SMART in Mathematics? – Exploring the Effects of In-Class Level Differentiation using SMARTboard on Math Proficiency

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Sofie J. Cabus	extsuperscript{1,2} Carla Haelermans	extsuperscript{3} Sonja Franken	extsuperscript{4}

Abstract

This paper explores the effects of in-class level differentiation by making innovative use of an interactive whiteboard (SMARTboard) on math proficiency. Therefore, we evaluate the use of SMARTboard in class, in combination with teacher training, using a randomized field experiment among 199 pre-vocational students in 7\textsuperscript{th}-grade in the Netherlands. During six weeks, students in the intervention group participated in math classes in which the SMARTboard was used to apply level differentiation. The teachers of these classes received a specific training (Technological Pedagogical and Content Knowledge” (TPACK)) in using the SMARTboard in class. Control classes were taught by teachers without the training, who did not use the SMARTboard in class. The results show that level differentiation in class, which was possible because of the efficient use of the SMARTboard, significantly increases math proficiency with 0.25 points.

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1 Introduction

Government officials and policymakers consent that an overall high student achievement boosts economic performance and countries’ competitiveness in an open economy (European Commission, 2010, 2011). Math and language skills lie at the basis of student achievement, but national tests in, for example, two European Union countries the Netherlands and Belgium have shown that many students do not have sufficient basic math and language skills (Funnekotter, 2012; KNAW, 2009). A potential way to increase these skills is the use of information and communication technology (ICT). ICT is assumed to foster student achievement, and can be used both at home and at school. Using ICT in the classroom is also assumed to better allow for level differentiation compared with teaching in a traditional classroom setting without ICT. It is therefore not surprising that schools are increasingly using computers, laptops, interactive whiteboards, and iPads in order to increase student performance (Borman, 2008; Cheung and Slavin, 2013). However, there is not much knowledge available on how these specific investments in ICT at schools translate into better educational outcomes (Haelermans and Ghysels, 2013). Many of the previous evaluations of ICT in education are wide in scope, as they evaluate, for example, increased budgets for ICT in schools, without knowing the specific destination for these budgets. We denote this strand of literature as ‘general evaluations’ on the effectiveness of ICT. Studies in this (first) strand of literature rely on the assumption that users have sufficient skills to implement and use ICT to their benefit and that it does not matter how or which type of ICT is used, in order to benefit educational outcomes. Yet, in practice, these general evaluations on the effectiveness of ICT offer mixed results. Some of them find no effect of ICT (Goolsbee and Guryan, 2006), whereas others find positive effects (Machin et al., 2007) and a third group of studies find negative effects of ICT (Angrist and Lavy, 2002; Leuven et al., 2007).

Other studies on the effectiveness of ICT focus on the comparison of computer directed versus traditional classroom teaching. This is a second strand of literature. A couple of meta-analyses with strict selection criteria with respect to methodology, show that in general, computer directed instruction does have small positive effects on student performance, compared with traditional classroom teaching, for both math and language (Cheung & Slavin, 2012, 2013; Kulik & Kulik, 1991).

A third strand of the literature focuses on ICT used in the classroom next to (traditional or new ways of) teaching, or as a way to assist the teaching of the teacher. Here, the educational technology can be used as an instruction tool on its own and often has a personalized nature. It can be applied both in school and/or as additional instruction time at home. In general, experimental studies find positive effects of individualized ICT-tools on math skills. Arroyo et al. (2010), for example, show that a math oriented, ICT-based individual tutoring system leads to improved student performance for middle school students. Burns et al. (2012), Pilli
and Aksu (2013), Haelermans and Ghysels (2013) and Banerjee et al. (2007) show similar results.\(^5\)

However, the third strand of literature discussed so far mainly focuses on individualized ICT-tools, and not on class based ICT-tools. This paper particularly contributes to the third strand of literature by exploring the effects of in-class level differentiation using an interactive whiteboard (further also denoted by SMARTboard) by means of a randomized experiment. To the best of our knowledge, the literature on the effects of interactive whiteboards hardly consists of (quasi-) experimental studies. The quasi-experimental studies by Lopez (2010) and Torff and Tirotta (2010) both show positive effects of working with an interactive whiteboard; the former showing effects on student performance and the latter on self-reported motivation by students. The PhD-thesis of Riska (2010) does not show significant results, but it should be noted that the sample size is limited to highly gifted students, leading to a rather small number of observations. Jena (2013) also finds positive effects in an experimental study. However, the author does not explain the experiment and identification strategy very well. There is also evidence from quantitative correlational analyses (e.g. Leung, 2008; Lewin et al., 2008). The authors from these studies, in general, conclude that there are positive associations between using interactive whiteboards in class and student performance. Lewin et al. (2008) also show that this particularly holds for children with above average performance.

Many other studies on interactive whiteboards are descriptive in nature or report on case studies (e.g. Glover et al., 2007; Hall & Higgins, 2005; Wood & Ashfield, 2008). Although we cannot draw any conclusion on the effectiveness of interactive whiteboards from descriptive studies, many authors discuss two important aspects of using interactive whiteboards in the classroom. Glover et al. (2007) and Hall and Higgins (2005), for example, both discuss the importance of increasing the knowledge on the possibilities of these technological devices among teachers. Only if teachers know how they are using the interactive whiteboard in an effective way to teach, the technology can be used to increase student achievement. Furthermore, as both Smith et al. (2005) and Wood and Ashfield (2008) point out, teachers do not only need knowledge on how to use the technology, they also need to know the pedagogy and the contents in order to transfer knowledge effectively. This is very much in line with the conceptual framework of Koehler and Mishra (2005) and Mishra and Koehler (2006) called “Technological Pedagogical Content Knowledge” (TPACK).

The starting point of the TPACK framework is the previous work of Shulman (1986), discussing that a teacher possesses two kinds of knowledge: pedagogy and contents (i.e. expertise). Koehler and Mishra (2005) and Mishra and Koehler (2006) add “[educational] technology” to the framework. It is well shown in the framework that technology in itself does not attribute to student achievement, but that it is the way how this technology is developed (by the teacher) and is used in teaching that makes the difference. As such, TPACK aims at “teaching content with appropriate pedagogical methods and technologies” (Schmidt et al., 2009, p.125). Consequently, using any kind of ICT-tool in the daily teaching practice not only requires teachers’ full understanding of how it works, but also of what works. Koehler et al.

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\(^5\) With respect to the effects on language skills, there are few experimental studies and none of them finds significant effects (Borman et al., 2008; Given et al., 2008; Potocki et al., 2013; Rouse & Krueger, 2004).
(2007) show the aspects of TPACK and describe the process of developing TPACK. Some studies already combine the importance of TPACK with the use of the interactive whiteboard, such as Jang and Tsai (2010; 2012, 2013). Furthermore, Abbitt (2011) indicates a positive relationship between TPACK and the self-efficacy of teachers. So far, there does not seem to be any literature on the effectiveness of TPACK on student performance. As such, this paper contributes to the previous literature by studying the effects of differentiated teaching with an interactive whiteboard on math proficiency in particularly taking teachers’ TPACK into account.

In conclusion, the two main contributions of our study to the previous literature are as follows. First, unlike many previous studies, we set-up a randomized field experiment to study the effects of in-class level differentiation when using the SMARTboard on math performance. Second, we specifically include the TPACK model into our intervention in order to enhance innovative teaching using ICT.

This paper proceeds as follows. Section 2 looks at the course and design of the intervention. Next, the identification strategy is explained in Section 3. The data and descriptive statistics are presented in Section 4. Section 5 discusses the results. Section 6 concludes.

2 The course and design of the intervention

The intervention takes place at one school in the Netherlands. The current focus on math performance in the Netherlands is mainly caused by the newly introduced mathematics reference levels (Commissie Meijerink, 2008). There is a large concern about the fact that the mathematics skill level of a vast amount of students entering secondary education is lagging behind the Dutch national reference levels (standards) defined for mathematics (KNAW, 2009; Scheltens, Hemker, & Vermeulen, 2013). These standards describe the contents of mathematics courses, with which students should be familiar at different grade levels of primary and secondary education. These contents have been established by the Meijerink commission, an expert group installed by the Dutch Ministry of Education (Commissie Meijerink, 2008). The majority of children do not perform according to the requested reference levels, and many Dutch schools are thus undertaking action in order to boost mathematics skills. For instance, they invest in additional regular teacher hours, remedial teaching, or, in line with the international literature presented above, many Dutch schools are investing in ICT (Kennisnet, 2012). We evaluate the effectiveness of one such ICT investment, namely SMARTboard that allows for in-class differentiation in grade 7. This is the first grade after the transition of primary to secondary education. This transition is considered difficult in the Netherlands, as students are tracked at the start of secondary education in different school types based on their score in the national standardized primary school exam (CITO-exam), and the track advice given by the primary school. There are three tracks: pre-vocational education (lowest level, up till age 16), general secondary education (age 17), and pre-university education (highest level, up till age 18). This paper only focusses on students in pre-vocational education tracks (lowest level). These are also the students that most frequently fail the national math tests, making it an interesting population to study.
In the literature, this system of student sorting across different school types based on ability levels is often referred to as “ability tracking” (for a discussion, see Bosker, 2005). And, although tracks are relatively homogenous with respect to average student performance, there are still differences in average math skills observed at the classroom level. In the Netherlands, these differences in skills are often measured by using the concept of didactic age equivalence (DAE). DAE denotes the total number of months of primary education a student has followed given his/her educational proficiency level. This can diverge from the actual months in education, as the measure is based on actual prior educational achievement (i.e. achievement in primary education, and, thus, prior to the intervention). For example, if a student has DAE equal to 40, then this student performs at the level of someone who has had 40 months of education in the primary school. Of course, in order to reach secondary education, one has had 6 years (60 months) of primary education. As such, this student has a delay of (60-40) 20 months at the start of secondary education. In conclusion, if the total number of months is lower than the expected value, then the student has rather low prior math proficiency.

Whereas the national standardized exam results at the end of primary education are used to track students into school types, DAE is used to assign students to classes at the start of secondary education. As a result of this school policy, homogeneity is obtained within classes and heterogeneity between classes with respect to average math performance. Based on average DAE, the school distinguishes between three levels: A, B, and C. Level A consists of the worst performers, whereas level C has the best performers.

Of course, the national and school policy has consequences for our assignment rule to either intervention group or control group. Therefore, stratification is used with respect to the three levels A, B, and C, before randomly assigning classes to the intervention group. With respect to level A, we randomly select two of the four classes into the intervention group, while for level B we only select one of the three classes, and for level C, we again randomly select two of the four classes. As such, there are 11 different classes in total in 7th grade, of which 5 participated in the intervention, and 6 were control classes. This experimental set-up is visualized in Figure 1.

[Figure 1 about here]

### 2.1 Teaching with SMARTboard

The intervention consists of in-class level differentiation, made possible by effectively teaching with SMARTboard. Therefore, the prime focus of teaching with SMARTboard is level differentiation between the students in class, as well as the speed at which a student can understand and perform math exercises in class. Treated students received 50 minutes of SMARTboard education in basic math skills each week over a period of 6 weeks between autumn and the Christmas break of 2013. Both control group and treatment group followed the same instruction book for math. However, next to the instruction book taught using the SMARTboard, the treated students received additional (digital) instruction material, such as education on the basis of notebook software, and websites especially designed for teaching mathematics with SMARTboard on the World Wide Web. They did not receive homework,
but, instead, treated students could practice in small (same level) groups in class, during instruction time, to work on their math assignments. In case they finished their math assignment earlier than the rest of the group, they could participate in another group in class working on another, more difficult, task. Owing to the use of SMARTboard, the traditional class teaching time of the teacher was reduced, so that the teacher could explain certain aspect in the level groups, but students could also explain to each other. Students performing at a higher level could often do without teacher explanation, allowing more time for the lower achievement groups for the teacher. Furthermore, for the students more time was available in class for the task that would otherwise be homework. Contrary to the intervention group, the control group only got classical instruction in class, and regular homework. At the end of their 50 minutes instruction time, they received homework tasks as usual to be individually prepared at home. As such, nothing changed for students in the control group, compared with students in earlier cohorts.

2.2 Teachers’ TPACK
It is strongly believed in the literature that ICT-devices can only increase student performance when teachers know how to effectively use these devices (e.g. Koehler et al., 2007; Abbitt, 2011). In order to meet this necessary requirement, teachers were selected into our experiment based on three criteria that assess their TPACK: (1) they have knowledge of ICT in general and of how to use ICT in the classroom; (2) they participated in the course “training-the-teacher using SMARTboard”; and (3) they have content knowledge of (teaching) mathematics. Teachers are on average the same, except that treated students only have math teachers who received ICT-training (i.e. fulfill requirement 2), while control students only have math teachers that did not have the ICT-training (yet).

2.3 Considerations
The course and design of our intervention have at least two important discussion points. First, it is important to note that both untreated and treated students have had education using SMARTboard in primary education. This reduces the innovation factor that only may boost student achievement in the short run (Beauchamps and Parkinson, 2005). The innovation factor implies that students are affected by using something ‘different’ than usual in class. If innovation fosters student motivation, and if motivation positively influences performance, then innovation may increase student performance. However, in the long-run, the innovation becomes established, wiping out the initial boost in motivation. Performance is then no longer affected by ‘the boost’. This is relevant for the intervention discussed in this paper. Since students have already worked with the SMARTboard before the intervention, the chances of an innovation effect is small, implying that a potential effect can be contributed to the intervention, and not to the fact that they are working with something new.

Second, differences in teaching exist, not only between the teachers within the intervention classes, but also between the teachers of the intervention group and control group. We argue that differences in teaching are captured in the empirical strategy (see next section). First, because we measure the same student twice over time, and, therefore, we capture all aspects that are constant or ‘fixed’ over time (such as the teacher). Second, because we use class dummies. Class dummies allow us to capture class fixed effects. As the intervention group
and the control group have had 6 weeks of instruction by the same teachers, the class fixed effects also captures the influence of the teachers on the students.

3 Estimation method
The purpose of this paper is to estimate the effect of in-class level differentiation by using SMARTboard as an instruction tool. Since we have both a pretest (before intervention) and a posttest (after intervention), it is possible to estimate three aspects: (1) whether students in the treatment group perform better than students in the control group, in general, so at both tests; (2) whether all students perform better in the pretest than they do in the posttest; and (3) the combination of the former two, namely whether the treatment students perform better in the posttest compared to the control group and the pretest. We estimate these aspects using a so-called difference-in-differences design. In this design we compare the math exam results of treated students with untreated students (first difference, first aspect), and over time (second difference, second aspect), and the interaction of the two (the third aspect).

Notwithstanding the ability level stratification and random assignment of students to the treatment, treated and untreated students may differ from each other based on student characteristics, such as age, gender and DAE. Therefore, observed student characteristics are included in the regression. However, there are also unobserved student characteristics, and we wish to correct for that as well. Furthermore, each student appears twice in the panel dataset, and we also need to account for this panel data structure in the regression. It is proposed in this paper to estimate random effects regressions in order to deal with previous necessary corrections of the estimates.

Next, we also have to control for the fact that the experiment took place at the class level. In fact, the random assignment of students to the intervention took place at the class level, and not the individual level. This implies that class composition and other class (group) level effects may have affected the course of the intervention. We control for this, by clustering the standard errors of the regression at the class level.

To conclude, as students are being taught in a class (and not individually), the class environment and individuals within the class have an influence on student performance. This influence, for example, comes from the teacher (as discussed above), but also from the other students (peers) in the class. Therefore, in the last model we include class dummies (class id) that control for all class level ‘fixed’ effects influencing performance of students within the same class.

The technical details of the estimation method are described in the technical appendix.

4 Data and descriptive statistics
The intervention took place in one pre-vocational school (vmbo) in the Netherlands. In total 199 students of 11 different classes participated in the intervention. Of these students, 5 classes ($N_I=80$) are in the intervention group, and 6 classes ($N_C=119$) in the control group. Table 1 summarizes the data and descriptive statistics of student background.
Students are, on average, 12.7 year old at the start of secondary education. Because of retention in grade, students can also be older (max. 15) than 12. About 1 in 2 students are female, and only a small share (7.4 percent) of students is non-native. Here, non-native is defined as coming from foreign countries (first-generation immigrants). Most students (51 percent) are enrolled in the pre-vocational practical tracks of education (i.e. the lowest levels of secondary education). About 49 percent follows a pre-vocational theoretical track.

Table 2 presents the results of the independent sample T-test. The latter table presents statistics of the mean differences between control group D(0) and treatment group D(1). Note that, although we randomly selected classes into the intervention, significant differences between intervention and control group can still be observed, because: (1) we could select only one out of three B level classes into the intervention; and (2) the relatively small sample size might lead to statistical problems. Based on the information from Table 2, we can indicate that treated and untreated students are, on average (except a few indicators, which are discussed below) similar in observable characteristics, so that the estimated effectiveness of the intervention is attributable to the teaching with the SMARTboard, and not driven by (observed) differences in student population between intervention and control group.

Students scored, on average, 8.1 points on the pretest, where test scores range between 0 and 10 (10 being the highest grade and 5.5 being sufficient). The independent sample T-test shows that treated and untreated students made the pretest, on average, the same (Table 2). However, the didactic age equivalence (DAE) significantly differs between the intervention group and the control group. It is expressed in months with a maximum of 60 (Table 1). We attribute this significant mean difference to having only one B level class in the intervention. When controlling for DAE in the regression, this should not account for this (see Section 2 for discussion on DAE). Notwithstanding the observed mean differences with respect to DAE, as much as 67 percent of treated students, as well as untreated students, are in need of personal assistance (pa) in the classroom. Also with respect to grade retention (26.6 percent) and math disorder (2.5 percent), treated students are, on average, comparable to untreated students. In Section 5, we control for all of these variables with respect to student background in a multivariate regression, as to see whether there is an effect of level differentiation via SMARTboard on math achievement.

5 Results
Table 3 summarizes the summary results of the effect of teaching with SMARTboard on student math achievement. Full model results are available at the authors upon request. We developed four models in total, each model gradually including more control variables. The first model is the basic model specification and includes the intervention indicator, the time indicator, and the interaction between the intervention and time indicator. In Model 2, we include the indicator for didactic age equivalence (DAE). In Model 3, we also capture information on student background (i.e. gender, age, and ethnicity), whether they need
personal assistance in the classroom, and whether they have a math disorder. The final model also controls for the class dummies (class id).

First, consider the estimate of the intervention indicator $\hat{\beta}$. The intervention indicator captures the mean differences in scores between the control group and the intervention group across both time periods. This indicator tells us whether treated students perform better than control students, in general. Without controlling for observed student characteristics, the estimate of $\hat{\beta}$ is not significantly different from zero. However, including DAE, gender, age, ethnicity, personal assistance specification, math disorder, and educational level into the model, the estimate of $\hat{\beta}$ is equal to 0.44 points significant at 5 percent level. This indicates that the intervention group has, on average, better test scores in both time periods, than the control group. This positive difference can be attributed to the uneven number of classes and the fact that classes are grouped by ability level. The estimate of $\hat{\beta}$ further increases to 0.58 points in Model 4, as we included dummies of class id in order to control for potential peer effects.

Next, consider the estimate of the time indicator $\hat{\delta}$. This estimate presents the evolution of average test scores over time for both the intervention group and the control group. We observe that the estimate of $\hat{\delta}$ is equal to -0.49 points in Model 1. We also observe that across all four models, this estimate does not change. Therefore, we conclude that both treated and untreated students together performed worse after the intervention than before the intervention; probably because this was a more difficult test. Further analysis of the data shows that this negative estimate is mainly driven by decreasing test results of the control group, while the test results of the intervention group remain stable over time.

The estimate of interest in our paper is $\hat{\theta}$. This estimates denotes the interaction between the time indicator and the treatment indicator. In other words, do treated students perform better than untreated students after they have had the treatment? It presents the effectiveness of in-class level differentiation using the SMARTboard. Controlling for at least DAE in Model 2, the estimate of $\hat{\theta}$ is equal to 0.25 points significant at the 6 percent level. Given our amount of observations, the chance of a Type II error is relatively large (i.e. falsely accepting the null hypothesis of no effect), and significance at the 6 percent level is not a bad result. The standardized effect size, in terms of standard deviations, is equal to 0.11. As such, our estimate of 0.25 points represents a small effect size. Given that the intervention only lasted for 6 weeks, it is very likely that the effect size would increase when the treatment would take place over a longer time period.

Further including student characteristics in Model 3, and class dummies in Model 4 does not alter the estimated effect. Therefore, we can conclude that in-class level differentiation using SMARTboard has a significant positive effect on math exam results. These results are robust to several model specifications and control variables.
6 Conclusion and discussion

There are widespread beliefs about using ICT in the classroom in order to foster student achievement. Indeed, schools are increasingly investing in educational technology, such as computers, laptops, whiteboards, and iPads. However, the previous literature on the (cost-)effectiveness of using ICT in the classroom shows only limited effect sizes. In this paper, we analyze the effects of using an interactive whiteboard (SMARTboard) in class by using a randomized experiment at the class level. The instruction tool SMARTboard allows teachers to differentiate between performances of (very low performing) students in Dutch secondary education. We find that teaching with SMARTboard is an effective method to increase students' math proficiency. The results indicate a standardized effect size of 0.11 significant at the 6% level.

As such, our experiment shows that the performances of students in classes, in which teachers worked with and without SMARTboard, are for sure not negatively different. On the contrary, student performances are at least similar, but, with 94% certainty, even significantly better for (low performing) students in classes with SMARTboards. This is very important given the shift from labor intensive to knowledge-based economies these days, which requires other skills than before (the so-called 21st-century skills), where students are supposed to be able to work in different ways, more independently, but also work with new technologies such as the SMARTboard (Allen & van der Velden, 2001, 2011; van Deursen & van Dijk, 2009).

Of course, the instructing of teachers to give them sufficient knowledge on the technology (TPACK) does not go without a cost. However, this is a one-time investment cost, while the time for collecting the returns to TPACK education is much longer. Furthermore, although we only find a small effect, this was only a six-week intervention in a small sample of students, indicating the potential of larger experiments over longer time periods.

To conclude, students in the Netherlands are supposed to achieve a certain level of math proficiency by the time they graduate. Many schools use approaches to increase math proficiency of which the effectiveness has yet to be shown. If the effectiveness of an approach is then shown, and if we can rule out an effect because it is a ‘new’ technology, since the students had already worked with it before, then these results should be taken seriously by schools seeking to change their policy, or to adapt a new policy, even though it is only a small effect size.
7 References


8 Figures and Tables

![Course and design of the intervention](image)

Table 1: Descriptive statistics of the full sample (N=199)

<table>
<thead>
<tr>
<th>Outcome variables</th>
<th>Obs.</th>
<th>Mean</th>
<th>Std. Dev.</th>
<th>Min</th>
<th>Max</th>
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<tbody>
<tr>
<td>Pre-test</td>
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<td>8.0789</td>
<td>1.3287</td>
<td>3.2</td>
<td>10.0</td>
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<td>Post-test</td>
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<td>7.6779</td>
<td>1.2222</td>
<td>3.5</td>
<td>10.0</td>
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<td>Individual characteristics</td>
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<td></td>
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<td>0.6</td>
<td>12.0</td>
<td>15.0</td>
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<td>0.4990</td>
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<td>1</td>
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<tr>
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<td>0.2647</td>
<td>0</td>
<td>1</td>
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<tr>
<td>DAE(^1)</td>
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<td>26.0</td>
<td>60.0</td>
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<td>Theoretical level C</td>
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Note 1: DEA denotes didactic age equivalence
Note 2: Pa denotes personal assistance
Table 2: Mean differences between treated and untreated individuals using the independent sample T-test(1)

<table>
<thead>
<tr>
<th>Outcome variable</th>
<th>Untreated D(0)</th>
<th>Treated D(1)</th>
<th>Diff. D(1)-D(0)</th>
<th>T-value</th>
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<td>7.9481</td>
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<td>-1.1274</td>
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<td>Age</td>
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<td>-1.0156</td>
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<td>Gender (female=1)</td>
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<td>0.6203</td>
<td>0.1203</td>
<td>1.6709 *</td>
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<td>0.0759</td>
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<td>DAE$^1$</td>
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<td>44.1</td>
<td>-5.5</td>
<td>-5.3454 ***</td>
</tr>
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<td>Needs pa$^2$</td>
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<td>0.6835</td>
<td>0.0252</td>
<td>0.3679</td>
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<tr>
<td>Math disorder</td>
<td>0.0167</td>
<td>0.0380</td>
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<td>0.937</td>
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<td>Pre-vocational levels</td>
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<td></td>
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<tr>
<td>Practical level A (incl. pa$^2$)</td>
<td>0.2583</td>
<td>0.2658</td>
<td>0.0075</td>
<td>0.1171</td>
</tr>
<tr>
<td>Practical level B</td>
<td>0.3000</td>
<td>0.1772</td>
<td>-0.1228</td>
<td>-1.963 *</td>
</tr>
<tr>
<td>Theoretical level level C</td>
<td>0.4417</td>
<td>0.5570</td>
<td>0.1153</td>
<td>1.5942</td>
</tr>
</tbody>
</table>

Note 1: DEA denotes didactic age equivalence
Note 2: Pa denotes personal assistance
Table 3: Summary output of the effectiveness of teaching with SMARTboard (coefficients are in points)(1)(2)

<table>
<thead>
<tr>
<th></th>
<th>Model 1</th>
<th>Model 2</th>
<th>Model 3</th>
<th>Model 4</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Intervention ((\hat{\beta}))</strong></td>
<td>-0.24</td>
<td>0.16 *</td>
<td>0.44 **</td>
<td>0.58 *</td>
</tr>
<tr>
<td></td>
<td>(0.34)</td>
<td>(0.28)</td>
<td>(0.17)</td>
<td>(0.29)</td>
</tr>
<tr>
<td><strong>Time ((\hat{\delta}))</strong></td>
<td>-0.49 ***</td>
<td>-0.49 ***</td>
<td>-0.49 ***</td>
<td>-0.49 ***</td>
</tr>
<tr>
<td></td>
<td>(0.10)</td>
<td>(0.10)</td>
<td>(0.10)</td>
<td>(0.10)</td>
</tr>
<tr>
<td><strong>Interaction ((\hat{\theta}))</strong></td>
<td>0.25 *</td>
<td>0.25 *</td>
<td>0.25 *</td>
<td>0.25 *</td>
</tr>
<tr>
<td></td>
<td>(0.14)</td>
<td>(0.14)</td>
<td>(0.14)</td>
<td>(0.14)</td>
</tr>
</tbody>
</table>

**Control variables**

- None
- DAE³
- Gender
- Age
- Ethnicity
- pa⁴
- Disorder level
- Class id

<table>
<thead>
<tr>
<th>Obs.</th>
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<tbody>
<tr>
<td>Groups</td>
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</tbody>
</table>

Note 1: Random effects model specification with standard errors clustered at the class level. Full estimation results available upon request.

Note 2: The standardized coefficient with respect to the interaction effect is equal to 0.11 in all model specifications.

Note 3: DEA denotes didactic age equivalence

Note 4: Pa denotes personal assistance