3. The cultural interactive model was set as follows:

Table 1
Science achievements and learning time of eight countries or regions.

	Achievements		ICC	Learning time (min)		*n*
	M	*SD*		*M*	*SD*	
Canada	516.46	91.62	0.106	276.45	168.34	18,713
United Kingdom	509.49	94.61	0.164	277.01	136.25	13,111
Australia	499.13	103.77	0.124	209.04	113.13	13,264
United States	495.87	97.49	0.108	235.99	141.56	5409
Japan	544.32	91.00	0.378	173.18	74.61	5812
South Korea	517.23	94.07	0.176	170.67	71.09	5461
Singapore	546.39	104.53	0.245	323.77	172.52	6016
Chinese Taipei	531.48	100.12	0.228	288.75	114.36	7618
Eight countries or regions	520.05	97.15	0.195/.328[a]	244.60	123.98	80,508

Note. ICC = intraclass correlation.
[a] 0.195 is the ICC value for school level, 0.328 is the ICC value for country level.

$$Score_{ijk} = \beta_{000} + \beta_{100}\ ztime + \beta_{200}\ ztime^2 + \beta_{300}\ cul + \beta_{400}\ cul{*}ztime + \beta_{500}\ cul{*}ztime^2 + e_{00k} + u_{0jk} + r_{ijk}, \tag{3}$$

where $Score_{ijk}$ denotes the science achievement for individual i in school j from country k; *cul* represents culture; e_{00k}, u_{0jk}, and r_{ijk} are residuals for country, school, and individual levels, respectively. We tested the cultural interactive effect by multiplying culture and learning time. Similar to Model 1, the intercept was set as the random effect, while the slope was set as the fixed effect. As did in Model 1b, we compared full time using the whole sample and time within 3 *SDs*.

Effect sizes (Cohen's *d*) in the large-sample multilevel analysis was computed (see Melhuish et al., 2008; Tymms, Merrell, & Henderson, 1997) according to the formula $d = 2 * \beta * SD/\sigma e$, where β is the parameter estimation value, *SD* is the standard deviation, and σe is the within school deviation in the null model. Specifically, the effect size for multilevel analyses indicates the standard deviation change of the outcome caused by the predictor.

3. Results

3.1. Descriptive statistics

Descriptive statistical results are summarized in Table 1. The results are shown in Fig. 1 and Fig. 2.

Fig. 1 is a scatter plot of learning time and achievement of 8 countries or regions, and Fig. 2 separately presents the scatter plot of the East and West. A large number of students learned less than 500 min per week, although a few of them spent extremely long-time learning science. Then, we conducted a *t*-test to compare the difference of learning time and science score between West and East learners. The result shows that the learning time of eastern learners ($M = 213.77$, $SD = 132.29$) was significantly lower than that of western learners ($M = 254.55$, $SD = 147.37$; $t = -36.95$, $p < .001$); the science score of eastern learners ($M = 533.25$, $SD = 99.13$) was significantly higher than that of western learners ($M = 506.31$, $SD = 97.23$; $t = 36.54$, $p < .05$).

3.2. Model selection

The results of the model fit are summarized in Table 2, and the results of parameter estimates are shown in Table 3. The functional predictions are shown in Fig. 3.

Comparing the model fit indices in Table 2, it was observed that the quadratic models (Model 1b) fit better than the linear model (Model 1a), the commonly used indictors in MLM, like log likelihood (LL), Akaike information criterion (AIC), Bayesian information criterion (BIC), and adjusted BIC (aBIC) in quadratic models were smaller than that in linear models. The smallest differences of AIC and BIC were 26 and 24 respectively in Korea while the biggest AIC and BIC differences were 249 and 242 in Singapore. Thus, the quadratic model fit better than the linear model.

The parameter estimations are shown in Table 3 for the two competitive models. In the linear model, learning time and science achievements are generally positively correlated. However, the quadratic model provided more details about this trend: science performance showed an inverted U-shaped trend that rose first and then fell as time increasing, despite the general trend might be increasing. Meanwhile, the optimal point also differed among countries and regions. For example, Japan moved fastest to the highest score with the increase of time (quadratic term coefficient β_2 is −12.52) while South Korea moved slowest to the optimal point (quadratic term coefficient β_2 is −2.62).

Particularly, the results from the sub-samples with learning time within 3 *SDs* are shown in Fig. 4. The results show that, except Australia, the other seven countries and regions can still fit the quadratic models. The coefficients of the first and second terms remained significant. The curves in Australia and the UK have been on the rise, and science achievement increased only with time increased. The curves of Japan and South Korea have more declining part (Japan: *ztime* from 0.71 to 3.00, the score dropped; South Korea: *ztime* from 0.63 to 3.00, the score dropped); while Singapore and Canada have less declining part (Singapore: *ztime* from 1.60 to 3.00, the score dropped; Canada: *ztime* from 1.30 to 3.00, the score dropped). Such difference suggests Japanese and Korean learners can reach the highest point of science performance in a shorter time, while Singapore and Canada learners need more time to get the best science performance.

Comparing the results of Model 1b (full time) and Model 1b (3 *SDs*), some nuance could be found. In Australia and UK, quadratic coefficient was significant in Model 1b (full time), whereas such a term turned to not significant in Model 1b (3 *SDs*).

3.3. The cultural interactive model

The cultural interactive model (Model 2a) results of MLM analysis are summarized in Table 4. We could obtain the full regression function:

$$Score = 492.34 + -2.02\ ztime^2 + 15.83\ ztime + 39.79\ cul + 14.30\ cul{*}ztime - 2.20\ cul{*}ztime^2.$$

Let $cul = 0$ be the western function and $cul = 1$ be the eastern function. The two functions are as follows:

$$Score_{west} = 492.34 + -2.02\ ztime^2 + 15.83\ ztime;$$

$$Score_{east} = 532.13 + -3.91\ ztime^2 + 30.13\ ztime.$$

As seen from Fig. 5, the symmetry axes of the two curves were very similar. This means that the optimal points in the cultures are close (optimal *ztime* is 3.85 in the East, optimal *ztime* is 3.92 in the West). For most, the absolute linear estimate of the function in the East ($\beta_2 = -3.91$) was greater than that in the West ($\beta_2 = -2.02$); the curve in the East was steeper, while the curve in the West was relatively flat, which means that the eastern students' achievement changed more dramatically with a standardized unit change in learning time. For example, when *ztime* increased from 1 to 2, the score of east increased 18.40, but the score of west increased 9.77; when *ztime* increased from 5 to 6, the score of east decreased 12.88, but the score of west decreased 6.39.

Aligned with Model 1, we used the time within 3 *SDs* to build a model with culture as the moderating variable:

$$Score_{west} = 492.40 + -2.23\ ztime^2 + 16.06\ ztime;$$

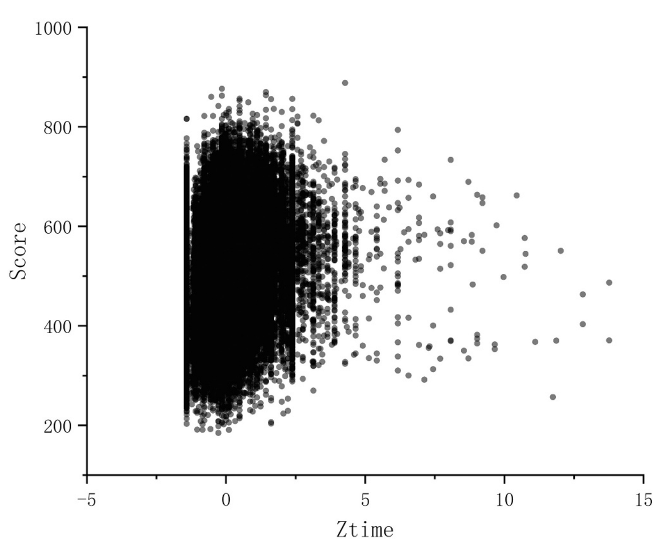

Fig. 1. Scatter plot of science learning time and science achievement in eight counties or regions.

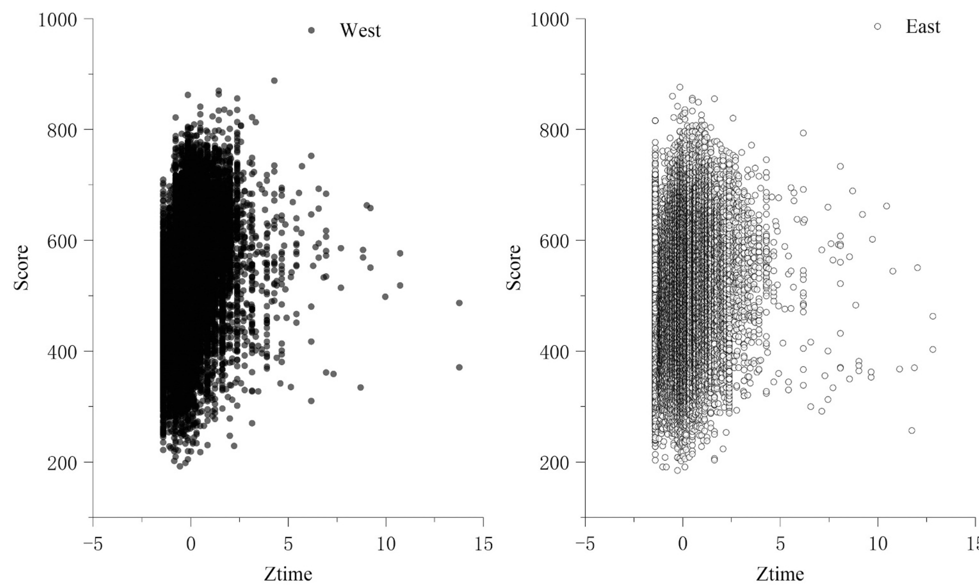

Fig. 2. Scatter plot of science learning time and science achievement which is divided into east and west cultures. The left one is the scatter plot in the east while the right one is in the west.

Table 2
Fitting degree of learning time and science achievement in linear and quadratic models.

	Australia		United States		United Kingdom		Canada	
	Linear	Quadratic	Linear	Quadratic	Linear	Quadratic	Linear	Quadratic
LL	−77,947	−77,917	−31,892	−31,869	−75,001	−74,913	−109,030	−109,011
AIC	155,906	155,847	63,797	63,752	150,014	149,840	218,073	218,036
BIC	155,951	155,900	63,837	63,798	150,058	149,892	218,120	218,091
aBIC	155,932	155,878	63,818	63,776	150,039	149,870	218,101	218,069
Scaled Chi-Square		72.39***		24.90***		1088.44***		34.81***

	Chinese Taipei		Japan		South Korea		Singapore	
	Linear	Quadratic	Linear	Quadratic	Linear	Quadratic	Linear	Quadratic
LL	−44,277	−44,247	−32,785	−32,768	−31,915	−31,900	−35,085	−34,960
AIC	88,566	88,507	65,581	65,549	63,841	63,815	70,183	69,934
BIC	88,607	88,556	65,621	65,596	63,882	63,860	70,223	69,981
aBIC	88,588	88,534	65,602	65,574	63,862	63,838	70,204	69,959
Scaled Chi-Square		49.95***		45.49***		40.10***		77.29***

Note. LL = Log likelihood, AIC = Akaike information criterion, BIC = Bayesian information criterion, aBIC = sample-size adjusted BIC. The smaller the absolute value of the fitting index, the better the fitting degree of the model.
According to Satorra and Bentler (2001), when using the MLR to estimate the model in MLM, we could use the Satorra-Bentler scaling correction to calculate the scaled Chi-Square to compare the two model which have a nested relationship, the formula is Scaled Chi-Square = $-2 * (L_1 - L_2) * (p_1 - p_2) / (p_1 * c_1 - p_2 * c_2)$, where L = Log likelihood value, p = Number of parameters, c = Scaling correction factor for MLR. The significance of Scaled Chi-Square value means that the latter model is superior to the former model.
*** $p < .001$.

$$Score_{east} = 535.94 + -9.20\, ztime^2 + 36.06\, ztime.$$

The eastern curve reached the highest point of achievement faster (when *ztime* = 1.96, the score got the highest point), and after exceeding the peak, the score decreased with time. However, in the western curve has been on the rise, but the degree of increase has been decreasing. The rising rate of the eastern curve is higher than that of the western curve: for example, if *ztime* increased from 0 to 1, the score of East increased 26.86 while the score of West increased 13.83.

Difference was found in the fitting results of Model 2a and Model 2b as well. In terms of the western curve, there was an obvious quadratic relationship between time and achievement given a wider time boundary; however, with a short time boundary, the quadratic relationship was replaced by linear relationship. For the curve in the East, although the quadratic model can fit in both wide and narrow time boundaries, there were still differences between them. The eastern curve fitted in a wider time boundary was relatively flat ($\beta_1 = -3.91$), and the score reached the highest point when *ztime* was 3.85; the curve fitted in a short time boundary was steeper ($\beta_1 = -9.20$), and the score reached the highest point when *ztime* was 1.96.

4. Discussion

4.1. Quadratic relationship between learning time and science achievement

In this study, we found an inverted U-shaped pattern between science learning time and science performance: before the optimal point, students' science achievement improved with an increase in learning time. After reaching the optimal point, science achievement would

Table 3
Linear and quadratic relation models of ztime and science achievement in eight countries and regions.

Model	Coefficient	Countries or regions			
		Australia	United States	United Kingdom	Canada
Model 1a	β	18.54***	28.44***	23.07***	6.22***
	Gender	7.42***	9.97***	5.22**	5.08***
	SES	31.31***	−0.07***	20.05***	24.47***
Model 1b (full time)	$β_1$	−3.02***	−3.05***	−4.28***	−1.24***
	$β_2$	22.41***	30.38***	32.25***	7.89***
	Gender	7.43***	9.77***	5.24**	5.11***
	SES	31.10***	−0.06***	19.66***	24.32***
Model 1b (3 *SDs*)	$β_1$	−2.02	−9.02***	−3.01***	−3.19***
	$β_2$	22.69***	28.14***	31.92***	8.30***
	Gender	7.44***	9.81***	5.40**	5.15***
	SES	31.03***	−0.04***	19.85***	24.57***

Model	Coefficient	Countries or regions			
		Chinese Taipei	Japan	South Korea	Singapore
Model 1a	β	19.01***	17.86***	12.14***	16.87***
	Gender	4.77*	15.07***	−1.15	8.65***
	SES	23.34***	11.75***	24.94***	24.94***
Model 1b (full time)	$β_1$	−3.03***	−12.52***	−2.62***	−5.21***
	$β_2$	25.18***	21.12***	23.11***	36.53***
	Gender	4.76*	15.11***	−1.09	9.14***
	SES	23.00***	11.47***	25.07***	23.75***
Model 1b (3 *SDs*)	$β_1$	−9.88***	−14.39***	−16.19***	−17.78***
	$β_2$	25.32***	20.51***	20.43***	56.92***
	Gender	4.61*	15.14***	−0.85	9.61***
	SES	22.90***	11.50***	24.86***	22.35***

Note. The β points the β in equation: $Score = β\ ztime + β_{0j}$, the $β_1$ and the $β_2$ in Model 1b point the $β_1$ and the $β_2$ in equation: $Score = β_1\ ztime^2 + β_2\ ztime + β_{0j}$. According to the quadratic equation and the formula: $- β_2/ (2 * β_1)$, we can know the optimal *ztime* (the symmetry axis) of the Model 1b (full time) corresponding to each country or region. They are: 3.71 (Australia), 4.98 (United States), 3.77 (United Kingdom), 3.19 (Canada), 4.16 (Chinese Taipei), 0.84 (Japan), 4.42 (South Korea), 3.51 (Singapore). Similarly, we can also know the optimal *ztime* of the Model 1b (3 SDs) corresponding to each country or region. They are 1.56 (United States), 5.30 (United Kingdom), 1.30 (Canada), 1.28 (Chinese Taipei), 0.71 (Japan), 0.63 (South Korea), 1.60 (Singapore).

* $p < .05$.
** $p < .01$.
*** $p < .001$.

decrease if learning time kept increasing. Such a quadratic relationship may help understand the inconsistent findings that the learning time may positively-, negatively-, or uncorrelated with academic performance.

As mentioned, a broader time boundary might be one of the alternatives to unify the inconsistent findings to an inclusive conclusion. In the present study, when using different time boundaries to build the model, the curve of model changes in some countries. For example, for Britain and Australia, when the time was within 3 standard deviations, the grades constantly increased without a downward trend; however, when the learning time expanded to more extreme situations, the corresponding achievement began to drop. There are possibly two kinds of time boundaries: *positive time boundary* including minimum learning time to optimum learning time and *negative time boundary* including optimum learning time to maximum learning time. On the one hand when learning time falls within the positive time boundary, it is positively correlated with science achievement (see Australia and UK in Fig. 4, and the west in Fig. 5). This happens when a small number of students spend long learning time but they do not affect the general prediction, as shown by Dolton et al. (2003). On the other hand, when a relatively large number of students with learning time falling into the negative time boundary, learning time may be negatively associated with the performance. Moreover, if the linear model is used instead of the quadratic model including both positive time boundary and negative time boundary, researchers may conclude no relationship between them (e.g., Wang, 2008).

Why the learning time may quadratically link to the performance with a broader time boundary? One possible explanation is the increasing and diminishing *marginal utility theory*, which is a universal theory applicable to many fields, including but not limited to economics and human resource management (Li & Wang, 2016). The theory suggests that as the total amount of the input increases, the output will not remain the same; some will increase, while others will decrease (Oswald, 2005). It is noteworthy that learning time is more than a resource in academic tasks; it is also a burden that occupies time for entertaining activities, requires energy support, and generates negative effects such as fatigue, stress, and anxiety in students (Yan, Sun, & Feng, 2018). As learning time increases, its benefits in improving achievement follow the law of diminishing marginal utility (if the time keeps increasing, the achievement will increase less efficiently), while its side effects like fatigue and stress follow the law of increasing marginal utility (with an increase in time, the increasing rate of burden becomes larger). For this reason, the relationship between learning time and science achievement is like an inverted "U" rather than a linear fashion.

4.2. The cultural difference on the relationship between learning time and achievement

In addition, we found the curves of two cultures are significantly different. The science achievement of eastern learners surged more noticeably as their learning time changed, while that of western learners did not alter sharply with an increase in learning time. This means that eastern learners exhibit greater changes in their science achievements than western learners given the same learning time. Such a pattern may be related to the family and school environment of East Asians, where typically push children to study and pursue high marks in examinations (Li, 2012).

One possible reason is that eastern learners hold a more positive attitude and respect diligence than the western learners, influenced by the daily communication with their parents (Li et al., 2008; Fu & Markus, 2014) and the desire for being diligent students in teacher's eyes (Li, 2012). This positive attitude toward diligent studying may enable them to listen to the teacher more attentively during regular class hours, which makes them more efficient in learning and produce a firmer grasp of knowledge. Such a positive attitude may also encourage eastern learners indeed learn deeper and store knowledge more effectively from the repeated revisions and the in-school examinations, which are more frequently administrated in senior high, junior high, and even in primary schools in Asian countries (Bae & Lee, 1988; Lee & Larson, 2000; Myers & DeWall, 2015). As a result, the eastern learners show potential of meaningful understanding of knowledge, flexibility of knowledge use, and a higher academic performance.

As far as the period following the optimal point, the period when achievement drops, we found that the science achievement of eastern learners drops more sharply with the increase of time. This effect may indicate the pressure of too much learning time leads to many adverse reactions in students, including myopia, helplessness, depression, anxiety, and a lack of exercise (e.g., Lee, Ku, & Lee, 1991; Wang & Liu, 2018). These physical and mental problems will result in a major decline in students' academic achievements (Balogun, Balogun, & Onyencho, 2017). However, note that the effect size of quadratic term was relatively small in Model 2. The quadratic relationship between time and achievement should be treated with caution since it may not be that strong as empirical guidance.

4.3. Limitations and future directions

First, this research was carried out based on data from PISA 2015. The trend of science achievement rising and declining with learning

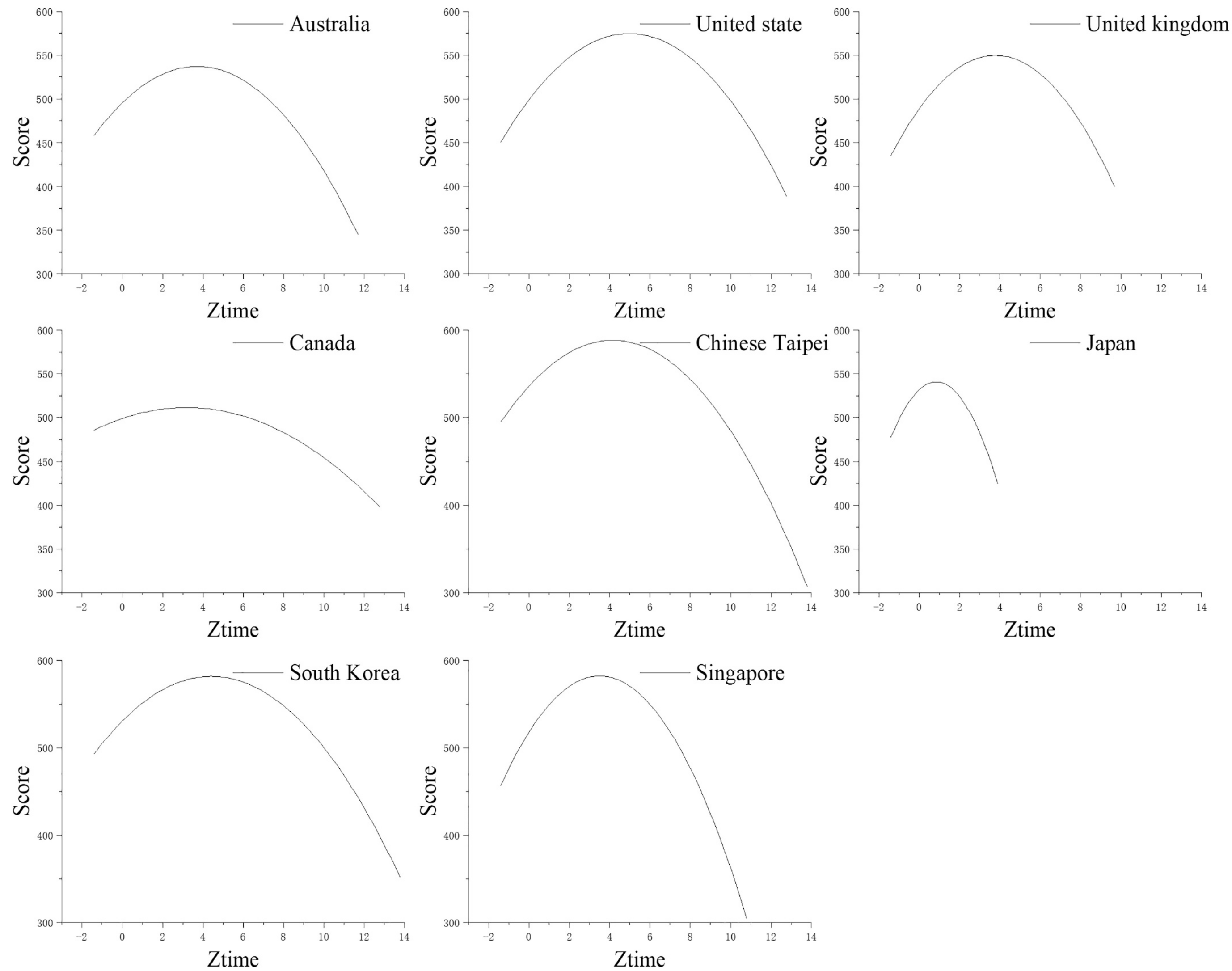

Fig. 3. Quadratic function images of learning time and science achievement in 8 countries or regions in different timespan. Functions of the curves respectively are: $score = -3.02\ ztime^2 + 22.41\ ztime + 495.44$ (Australia); $score = -3.05\ ztime^2 + 30.38\ ztime + 499.00$ (U.S.A); $score = -4.28\ ztime^2 + 32.25\ ztime + 488.87$ (United Kingdom); $score = -1.24\ ztime^2 + 7.89\ ztime + 499.00$ (Canada); $score = -3.03\ ztime^2 + 25.18\ ztime + 536.14$ (Chinese Taipei); $score = -12.52\ ztime^2 + 21.12\ ztime + 531.99$ (Japan); $score = -2.62\ ztime^2 + 30.38\ ztime + 499.00$ (South Korea); $score = -5.21\ ztime^2 + 36.53\ ztime + 517.96$ (Singapore).

time does not mean that time "causes" science achievement unilaterally. There are many factors that would influence academic performance other than engaged learning time, SES, gender, school/country difference as controlled in the present study. For example, students' prior achievement is one of the covariates that may confront the findings but it is not provided in the PISA survey due to its cross-sectional characteristics. Learning subject/domain may also differentiate the findings as it may be included as a grouping variable (e.g., Masui et al., 2014). Future study may adopt longitudinal or experimental designs to control for more confront factors or consider other grouping variables that might differentiate the findings.

Second, although we explored the cultural interactive effect on the relationship between scientific literacy scores and scientific learning time, the cultural effect is indeed a dummy variable. We created such a variable by fitting the theoretically driven countries into the Confucian-Socratic framework, however, we did not explore/measure on the antecedents of cultural causes. The individual factors that aggregate to culture, like learning attitude, psychological stress, diligent learning is not measured in the PISA survey; while some culture level factors, such as individualism-collectivism, could also be explanations of cultural difference. The present study may only reflect the descriptive level, illustrating the difference in curves and reveal the potential aspects that might lead to cultural moderations. Nevertheless, a stronger explanative level including empirically cultural measures may be the future directions, which would infer about "what" causes the cultural difference.

Furthermore, we explored relationship between learning time and science achievement based on the learning time in regular school science courses. However, the method used to measure learning time may affect the results of our study. If the definition and measurement of learning time is more specific and accurate (e.g., decompose the time to in- and out-of-school), our result will be more valid. Future study may compare the difference between types of learning time, such as provided learning time, engaged time, after-school learning time, and so on.

5. Conclusions and recommendations

In summary, our research finds that (a) science learning time and achievement have a quadratic relationship: there is an optimal point of learning that would yield best performance, before or after which the academic performance would both be unsatisfactory; (b) the eastern learners are more sensitive to the quadratic relationship with a more dramatically changing rate in achievement with the increase of learning

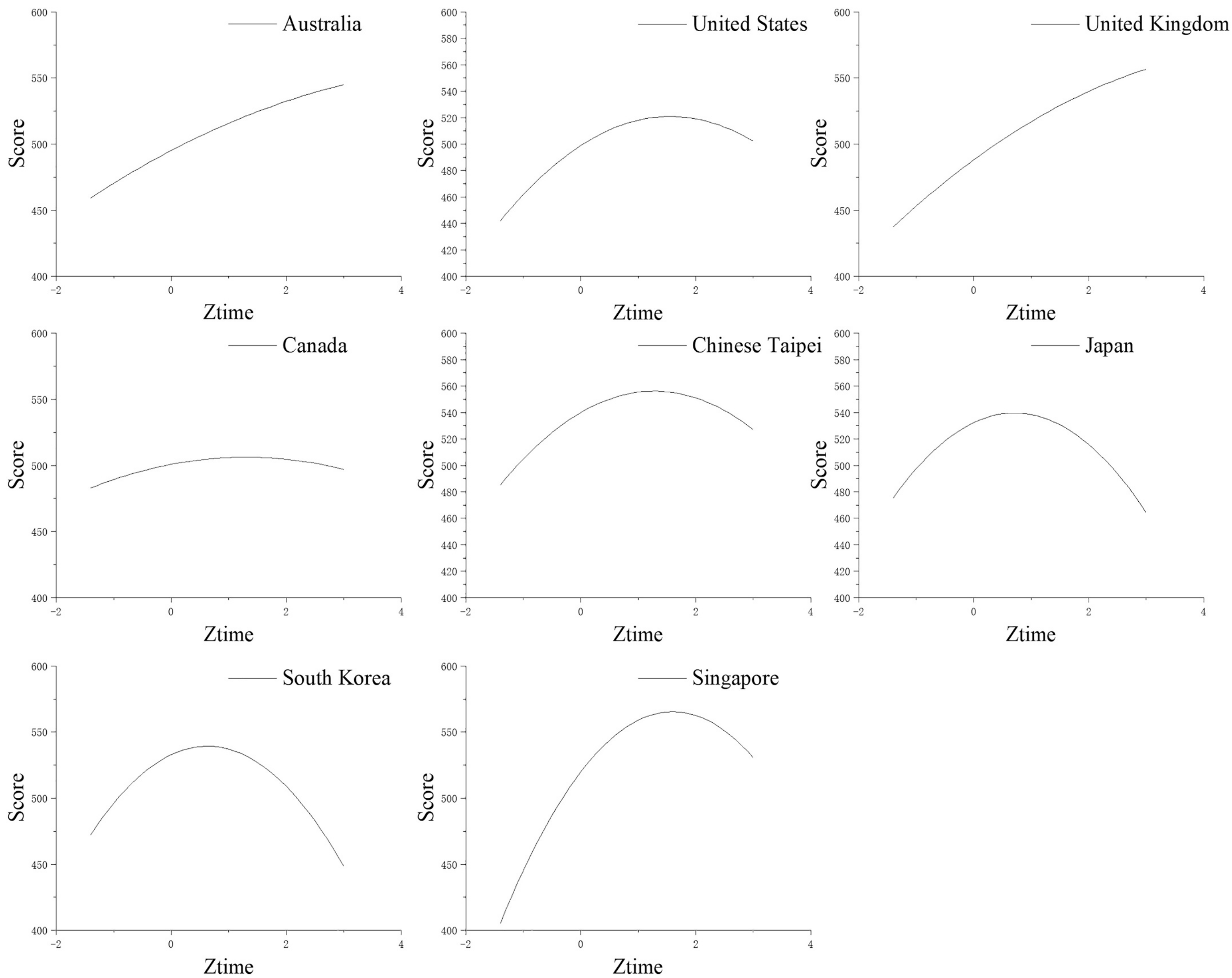

Fig. 4. Quadratic function images of learning time and science achievement in eight countries or regions in *ztime* within 3. Functions of the curves respectively are: $score = -2.02\ ztime^2 + 22.69\ ztime + 495.06$ (Australia); $score = -9.02\ ztime^2 + 28.14\ ztime + 498.90$ (U.S.A); $score = -3.01\ ztime^2 + 31.92\ ztime + 488.01$ (United Kingdom); $score = -3.19\ ztime^2 + 8.30\ ztime + 500.76$ (Canada); $score = -9.88\ ztime^2 + 25.32\ ztime + 539.94$ (Chinese Taipei); $score = -14.39\ ztime^2 + 20.51\ ztime + 532.32$ (Japan); $score = -16.19\ ztime^2 + 20.43\ ztime + 532.81$ (South Korea); $score = -17.78\ ztime^2 + 56.92\ ztime + 519.84$ (Singapore).

Table 4
Parameter estimations of the cultural interaction model.

	Model 2a			Model 2b		
	SD	β	*d*	*SD*	β	*d*
ztime	0.88	15.83***	0.33	0.78	16.06**	0.29
ztime^2	3.07	−2.02**	−0.15	1.00	−2.23*	−0.05
cul	0.50	38.79***	0.47	0.50	43.53***	0.51
*cul * ztime*	0.59	14.30*	0.20	0.51	20.00*	0.24
*cul * ztime*^{2}	2.20	−1.89*	−0.10	0.68	−6.97***	−0.11
gender	0.50	6.57***	0.08	0.50	6.61***	0.08
SES	0.87	23.74***	0.49	0.87	23.73***	0.49

Note. *d* represented the effect size. Model 2a represented the Culture Interactive Model established by full time, the functions of Model 2a are: $score_{west} = -2.02\ ztime^2 + 15.83\ ztime + 492.34$, $score_{east} = -3.91\ ztime^2 + 30.13\ ztime + 532.13$; Model 2b represented the Culture Interactive Model established within 3 *SDs*, the functions of Model 2b are: $score_{west} = -2.23\ ztime^2 + 16.06\ ztime + 492.40$, $score_{east} = -9.20\ ztime^2 + 36.06\ ztime + 535.94$.
* $p < .05$.
** $p < .01$.
*** $p < .001$.

time, compared to their western counterparts.

The results of this study can provide a reference for students' learning policies relative to reducing pressures and burdens to some extent. From this quadratic curve, we can see that an unlimited investment of time and energy in learning does not promise continuous improvement in science performance. Typically for the eastern students, the "infinite" learning time may instead shrink the advantage brought by adequate learning and probably fall behind their counterparts. A medium level of learning is an effective way to take full advantage of learning efficiency. Therefore, schools, teachers, and parents, typically in Asian organizations are suggested to change their concepts and properly treat the relationship between students' lifelong development and their current academic achievements and academic burdens. This change requires teachers to adequately assign tasks to students, reduce the amount of excessive homework, and select representative examples for training and strengthening students' knowledge and skills.

In addition, the optimal time may not be the same for every student, and the knowledge learned may not only be consolidated during school. Forcing students to enroll in numerous cram schools also means that they will bear a greater learning burden and fail to solve problems in a severe manner. If schools and parents pay attention to developing

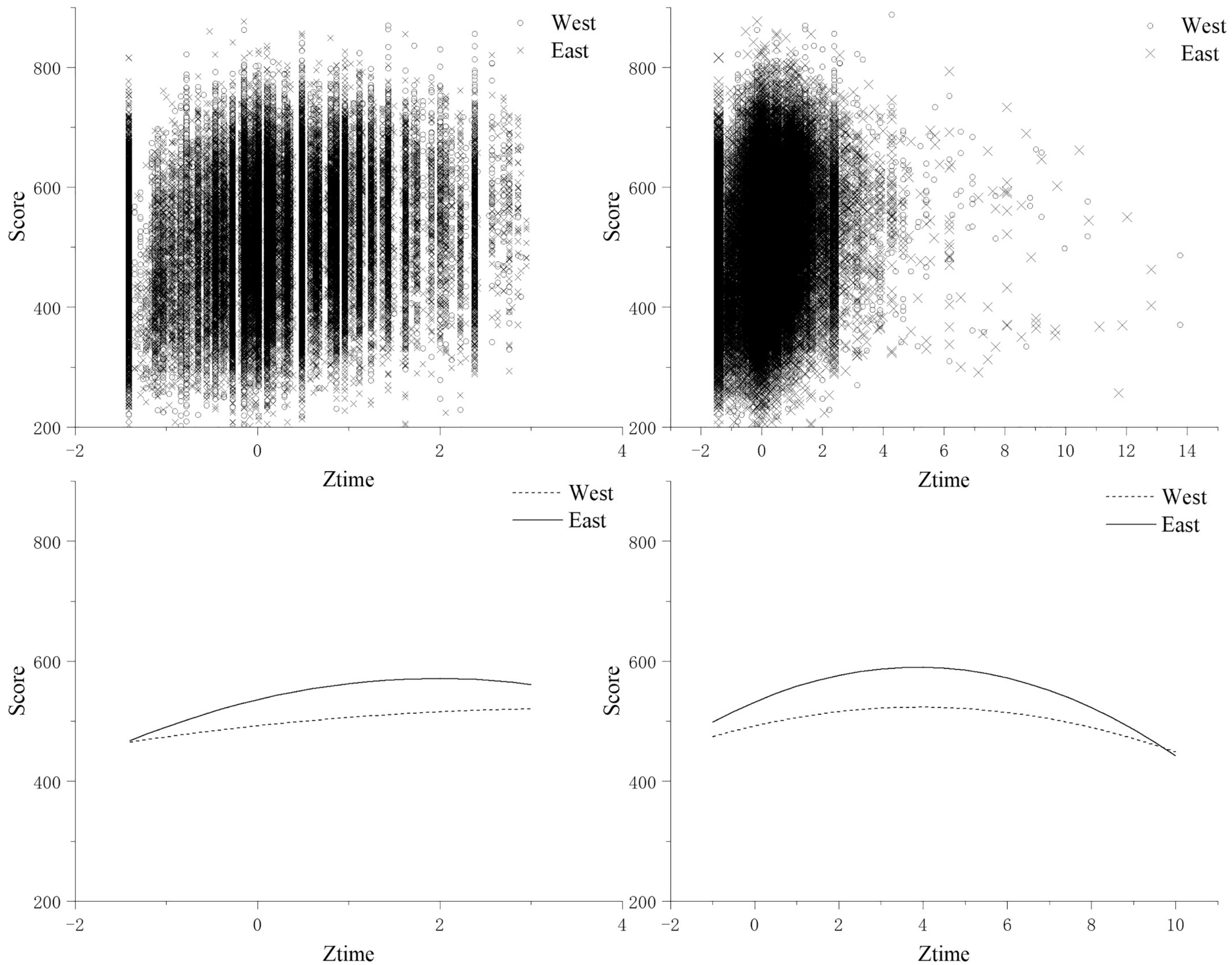

Fig. 5. Scatter plot and estimated line graph of learning time and science achievement between east and west. The left figure shows the scatter plot and graph obtained by *ztime* within 3, while the right figure shows the plot and graph obtained by *ztime* from −2 to 10.

students' self-study ability, students will be able to self-regulate and complete tasks independently and without supervision to make better use of time and improve their learning efficiency.

Declaration of competing interest

There is no conflict of interest.

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