Do Computer Games Jeopardize Educational Outcomes?
A Prospective Study on Gaming Times and Academic Achievement

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Abstract

Playing computer and video games is a popular pastime activity for many adolescents worldwide. However, the increasing amount of time spent on these games each day raised fears that this comes at the expense of school and, over the long run, impairs academic achievement. Extending prior research, the present study on a sample of N = 3,554 German adolescents (56% girls) adopted a prospective design and examined the effects of the time playing computer games each day on grades and domain-specific competences in mathematics and reading over time. Robust polynomial regressions combined with specification curve analyses showed that longer gaming times predicted worse grades two years later. These results could be replicated after controlling for initial grades and reasoning abilities. In contrast, mathematical and reading competences were not affected by gaming times. Thus, playing computer and video games can result in a noticeably, albeit small, loss of educational returns, but it does not affect basic competences.

Keywords: computer game, video game, grade, competence, longitudinal

Public Relevance Statement

Prospective effects of computer gaming on academic achievements were studied in a sample of N = 3,554 German students in class 9. Gaming times predicted worse grades two years later, whereas mathematical and reading competences as measured by objective achievement tests were not affected. Detrimental effects of computer gaming on educational outcomes seem to be small and vehement warnings regarding potential dangers of computer gaming are exaggerated.

Do Computer Games Jeopardize Educational Outcomes: A Prospective Study on Gaming Times and Academic Achievement

Every day, millions of teenagers roam the virtual expanse of *World of Warcraft*, battle hostile forces in *Call of Duty*, commit insidious crimes in *Grand Theft Auto*, or explore other simulated realms. Commercial computer games are a sizeable and still growing cultural phenomenon entertaining millions of people worldwide. More than two thirds of US teenagers report playing recreational computer games on their consoles, personal computers, and smartphones (Lenhart, Smith, Anderson, Duggan, & Perrin, 2015). At the same time, parents and teachers are worried that these leisure habits might have undesirable repercussions. Research on problematic effects of computer games focused on violent video games and aggression among youths (e.g., Anderson et al., 2010). Others investigated potential health problems stemming from long screen times (e.g., Hoare, Milton, Foster, & Allender, 2016). With respect to educational outcomes, some research suggested negative effects of intensive computer and video gaming on school achievement (e.g., Anand, 2007; Jackson, von Eye, Fitzgerald, Witt, & Zhao, 2011; Weaver, Kim, Metzer, & Szendrey, 2013) whereas other research implied positive effects (e.g., Kovess-Masfety et al., 2016; Posso, 2016). The existing studies on gaming and achievement are, however, faced with substantial limitations, including the predominance of cross-sectional research designs that do not allow for robust causal interpretations. Do computer gaming activities result in poorer academic achievement or, rather, are academic underperformers more likely to play computer and video games? The present study extends the gaming research literature by adopting a longitudinal perspective. We examined linear and non-linear effects of the time playing computer games each day among German 15-year-olds on academic achievement three years later.

Computer Gaming and Academic Achievement

Theory and empirical findings outlined different paths as to how recreational computer gaming might affect academic achievement. According to the *time displacement hypothesis* computer gaming replaces time that should be invested in academic activities (see Subrahmanyam & Renukarya, 2015). Thus, heavy gamers spend less time on homework, learning activities, and preparation for mandatory achievement tests than non-gamers and, in turn, perform worse at school. Empirical findings offer some support for this view. On an average weekday children who play computer games dedicate about a third less time to homework than children who do not play on the computer (Cummings & Vandewater, 2007). This is also mirrored by repeated complaints from video gamers about not having enough time for school assignments (Hellström, Nilsson, Leppert, & Slund, 2012). To some degree, these findings are also reflected in students' school performances. In an experimental field study Weis and Cerankosky (2010) offered some children a free video console. After four months, children who played on their video console achieved significantly lower scores on standardized tests in reading and writing (but not in mathematics) than the control group. Moreover, the decline in achievement was mediated by the time spent on video games. However, the respective effects were rather small: video console ownership explained only 4 to 8 percent of variance in changes of competence scores. In contrast, similar field experiments with substantially larger samples found no evidence for the influence of owning a computer on educational outcomes (Beuermann, Cristia, Cueto, Malamud, & Cruz-Aguayo, 2015; Fairlie, 2016; Fairlie & Robinson, 2013). Thus, the available empirical evidence offers no consistent support for the time displacement hypothesis. In a related vein, the *sleep displacement hypothesis* (for a review see Hale & Guan, 2015) focuses more specifically on the psychophysiological consequences of presleep activities and implies that intensive computer gaming not only reduces the quantity of sleep but also its quality. Heavy gamers go to bed later at night and thus accumulate reduced total sleep times (e.g., King et al., 2013). Moreover, exciting and emotionally stimulating computer games (e.g., with an action-related focus) can induce physiological arousal as well as cognitive alertness, thereby contributing to wakefulness before bedtime and, in turn, reducing the amount of REM sleep (e.g., Higuchi, Motohashi, Liu, & Maeda, 2005; Ivarsson, Anderson, Åkerstedt, & Lindblad, 2013; Weaver, Gradisar, Dohnt, Lovato, & Douglas, 2010). The next day, inadequate amount of sleep contributes to poorer cognitive processing and attention deficits (Dworak, Schierl, Bruns, & Strüder, 2007; Wolfe et al., 2014) and may be a cause of poorer academic performances. Furthermore, the *attention deficit hypothesis* (Gentile, Swing, Lim, & Koo, 2012) addresses concerns regarding attention problems, lower self-control, and increased impulsiveness resulting from computer and video games. Similar to other displacement hypotheses, it is assumed that prolonged computer gaming takes away time from tasks that would otherwise contribute to the development of sustained attention. The few empirical findings support this assumption: some adolescents tend to suffer from greater attention problems after playing more hours of video and computer games (Chan & Rabinowitz, 2006), even longitudinally after controlling for initial levels of attention problems and sociodemographic differences (Gentile et al., 2012; Swing, Gentile, Anderson, & Walsh, 2010). A meta-analytic summary across seven studies derived a moderate association between screen time (a composite of television use and video gaming) and attention problems of r = .32 (Nikkelen, Valkenburg, Huizinga, & Bushman, 2014).

In contrast to these critical views, the *cognitive enhancement hypothesis* (Powers, Brooks, Aldrich, Palladino, & Alfierie, 2013) takes a more optimistic perspective. Many commercial video games are rather complex and tap into similar cognitive processes as standard tests of intelligence (Foroughi, Serraino, Parasuraman, & Boehm-Davis, 2016; Quiroga et al., 2015). Consequently, it has been suggested that these games might also act as training programs for various cognitive skills. By playing computer and video games on a regular basis, players incidentally train, for example, attentional capacity, visual orientation, and memory which, in the long run, might improve their mental abilities. In line with this hypothesis, several researchers found significantly better performance on standardized tests of cognitive abilities among gamers as compared to non-gamers (see Green & Seitz, 2015, for a review). Meta-analyses (Powers et al., 2013; Wang et al., 2016) estimated that regularly playing computer games was associated with cognitive gains corresponding to Cohen's *d* between .30 to .70. Notable are the pronounced effects of computer gaming on different aspects of cognitive functioning that are also key determinants of academic achievement. For example, computer gaming improved executive functioning (Chiappe, Conger, Liao,Caldwell, & Vu, 2013) and working memory (Sungur & Boduroglu, 2012) which are central for students' academic success (see Bull, Espy, & Wiebe, 2008; Samuels, Tournaki, Blackman, & Zilinski, 2016). To a lesser degree, gaming effects have also been observed for measures of fluid intelligence (Basak, Boot, Voss, & Kramer 2008) and the ability to multitask (Strobach, French, & Schubert, 2012). Furthermore, cross-sectional studies observed similar or even stronger associations between computer gaming and cognitive skills in children as for adults (Dye & Bavelier, 2010; Wang et al., 2016). Taken together, these findings indicate that playing computer and video games might train basic cognitive abilities that are also key determinants of academic achievement and, thus, might indirectly improve educational outcomes. Recent cross-sectional findings provide partial support for this assumption. The time spent on computer games was positively associated with teacher reports of students' overall school competence among six to 11 years old children (Kovess-Masfety et al., 2016). Moreover, in a representative sample of Australian adolescents online video game usage was related to higher competence scores in mathematics, reading, and science (Posso, 2016). Unfortunately, many studies on gaming and cognitive abilities suffer from severe methodological shortcomings (for reviews see Boot, Blakely, & Simons, 2011; Green, Strobach, & Schubert, 2014; Latham, Patston, & Tippett, 2013) that make the available evidence difficult to evaluate. In recent experimental and quasi-experimental studies that overcame these limitations (e.g., Drummond & Sauer, 2014; Gnambs & Appel, 2017; van Ravenzwaaij, Boekel, Forstmann, Ratcliff, & Wagenmakers, 2014; Unsworth et al., 2015) and respective meta-analytic summaries (Sala, Tatlidil, & Gobet,

2018) little evidence of cognitive benefits stimulated by frequent computer gaming was found. These results also fall in line with conclusions from a systematic review on commercial "Brain Training" programs that found only modest training effects which rarely translate to real-life performance (Simons et al., 2016). Together, these results indicate only weak evidence for the cognitive enhancement hypothesis.

Taken together, depending on the adopted theoretical stance authors argued either for positive or negative effects of recreational computer gaming on academic outcomes. The available empirical evidence seems to support both perspectives to some degree: whereas some studies reported worse grades and poorer test performance for students devoting a lot of their leisure time to computer games (e.g., Anand, 2007; Jackson et al., 2011; Weaver et al., 2010), others found beneficial effects of time spent on computer games on educational outcomes (e.g., Kovess-Masfety et al., 2016; Posso, 2016), or no effects at all (e.g., Drummond & Sauer, 2014). Unfortunately, most of these studies relied on cross-sectional research designs that preclude from drawing causal conclusions. However, even the few available longitudinal studies provided no clear answer regarding the academic repercussions of computer gaming. For example, in a prospective study, Sharif, Wills, and Sargent (2010) reported worse school performance (i.e., a composite of grades and self-perceived school achievement) after two years for students engaging longer in computer games. However, with a correlation of -.10, the respective effect was rather small. In contrast, Bowers and Berland (2013) found slightly larger competence scores for moderate gamers as compared to non-gamers or excessive gamers.

Present Investigation

The aim of the present study was to examine the relationship between computer gaming and academic achievement in mathematics and reading. Importantly, we extended previous findings on three central accounts. For one, gaming research has a lack of longitudinal studies which renders causal conclusions mostly impossible. Most studies on the effects of gaming devoted to academic performance relied on cross-sectional designs. Therefore, it remains unclear to what extent previous findings are confounded by selection effects. Another problem with many studies (including the aforementioned few longitudinal studies) arises from different conceptualizations of academic achievement. Some authors focused on grades, whereas other measured domain-specific competences. However, grades and competences are different constructs with different antecedents (Kenney-Benson, Pomerantz, Ryan, & Patrick, 2006). Whereas school grades require effort and persistence over longer periods of time, performance on standardized competence tests are measured at one point of time. Therefore, it is conceivable that students playing computer games on a regular basis do not invest the required long-term effort in class that would be necessary for good grades (e.g., by doing their homework properly), whereas they might be motivated enough to perform well in a single assessment. Finally, most gaming research is limited to the examination of linear trends (e.g., Hambrick, Oswald, Darowski, Rench, & Brou, 2010; Unsworth et al., 2015). However, it is conceivable that computer gaming might also yield non-linear effects (cf. Gnambs & Appel, 2017). For example, moderate computer gaming might train cognitive abilities (Powers et al., 2013), whereas excessive gaming is likely to yield more dire consequences because of its known association with various psychiatric disorders (Andreassen et al., 2016). Therefore, we analyzed linear and potential non-linear effects of computer gaming.

Previous gaming research has adopted a range of different research designs and analytical approaches, for example, with regard to the analyses of latent relationships versus observed score effects or the (non-)inclusion of various control variables. Given the difficulty in successfully reproducing various seemingly established effects in psychology (e.g., Hagger et al., 2016; Wagenmakers et al., 2016), it has been suggested that many findings might be false positives (Ionnadis, 2005). Particularly, with greater flexibility in sample selection, construct operationalizations, and analytical choices (so-called, researcher degrees of freedom; cf. Simmons, Nelson, & Simonsohn, 2011), most results can be presented as significant. Therefore, it is important to examine to what degree methodological choices might have affected the results of a study (cf. Steegen, Tuerlinckx, Gelman, & Vanpaemel, 2016; Zinn & Gnambs, 2018). To address this problem, the present study used a large sample of German students to examine the prospective effects of playing recreational computer games on academic achievement two to three years later. We evaluated different academic outcomes (grades and competences) in two different domains (reading and mathematics). Importantly, the robustness of our findings were evaluated using *specification curve analyses* (Simonsohn, Simmons, & Nelson, 2015) by examining our results across a large range of reasonable model specifications that resulted from different researcher degrees of freedom.

Method

Sample and Procedure

The sample is part of the longitudinal German National Educational Panel Study (NEPS) that tracks a representative sample of German students across their school careers (see Blossfeld, Roßbach, & von Maurice, 2011). Details on the sampling procedure are described in Steinhauer et al. (2015). For this study, we analyzed responses from $N = 3,554$ students (56% female) across several years beginning in the ninth grade. Those students attended 336 classes in 176 different secondary schools across the country. We focus on three measurement waves in 2010 (class 9), 2012 (class 11), and 2013 (class 12). In all waves, the tests were administered at the beginning of the respective school year between October and December. One exception from this design was the first measurement of reading competence that was conducted in spring of 2011. The mean age at the time of the first wave was $M = 14.47$ ($SD = 0.57$) years. Students were typically tested in small groups at their respective schools by a professional survey institute. Students that left their original school over the course of the longitudinal study were tracked and individually tested at home by experienced interviewers. Details on the data collection process including the survey execution, the interviewer selection, and the tracking of respondents are documented in the field reports provided on the project website (http://www.neps-data.de).

Instruments

The time spent on computer and video games was assessed in class 9 with three items asking about how long students played (a) online role-playing games (e.g., World of Warcraft, Gild Wars), (b) games of skill or strategy, and (c) other computer or video games on a normal school day. The responses were recorded on five-point scales with 1 = *never*, 2 = *up to 1 hour*, 3 = *1 to 2 hours*, 4 = *2 to 4 hours*, and 5 = *more than 4 hours*. Because of the unequal spacing of the response categories, we applied a non-linear transformation. The average time spent playing computer games each day (in hours) was approximated by recoding the five response options into values of 0.0, 0.5, 1.5, 3.0, and 4.5, respectively (i.e., representing the average hours playing computer games) and summing up the three item scores. On average, the students played about $M = 1.45$ ($SD = 1.98$) hours computer games during a regular school day (see left panel of Figure 1).

In classes 9 and 11, students were asked about their grades in mathematics and German on their last annual report cards. In Germany, grades are indicated by numeric values with 1 = *very good*, 2 = *good*, 3 = *satisfactory*, 4 = *passing*, 5 = *poor*, and 6 = *failing*. Because less than 5 percent of the students reported poor or failing grades, the three highest categories were collapsed. Therefore, in the present study grades ranged from 1 to 4. For ease of comprehension, we inversed the scale, thus, higher values indicate better grades. In both years and for both school subjects the median grade was $Mdn = 2$ (see middle panel of Figure 1).

Mathematical and reading competences were measured in classes 9 and 12 with achievement tests that were specifically constructed for administration in the NEPS. The adopted theoretical frameworks for these tests are described in Neumann et al. (2013) and Gehrer, Zimmerman, Artelt, and Weinert (2013). Each item required either a (complex or single) multiple-choice or a short constructed response. In multiple-choice items the testtakers had to identify a correct solution to a question from several (typically four) response options, whereas for short constructed responses the students had to write down their answers to the questions in a blank field. Different tests with either 22 or 29 items in mathematics and 31 or 28 items in reading were administered in both waves. The tests were targeted at the competence levels of the average student in the respective class. All tests were scaled using models of item response theory (see Pohl & Carstensen, 2013). Competence scores were estimated as weighted maximum likelihood estimates (WLE; Warm, 1989) and linked across classes to allow for valid mean level comparisons across the two measurement waves (see Fischer, Rohm, Gnambs, & Carstensen, 2016). The WLE reliabilities were good with .79 and .75 for the mathematical tests, and .75 and .80 for the reading tests, respectively. Detailed psychometric properties of the administered mathematical tests are reported in Durchardt and Gerdes (2013) and Fischer, Rohm, and Gnambs (2017), whereas respective results for the reading tests are summarized in Haberkorn, Pohl, Hardt, and Wiegand (2012) and Gnambs, Fischer, and Rohm (2017).

Reasoning abilities were measured in class 9 with a Raven (1977)-type test including 12 items (see Brunner, Lang, & Lüdtke, 2014). Each item consisted of one blank field and a number of fields containing geometrical elements that followed various logical rules. Participants had to identify the underlying rules to insert the correct element into the blank field from a series of available response options. The number of correctly solved items served as the indicator of students' reasoning abilities. On average, the participants correctly solved $M = 9.86$ ($SD = 1.73$) items. The omega hierarchical reliability of this measure was $\omega_h = .78$ (cf. Rodriguez, Reise, & Haviland, 2016).

Statistical Analyses

The effects of playing computer games on grades and competence development were examined with polynomial regression analyses that specified either grades or competences at the second measurement occasion as criterion. Because the two criteria differed with regard to their measurement levels, we adopted different statistical procedures. For grades we estimated ordinal logistic regression models (see Agresti, 2013), whereas competences were examined using linear regression analyses (Fox, 2015). Linear and non-linear effects of the time spent on computer games were investigated by including linear and quadratic polynomials of computer gaming time as predictors in these regression models. In addition, grades or competences measured in class 9 were added to these models in order to estimate changes in academic achievement across time. Furthermore, students' basic reasoning abilities were included as control variable. Moreover, given pronounced sex differences in gaming behavior (e.g., Gnambs & Appel, 2017), all analyses controlled for the students' gender. Because the students were sampled from different schools, these dependencies were acknowledged by estimating cluster-robust standard errors (Cameron & Miller, 2015). About 12 percent of the respondents exhibited missing values on one or more variables used in this study. Therefore, the analyses are based on multiple imputations where missing values were imputed 20 times using predictive mean matching (van Buuren, 2012).

Specification curve analyses. Empirical research requires a multitude of decisions on part of the researcher (so called researcher degrees of freedom; Simmons et al., 2011). These decisions might involuntary affect the results of a study. Therefore, we examined the robustness of our findings with regard to several of our decisions using specification curve analyses (Simonson et al., 2015). This procedure involves three steps: (i) First, reasonable model specifications based on methodological choices by the researcher are identified (e.g., different ways of creating a scale score). (ii) Then, each model specification is analyzed and described with regard to the focal effects (in our case, gaming effects on academic achievement). (iii) Finally, statistical inferences across all model specifications are made to evaluate the robustness of the effects. We decided to examine four methodological choices (see Table 1):

1. We evaluated two ways of calculating our gaming scores. On the one hand, we approximated the average time spent playing computer games each day (in hours) using a nonlinear transformation of the respondents' item scores (see above); on the other hand, we also created an index of gaming intensity by calculating the sum across the untransformed item responses.
2. We examined two different types of cognitive scores. The available data file provided competence estimates for each respondent in the form of WLEs (Warm, 1989). An alternative way of modeling competences in large scale assessments are plausible values (see Braun & von Davier, 2017, von Davier, Gonzalez, & Mislevy, 2009, or Wu, 2005, for an introduction into the plausible value technique). Whereas WLEs represent point estimates and, thus, are afflicted by measurement error, plausible values acknowledge the uncertainty in the competence measurements and allow for the analysis of latent relationships (similar to latent variable modeling in structural equation modeling). Therefore, we also drew 20 plausible values for each respondent.
3. To evaluate the impact of extreme gaming scores (defined as the one percent largest scores), we either included all outliers in our analyses or recoded outliers as missing values and, subsequently, imputed respective gaming scores (see above).
4. Because the choice of control variables included in a regression model can influence the identified effects (Becker et al., 2016), we analyzed the impact of computer gaming on academic achievement either controlling for or not controlling for basic reasoning abilities.

The combination of these four methodological choices gave rise to 2 x 2 x 2 x 2 = 16 different model specifications (see Table 1). Thus, our analyses were repeated 16 times, once for each model specification. Following Simonsohn et al. (2015), we applied permutation tests considering all specifications jointly to examine whether the results were inconsistent with the null hypothesis of no effect (see Appendix A for further details).

Evaluation of effects. The interpretation of effects size frequently follows various rules of thumbs, for example, those by Cohen (1992) who considered correlations of .10, .30, and .50 as small, medium, and large effects. In contrast, empirical effect size distributions in various psychological domains (Bosco, Aguinis, Signh, Field, & Pierce, 2015; Gignac & Szodorai, 2016; Paterson, Harms, & Steel, 2016) typically exhibit a median effect size around r = .20 (with the 25th and 75th percentiles around .10 and .30). Similar, in Hattie's (2011, 2015) highly cited meta-analysis on predictors of school achievement effects falling below r = .20 were considered negligible, not worth wasting educator's time. In our study, we considered effect sizes of about r = .10 as small and effects exceeding r = .20 as practically relevant. These thresholds correspond to standardized regression weights (β) of .10 and .20 or odds ratios (OR) of 1.40 (or 0.70) and 2.00 (or 0.50), respectively.

Statistical software. The analyses were conducted in *R* version 3.5.0 (R Core Team, 2018) using the *MASS* package version 2015.6-28 (Venables & Ripley, 2002), *sandwich* version 2.4-0 (Zeileis, 2004, 2006), *TAM* version 2.11-93 (Robitzsch, Kiefer, & Wu, 2018), and *mice* version 2.30 (van Buuren & Groothuis-Oudshoorn, 2011).

Data and Code Availability

This paper uses data from the National Educational Panel Study in Germany (cf. von Maurice, Wolter, & Zinn, 2017). The anonymized data is available to the international research community free of charge at http://www.neps-data.de. Moreover, the *R* code and the results of the statistical analyses reported in this manuscript can be accessed at https://osf.io/pjb24/. An overview of further resources accompanying this manuscript is given in Appendix B.

Results

Descriptive Analyses

Of the 3,554 students, about 70 percent reported playing computer and video games at least occasionally, and more than 20 percent even for more than two hours on a regular school day[1]. Only 30 percent of the sample indicated that they never played computer games at all (see left panel in Figure 1). Boys (*M* = 2.45, *SD* = 2.36) dedicated significantly, $t(2134.08) = 27.12$, $p < .001$, $d = 0.95$, more time to computer and video games than girls (*M* = 0.69, *SD* = 1.13). Similarly, there were pronounced sex differences in grades and competences. In the mathematical domain, male students (*M* = 1.72, *SD* = 1.05) exhibited significantly, $t(3305.79) = 18.69$, $p < .001$, $d = 0.63$, higher competence scores in class 12 than female students (*M* = 1.07, *SD* = 1.01). This difference was also mirrored by the respective grades, $t(375714.64) = -3.81$, $p < .001$, $r_s = -.07$. In contrast, girls (*M* = 1.03, *SD* = 0.83) had a significantly, $t(3,220.54) = -5.93$, $p < .001$, $d = -0.20$, higher reading competence than boys (*M* = 0.85, *SD* = 0.91) and also better grades in German, $t(84887.60) = 12.32$, $p < .001$, $r_s = .23$.

Cross-Sectional Effects of Computer Gaming on Academic Achievement

The correlations between the time spent on computer games and the measures of academic achievement in class 9 revealed slightly negative effects of intensive computer gaming (see Table 2). After controlling for the respondents' sex, the partial correlations between the hours playing computer games and grades in mathematics and German were $r = -.06$ ($p < .001$) and $r = -.07$ ($p < .001$), respectively. Similarly, controlling for the respondents' sex computer gaming time was negatively correlated with mathematical competence in class 9, $r = -.07$ ($p < .001$). In contrast, reading competence was not associated with gaming time, $r = .00$ ($p = .970$). Thus, the time spent on computer and video games was cross-sectionally associated with somewhat lower competences in mathematics and slightly lower grades in both domains.

[1] The descriptive analyses are based on analysis strategy 5 (see Table 1).

Prospective Effects of Computer Gaming on Grades

The grades measured in class 11 were regressed on the respondents' computer gaming times in class 9 using linear and quadratic polynomials to acknowledge potential curvilinear associations. Moreover, given the pronounced sex differences in the time spent on computer games and grades, sex was included as covariate in these models. To examine the robustness of the results, these regressions were repeated for 16 different analyses strategies (see Table 1). The main effects of computer gaming on grades from these analyses are summarized in Figure 2 (top row). In line with the cross-sectional analyses, we identified linear effects of gaming times on academic achievement for most analyses strategies. However, the identified effects were quite small. The median odds ratio across the 16 analyses strategies was OR = 0.91 for mathematics and OR = 0.88 for German. The inferential specification curve analyses in Table 3 suggested that the number of significant effects did not result by chance, p =.014 and p = .034, but reflected robust gaming effects. We found no consistent support for non-linear effects of computer gaming on grades as indicated by the non-significant ($p > .05$) quadratic terms of gaming time (see supplemental material). The median quadratic effects across the different analyses strategies were OR = 1.00 for both domains.

The linear effects of gaming could also be replicated for respondents' changes in grades for mathematics (see bottom row of Figure 2). After including the grades measured in class 9 to our regression models, the median effect of computer gaming on grades in mathematics hardly changed OR = .91, whereas the respective effect in German slightly reduced to OR = .92. Again, the inferential specification curve analyses (see Table 3) suggested robust results beyond chance, p =.014 and p = .048. We found no significant quadratic effects (see supplemental material). Thus, the time spent on computer and video games predicted changes in grades two years later for both school subjects. The respective median effects across the different model specifications are plotted in Figure 3.

Prospective Effects of Computer Gaming on Competences

To examine similar effects for mathematical and reading competences, we regressed competences measured in class 12 on the respondents' computer gaming times in class 9. Again, sex was included as covariate in these analyses. The results for the different analyses strategies are summarized in Figure 4 (top row). These showed no consistent effect of computer and video gaming on competences in either domain. Although the untransformed gaming measure exhibited small effects on mathematical competences in some conditions, these effects were not robust and did not replicate after controlling for reasoning abilities. For reading competences, no systematic gaming effects could be observed. As a result, the median gaming effects across the 16 model specifications were negligible resulting in $\beta = .01$ for mathematics and $\beta = .03$ for reading. However, these effects were qualified by small non-linear trends, $Mdn(\beta) = -.09$ / $-.07$ (see supplemental material). Similar, the time dedicated to computer and video games had no effect on students' competence development over the course of three years (bottom row in Figure 4). Overall, these analyses do not indicate replicable effects of computer gaming on (changes in) mathematical or reading competences.

Discussion

The aim of the current study was to examine the association between computer gaming and academic outcomes in a longitudinal design. Our analyses were based on a large sample of German students that were tracked over the course of three years. Computer gaming was measured continually, which allowed us to examine potential linear as well as non-linear associations with academic outcomes. Moreover, we overcame a frequent shortcoming in the previous empirical literature by assessing different aspects of academic achievement, grades as well as domain-specific competences, in two domains. The analyses provided three central findings. First, students' grades suffered from intensive computer gaming. Cross-sectional as well as longitudinal effects pointed to moderately lower grades for students that spent more hours on computer games on a regular school day. Second, the lower grades were not mirrored by a respective decline in domain-specific competences. Neither mathematical nor reading competences showed a consistent change over time as a result of the time spent on computer games. Rather, competences were quite invariant to the students' gaming behavior. Overall, the size of the identified effects were in stark contrast to the attention gaming research receives in the public eye as reflected in press headlines such as "Video game use linked to worse GCSEs, study suggests" (Meredith, 2015) or "Online gaming could improve a teenager's academic performance" (Williams, 2016). All effects of computer gaming times on academic outcomes were quite small according to conventional standards. For example, students playing about two hours each day reduced the odds of receiving a better grade in mathematics or German than two years earlier by a factor of 0.80. Even for the most extreme gamers that play up to eight hours the respective odds decreased only by a factor of about 0.50. As compared to Hattie's (2011, 2015) influential meta-analysis on teacher effects in school, playing computer games seems to have a negligible or rather small effect at the most. However, given our longitudinal perspective that spanned up to three years short-term effects (e.g., within a term or a school year) could be more substantial.

The reported results offer no support for the cognitive enhancement hypothesis (Powers et al., 2013) in the academic realm. Commercial computer games are no effective training programs for cognitive abilities that might benefit academic achievements (for similar conclusions see Gnambs & Appel, 2017). Rather, our results confirmed fears of minor disadvantages for children with higher gaming times. In line with displacement hypotheses (Hale & Guan, 2015; Subrahmanyam & Renukarya, 2015) computer gaming prospectively resulted in somewhat lower grades. Adolescents who spend more time playing computer games might invest less time in homework and other extracurricular tasks, thus, get less practice of school subject matters. However, this explanation remains speculative as long as the respective mediating mechanism has not been corroborated empirically; for example, Marker, Gnambs, and Appel (2018) found no time displacement effects from the use of online social networking sites. Moreover, the increased time that they have spent in virtual environments might also contribute to gamers' decreased involvement in class (e.g., reduced participation in school activities). Because grades not only integrate performance on individual academic achievement tests but also continuous participation in class (e.g., homework), this might explain why computer gaming is reflected in lower grades but there is no according impact on students' competences. Furthermore, and in line with previous research (e.g., Weis and Cerankosky, 2010), these effects were slightly more pronounced in students' development of grades in German than in mathematics. One possible explanation might be that computer gaming could to some extent still be beneficial to students' reasoning skills and strategic thinking (e.g., Bakker, van den Heuvel-Panhuizen, & Robitzsch, 2015; Bottino, Ferlino, Ott, & Tavella, 2007) which in turn might first and foremost impact their interest and engagement in mathematics rather than in language domains. Although recent studies showed that the stereotype of a socially isolated and pale gamer does not hold (e.g., Kowert, Festl, & Quandt, 2014), it might still be an image that especially male computer gamers are confronted with (cf. Paaßen, Morgenroth, & Stratemeyer, 2017). To this end, it should be interesting to examine teachers' images of their students with respect to computer gaming and how this is reflected in their grades. Moreover, these results might further reflect a decreased engagement in social interactions for children who spent more time on computer gaming. Hence, it is possible that students' language skills and social communication as well as their involvement in the classroom is more restricted for students due to the amount of time spent in virtual than in offline environments. However, so far, these mediating mechanisms remain speculative and need to be explored further.

Limitations and Directions for Future Research

The presented results offer intriguing possibilities for future research. First, the study focused on a specific academic outcome of gaming in the form of the time spent on computer and video games on a regular school day. Besides this quantitative perspective, it seems mandatory to focus more closely on qualitative factors of computer game play. In what way does the specific content of a computer game affect academic achievement? For example, particularly violent game scenarios do not seem to have a pronounced effect on academic outcomes (Anderson & Gentile, 2014). In contrast, instructional games that have been explicitly developed for learning (i.e., ”serious games”) have been shown to train academic competences (Wouters, van Nimwegen, van Oostendorp, & van der Spek, 2013). Thus, it seems worthwhile to study specific features of a computer game to determine to what degree it requires specific cognitive abilities (e.g., memory abilities) or competences (e.g., mathematical skills) that might be relevant for a student’s academic career. For these types of games, longer play times are unlikely to yield the observed negative consequences. In contrast, games that are particularly immersive (cf. Schüler, 2012) or games that penalize absence from gaming may decrease the likelihood that students adjust their gaming times effectively to allow for enough sleep and preparation for school.

Second, our study did not include a longitudinal perspective on gaming times but, rather, used gaming times measured in class 9 to predict changes in grades and competences prospectively. Given some evidence that the time spent on computer and video games each day has a rather low temporal stability (i.e., r = .37 to .57 over one year; Lobel, Engels, Stone, Burke, & Granic, 2017), future research should adopt balanced longitudinal designs to study how changes in computer gaming are associated with respective changes in academic achievement. Moreover, in line with previous research we relied on self-reported gaming times. However, the validities of these measures have recently been called into question because many computer gamers tend to underreport their actual time spent on computer games (Kahn, Ratan, & Williams, 2014). Therefore, in the future it might be advisable to explore the possibilities given by behavioral data such as observer reports (e.g., by parents) or procedural data (e.g., computer generated log files) that might give additional insights into the specifics of students’ time spent on computer gaming.

Finally, although we included reasoning abilities as predictor of academic achievement it could be fruitful to consider other individual differences that might cushion potential detrimental effects of computer gaming. For example, for academic performance self-control can exhibit a stronger predictive power than intelligence (Duckworth & Seligman, 2005). Thus, intensive computer gamers with high levels of self-control might manage to regulate their gaming intensity when the school demands more attention (e.g., during exam season) and resume their gaming activities afterwards. In contrast, other excessive gamers without proper self-control might fail to regulate their gaming behavior accordingly. Therefore, future studies are encouraged to include relevant measures of individual differences (e.g., self-regulation, academic motivation) as moderators in their gaming research.

Conclusion

The numerous hours teenagers worldwide devote to playing computer and video games has raised concerns that these activities might come at the cost of school achievement. Because available cross-sectional research on this matter was rather inconclusive, the present study adopted a prospective design and studied how computer gaming is associated with changes in grades and competences over time. The time playing computer games each day resulted in slightly lower grades in mathematics and German two years later. However, respective effects on domain-specific competences failed to exhibit a similar pattern. Overall, the detrimental effects of computer gaming on educational outcomes seem to be quite small. It remains doubtful whether casual computer playing yields practically relevant consequences for the majority of students. Rather, the public debate regarding potential dangers of computer gaming seem to be exaggerated.

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Appendix A: Inferential Specification Curve Analyses

The specification curve analyses were conducted for 16 model specifications (see Table 1). Inferential tests were conducted with permutation tests following Simonsohn et al. (2015). For these tests, we created 500 new data sets from the raw data by shuffling the independent variable; that is, the gaming scores were randomly assigned to the respondents in each new data set. Subsequently, the same specification analyses as described above were repeated on each of these 500 samples. This resulted in a distribution under the null hypothesis because, by design, the gaming scores were unrelated to the outcomes.

The number of significant *p*-values ($p < .05$) across the 16 model specifications were used as test statistic for the permutation test (cf. Simonsohn et al., 2015). Thus, the 500 samples created a distribution for the number of significant *p*-values under the null. Then, we compared the test statistic observed in our original data to the distribution of this test statistics from the 500 new data sets. This allowed us to assess whether the null hypothesis of no gaming effect on academic achievement could be rejected. Specifically, the number of new samples with at least as many significant specifications represented the *p*-values for the permutation test. These *p*-values reflected the probability of observing as many or more specifications under the assumption of no gaming effect (i.e., the null).

Appendix B: Index of Supplemental Information

Supplemental material	Source
Study material (e.g., sample recruitment, instruments, survey design and execution)	http://www.neps-data.de
Raw data of study	http://dx.doi.org/10.5157/NEPS:SC4:9.1.1
Coefficient estimates for regression models	Tables S1 to S8 in supplemental material
R code for analyses	https://osf.io/pjb24/
Results of statistical analyses	https://osf.io/pjb24/

Table 1.

Examined Researcher Degrees of Freedom

			Potential analyses strategies															
	Researcher degree of freedom		1.	2.	3.	4.	5.	6.	7.	8.	9.	10.	11.	12.	13.	14.	15.	16.
1.	Gaming score	Original items scores (codes: 0, 1, 2, 3, 4)	x	x	x	x					x	x	x	x				
		Transformed item scores to approximate hours played (codes: 0.0, 0.5, 1.5, 3.0, 4.5)					x	x	x	x					x	x	x	x
2.	Cognitive scores	Point estimates as weighted maximum likelihood estimates	x	x			x	x			x	x			x	x		
		Plausible values to account for measurement error			x	x			x	x			x	x			x	x
3.	Extreme scores	Extreme gaming scores included	x		x		x		x		x		x		x		x	
		Extreme gaming scores treated as missing		x		x		x		x		x		x		x		x
4.	Covariates	Controlling for sex	x	x	x	x	x	x	x	x								
		Controlling for sex and reasoning									x	x	x	x	x	x	x	x

Table 2.

Means, Standard Deviations, and Correlations between Study Variables

					Correlations									
	Measure	*M*	*SD*	MV	1.	2.	3.	4.	5.	6.	7.	8.	9.	10.
Class 9														
1.	Hours playing computer games	1.46	1.99	3.77		-.06*	.07*	-.07*	.00	.01	-.08*	-.09*	-.08*	-.04*
2.	Grade in mathematics	2.38	0.94	2.81	-.04*		.37*	.40*	.18*	.20*	.61*	.32*	.38*	.20*
3.	Grade in German	2.44	0.79	2.76	-.17*	.35*		.23*	.27*	.07*	.29*	.55*	.18*	.27*
4.	Mathematical competence	0.94	1.18	0.03	.06*	.40*	.15*		.37*	.35*	.39*	.20*	.64*	.42*
5.	Reading competence	0.84	1.05	3.74	-.05*	.18*	.28*	.33*		.25*	.16*	.25*	.34*	.50*
6.	Reasoning	9.86	1.74	3.60	.04*	.20*	.06*	.35*	.25*		.18*	.06*	.32*	.22*
Class 11														
7.	Grade in mathematics	2.35	0.98	1.74	-.04*	.61*	.26*	.39*	.15*	.18*		.36*	.40*	.20*
8.	Grade in German	2.47	0.83	1.83	-.18*	.30*	.57*	.12*	.26*	.04*	.34*		.14*	.28*
Class 12														
9.	Mathematical competence	1.35	1.08	0.45	.06*	.38*	.10*	.67*	.29*	.32*	.40*	.06*		.42*
10.	Reading competence	0.95	0.87	0.96	-.08*	.20*	.29*	.38*	.51*	.22*	.19*	.29*	.37*	

Note. N = 3,554. MV = Percentage of missing values. Zero-order correlations are below the diagonal and partial correlations accounting for the respondents' sex are above the diagonal. Results are based on 20 multiple imputed datasets using analysis strategy 5 (see Table 1).

$^{*}p < .05$

Table 3.

Inferential Specification Curve Analyses

	Domain: Mathematics				Domain: German / reading			
	Median effect	$k_{sign.}$	k_0	p	Median effect	$k_{sign.}$	k_0	p
Grades								
Gaming time: linear	0.91	10	7	.014	0.88	12	17	.034
Gaming time: quadratic	1.00	1	53	.106	1.00	2	70	.140
Competences								
Gaming time: linear	0.01	5	6	.012	0.03	2	37	.074
Gaming time: quadratic	-0.09	9	0	.000	-0.07	3	13	.026
Changes in Grades								
Gaming time: linear	0.91	10	7	.014	0.93	8	24	.048
Gaming time: quadratic	1.00	0	500	1.000	1.00	0	500	1.000
Changes in Competences								
Gaming time: linear	0.01	0	500	1.000	-0.04	0	500	1.000
Gaming time: quadratic	-0.05	4	18	.036	-0.00	0	500	1.000

Note. $N = 3,554$. Median effect = Median standardized coefficient estimate (OR or β) across 16 model specifications (see Table 1) in original sample. k_{sign} = Number of significant ($p < .05$) effects among 16 model specifications in original sample. k_0 = Test statistic of permutation test as the number of shuffled samples with at least k_{sign} significant effects. p = p-value of permutation test as the percentage of k_0 among 500 shuffled samples.

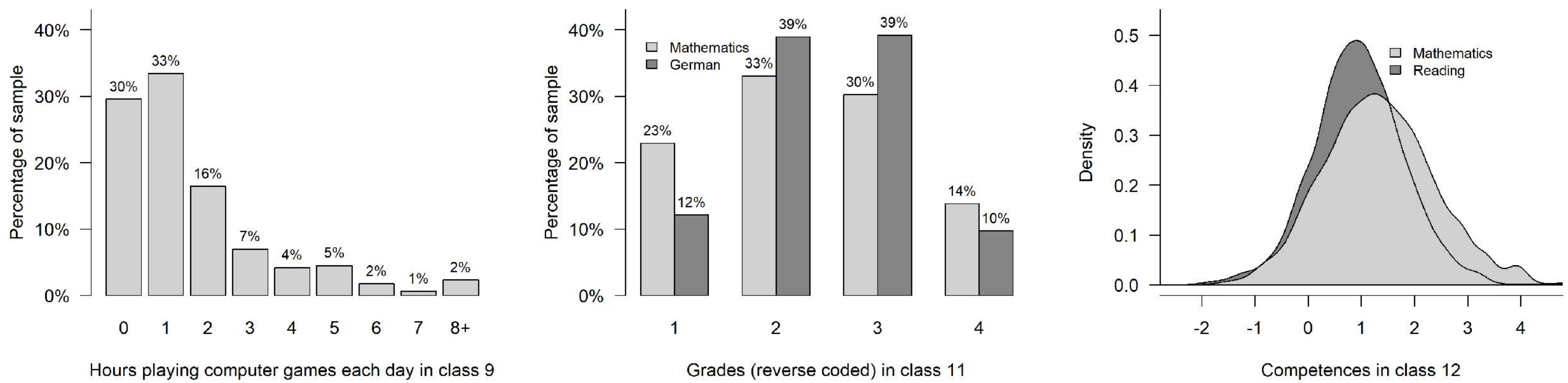

Figure 1. Distributions of hours playing computer and video games, grades, and competences (with higher values representing better grades and competences). Results are based on 20 multiple imputed datasets using analysis strategy 5 (see Table 1).

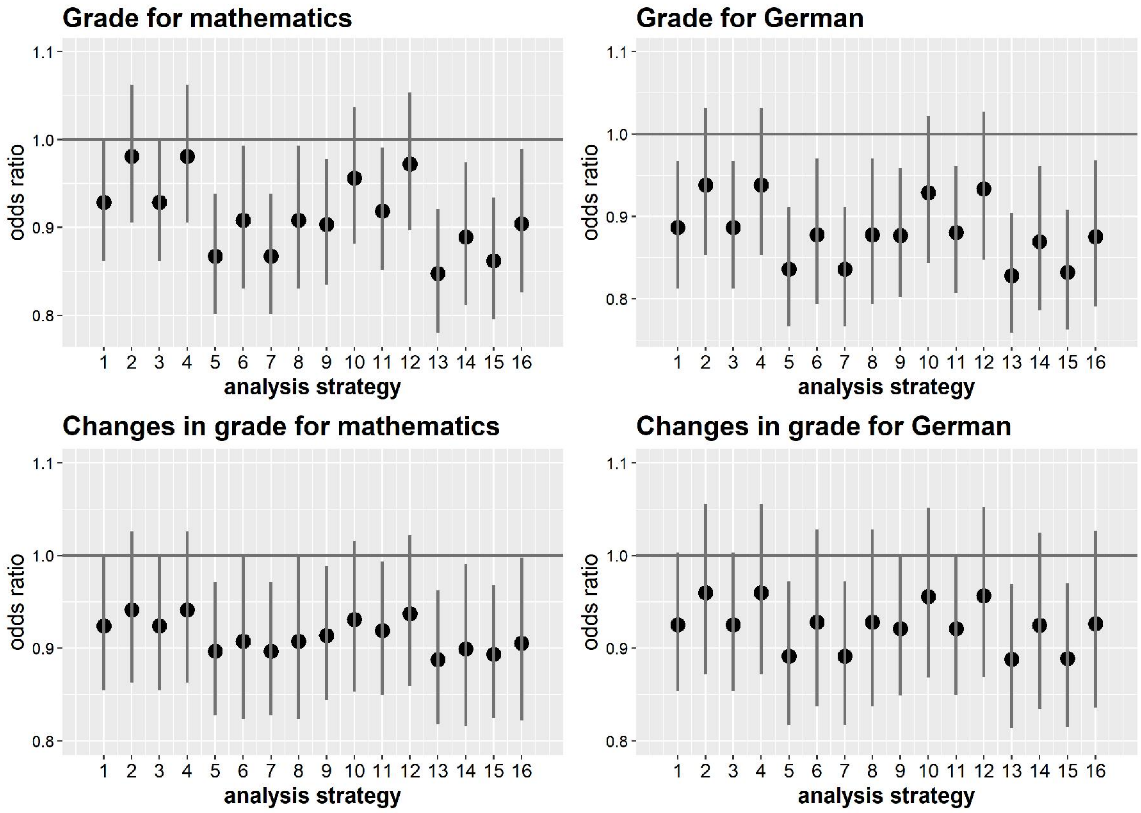

Figure 2. Estimated coefficients (with 95% confidence intervals) for the linear effect of gaming on grades for different analyses strategies (see Table 1). The full results of the regression analyses are reported in Tables S1 to S4 of the supplemental material.

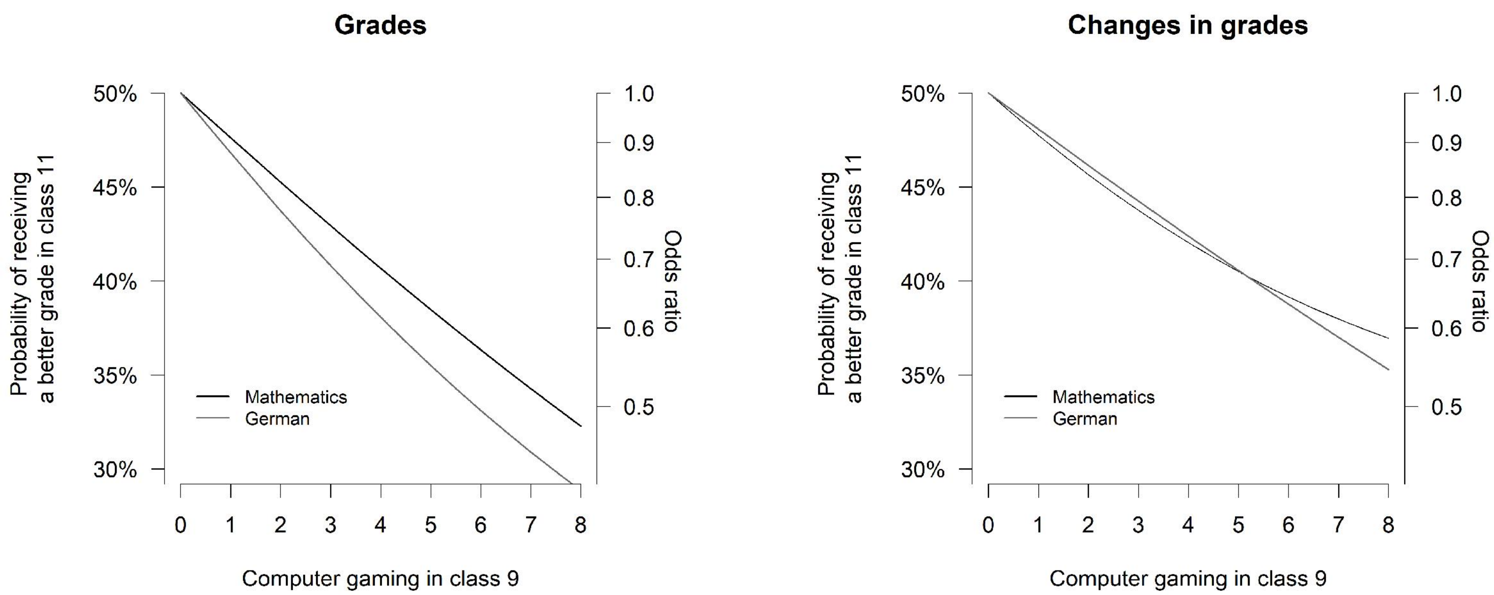

Figure 3. Longitudinal effects of computer gaming on grades (controlling for sex). Results are based on the median coefficient estimates for the different analyses strategies (see Table 1).

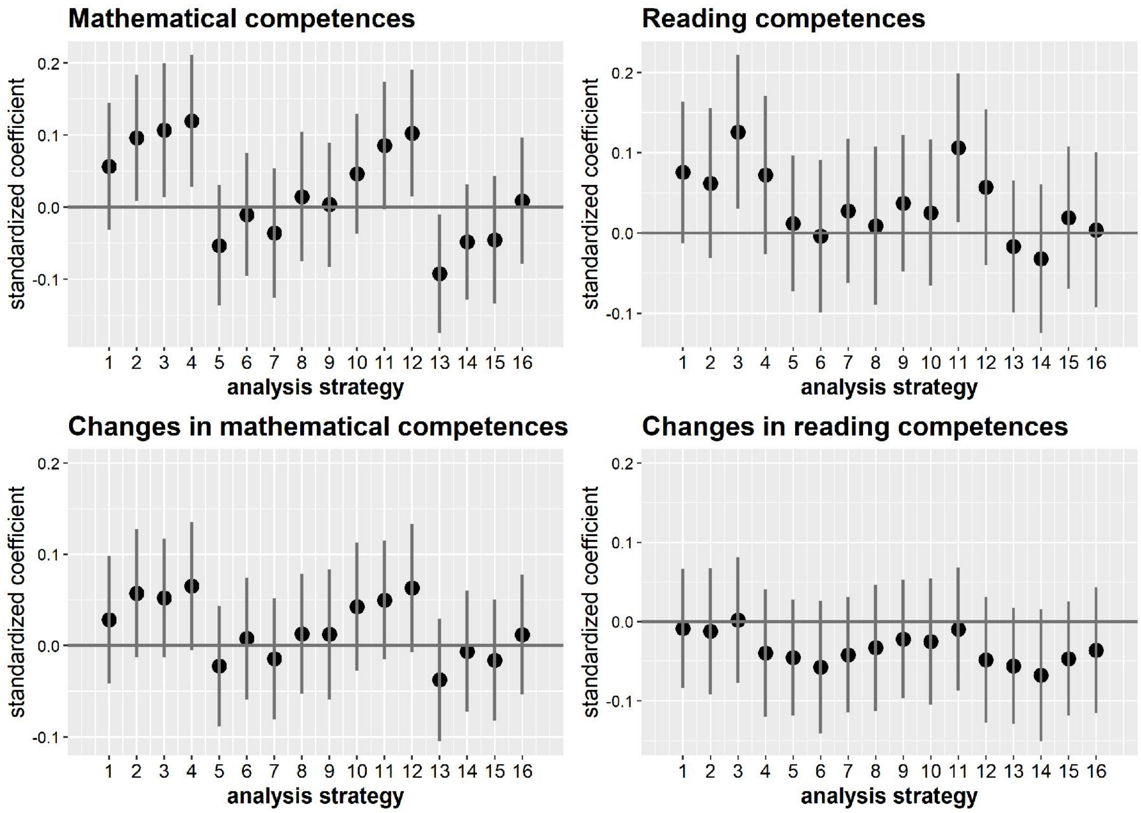

Figure 4. Estimated coefficients (with 95% confidence intervals) for the linear effect of gaming on competences for different analyses strategies (see Table 1). The full results of the regression analyses are reported in Tables S5 to S8 of the supplemental material.

Supplemental Material for

„How Computer Games Jeopardize Educational Outcomes?

A Prospective Study on Gaming Times and Academic Achievement"

Figure S1: Distributions of grades and competences at both measurement occasions (with higher values representing better grades and competences).

Figure S2: Estimated coefficients (with 95% confidence intervals) for the interaction effect between gaming and prior grades on grades in class 11 for different analyses strategies.

Figure S3: Estimated coefficients (with 95% confidence intervals) for the interaction effect between gaming and prior competences on competences in class 12 for different analyses strategies.

Figure S4: Longitudinal effects of computer gaming on competences (controlling for sex). Results are based on pooled coefficient estimates for the different analyses strategies.

Table S1: Estimated coefficients of regression models for grades in mathematics measured in class 11 for different analyses strategies.

Table S2: Estimated coefficients of regression models for changes grades in mathematics measured in class 11 for different analyses strategies.

Table S3: Estimated coefficients of regression models for grades in German measured in class 11 for different analyses strategies.

Table S4: Estimated coefficients of regression models for changes in grades in German measured in class 11 for different analyses strategies.

Table S5: Estimated coefficients of regression models for mathematical competences measured in class 12 for different analyses strategies.

Table S6: Estimated coefficients of regression models for reading competences measured in class 12 for different analyses strategies.

Table S7: Estimated coefficients of regression models for changes in mathematical competences measured in class 12 for different analyses strategies.

Table S8: Estimated coefficients of regression models for changes in reading competences measured in class 12 for different analyses strategies.

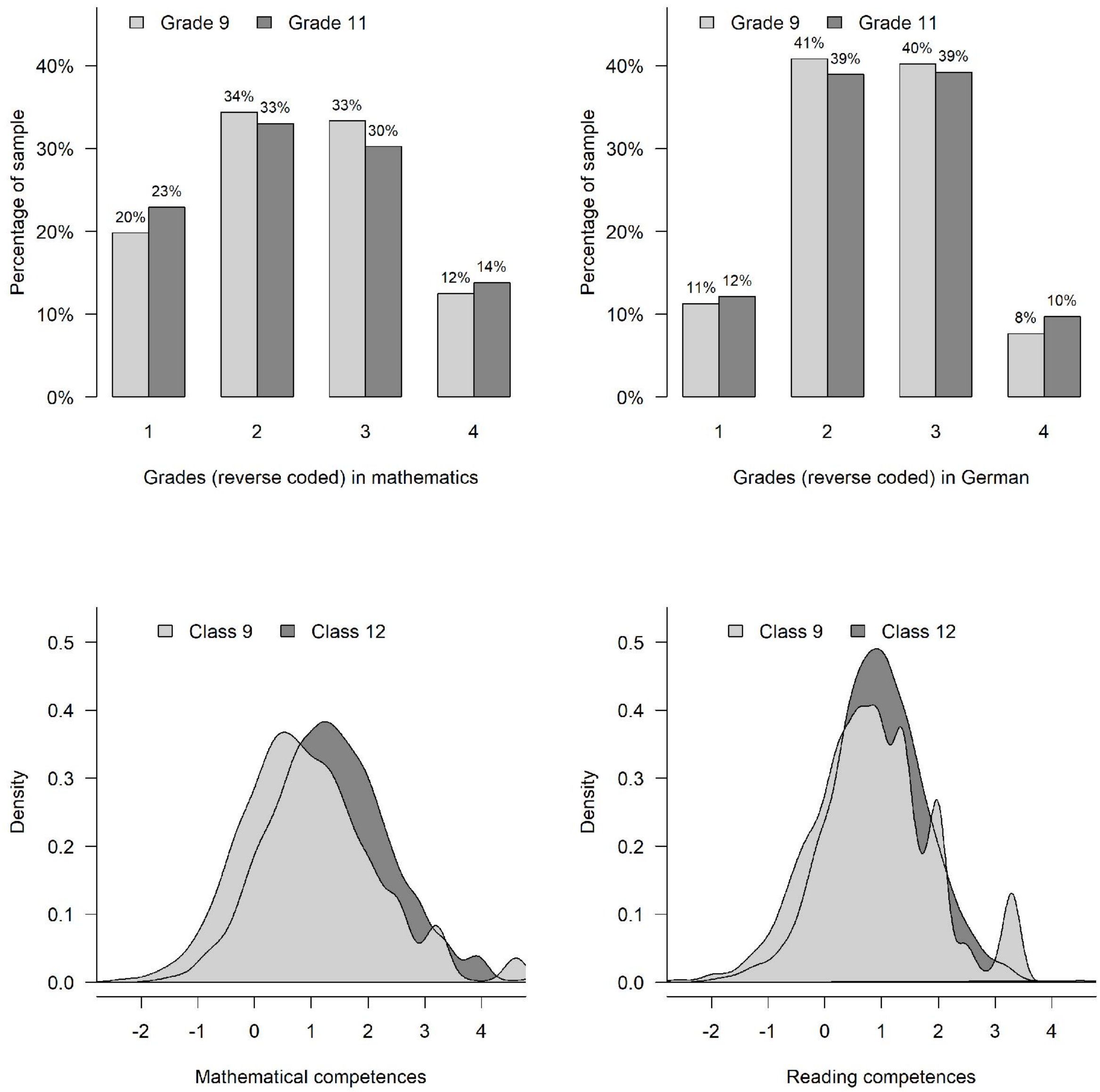

Figure S1. Distributions of grades and competences at both measurement occasions (with higher values representing better grades and competences). Results are based on 20 multiple imputed datasets using analysis strategy 5 (see Table 1).

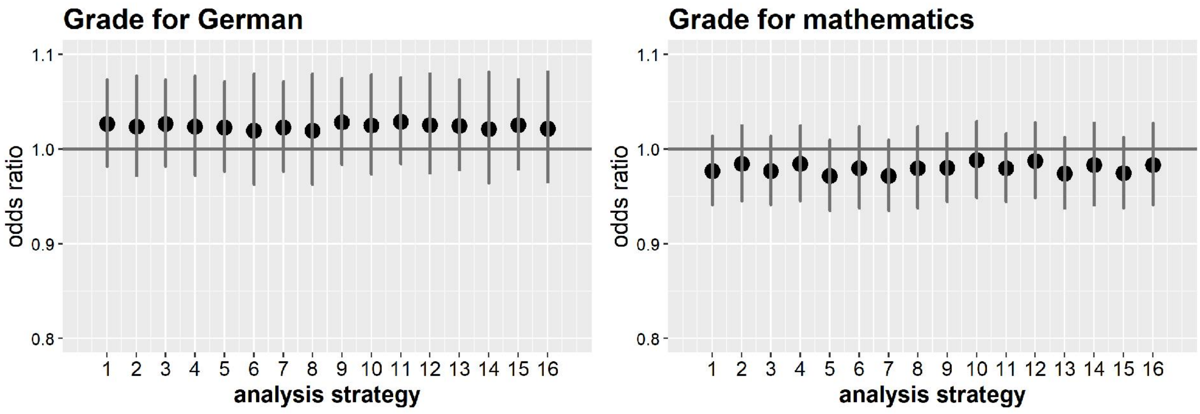

Figure S2. Estimated coefficients (with 95% confidence intervals) for the interaction effect between gaming and prior grades on grades in class 11 for different analyses strategies (see Table 1).

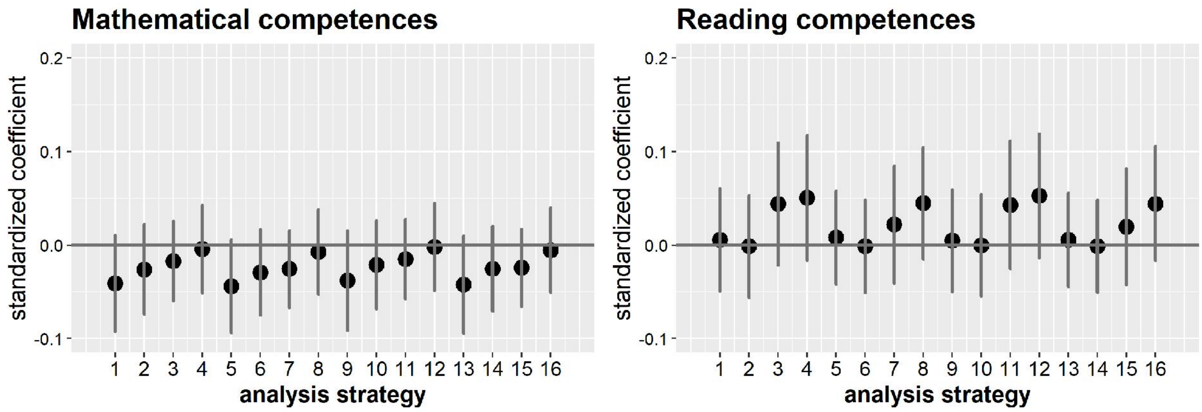

Figure S3. Estimated coefficients (with 95% confidence intervals) for the interaction effect between gaming and prior competences on competences in class 12 for different analyses strategies (see Table 1).

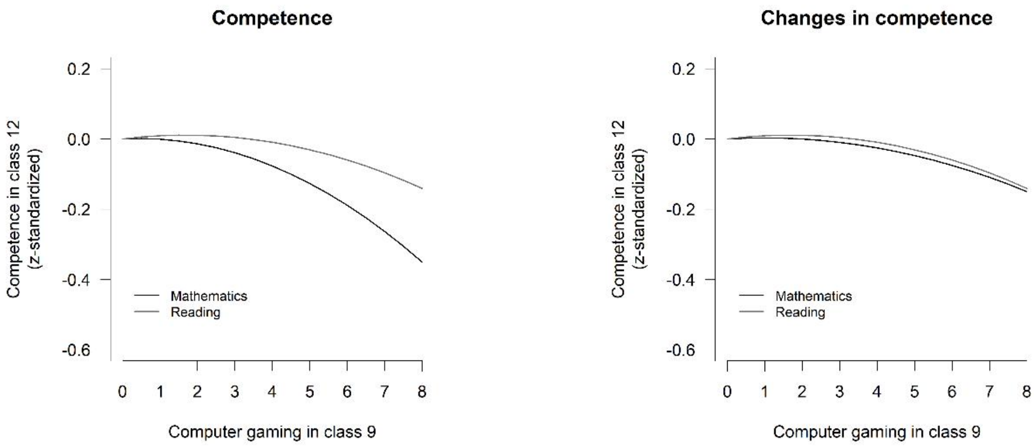

Figure S4. Longitudinal effects of computer gaming on competences (controlling for sex). Results are based on the median coefficient estimates for the different analyses strategies (see Table 1).

Table S1.

Estimated Coefficients of Regression Models for Grades in Mathematics Measured in Class 11 for Different Analyses Strategies

	Strategy 1			Strategy 2			Strategy 3			Strategy 4		
	B	*(SE)*	OR	*B*	*(SE)*	OR	*B*	*(SE)*	OR	*B*	*(SE)*	OR
Gaming time: linear	-0.07^{+}	0.04	0.93	-0.02	0.04	0.98	-0.07^{+}	0.04	0.93	-0.02	0.04	0.98
Gaming time: quadratic	0.00	0.00	1.00	-0.01^{+}	0.01	0.99	0.00	0.00	1.00	-0.01^{+}	0.01	0.99
Sex	0.41*	0.07	1.50	0.40*	0.07	1.50	0.41*	0.07	1.50	0.40*	0.07	1.50
Reasoning												
Pseudo-R^2	0.01			0.01			0.01			0.01		
	Strategy 5			Strategy 6			Strategy 7			Strategy 8		
	B	*(SE)*	OR	*B*	*(SE)*	OR	*B*	*(SE)*	OR	*B*	*(SE)*	OR
Gaming time: linear	-0.14*	0.04	0.87	-0.10*	0.05	0.91	-0.14*	0.04	0.87	-0.10*	0.05	0.91
Gaming time: quadratic	0.01^{+}	0.00	1.01	-0.00	0.01	1.00	0.01^{+}	0.00	1.01	-0.00	0.01	1.00
Sex	0.44*	0.08	1.56	0.44*	0.08	1.55	0.44*	0.08	1.56	0.44*	0.08	1.55
Reasoning												
Pseudo-R^2	0.01			0.02			0.01			0.02		
	Strategy 9			Strategy 10			Strategy 11			Strategy 12		
	B	*(SE)*	OR	*B*	*(SE)*	OR	*B*	*(SE)*	OR	*B*	*(SE)*	OR
Gaming time: linear	-0.10*	0.04	0.90	-0.05	0.04	0.96	-0.09*	0.04	0.92	-0.03	0.04	0.97
Gaming time: quadratic	0.00	0.01	1.00	-0.01	0.01	0.99	0.00	0.00	1.00	-0.01	0.01	0.99
Sex	0.39*	0.07	1.47	0.39*	0.07	1.47	0.40*	0.08	1.49	0.39*	0.07	1.48
Reasoning	0.19*	0.02	1.21	0.19*	0.02	1.21	0.11*	0.02	1.12	0.11*	0.02	1.12
Pseudo-R^2	0.04			0.05			0.03			0.03		
	Strategy 13			Strategy 14			Strategy 15			Strategy 16		
	B	*(SE)*	OR	*B*	*(SE)*	OR	*B*	*(SE)*	OR	*B*	*(SE)*	OR
Gaming time: linear	-0.17*	0.04	0.85	-0.12*	0.05	0.89	-0.15*	0.04	0.86	-0.10*	0.05	0.90
Gaming time: quadratic	0.01*	0.00	1.01	0.00	0.01	1.00	0.01^{+}	0.00	1.01	-0.00	0.01	1.00
Sex	0.42*	0.08	1.52	0.41*	0.08	1.51	0.43*	0.08	1.54	0.42*	0.08	1.53
Reasoning	0.19*	0.02	1.21	0.19*	0.02	1.21	0.11*	0.02	1.12	0.11*	0.02	1.11
Pseudo-R^2	0.05			0.05			0.03			0.03		

Note. Ordinal logistic regressions with robust standard errors. Sex was dummy coded with 0 for girls and 1 for boys. *B* = Regression weight, *SE* = Standard error for *B*, OR = Odds ratio, Pseudo-R^2 = Nagelkerke R^2. The analyses strategies are summarized in Table 1.

* $p < .05$, $^{+}$ $p < .10$

Table S2.

Estimated Coefficients of Regression Models for Changes in Grades in Mathematics Measured in Class 11 for Different Analyses Strategies

	Strategy 1			Strategy 2			Strategy 3			Strategy 4		
	B	*(SE)*	OR	*B*	*(SE)*	OR	*B*	*(SE)*	OR	*B*	*(SE)*	OR
Gaming time: linear	-0.08*	0.04	0.92	-0.06	0.04	0.94	-0.08*	0.04	0.92	-0.06	0.04	0.94
Gaming time: quadratic	0.00	0.00	1.00	-0.00	0.01	1.00	0.00	0.00	1.00	-0.00	0.01	1.00
Sex	0.35*	0.08	1.41	0.34*	0.08	1.41	0.35*	0.08	1.41	0.34*	0.08	1.41
Grades in grade 9	1.55*	0.05	4.73	1.55*	0.05	4.73	1.55*	0.05	4.73	1.55*	0.05	4.73
Reasoning												
Pseudo-R^2	0.41			0.41			0.41			0.41		
	Strategy 5			Strategy 6			Strategy 7			Strategy 8		
	B	*(SE)*	OR	*B*	*(SE)*	OR	*B*	*(SE)*	OR	*B*	*(SE)*	OR
Gaming time: linear	-0.11*	0.04	0.90	-0.10*	0.05	0.91	-0.11*	0.04	0.90	-0.10*	0.05	0.91
Gaming time: quadratic	0.01	0.00	1.01	0.00	0.01	1.00	0.01	0.00	1.01	0.00	0.01	1.00
Sex	0.36*	0.08	1.43	0.36*	0.08	1.43	0.36*	0.08	1.43	0.36*	0.08	1.43
Grades in class 9	1.55*	0.05	4.73	1.55*	0.05	4.71	1.55*	0.05	4.73	1.55*	0.05	4.71
Reasoning												
Pseudo-R^2	0.41			0.41			0.41			0.41		
	Strategy 9			Strategy 10			Strategy 11			Strategy 12		
	B	*(SE)*	OR	*B*	*(SE)*	OR	*B*	*(SE)*	OR	*B*	*(SE)*	OR
Gaming time: linear	-0.09*	0.04	0.91	-0.07	0.04	0.93	-0.08*	0.04	0.92	-0.07	0.04	0.94
Gaming time: quadratic	0.00	0.00	1.00	0.00	0.01	1.00	0.00	0.00	1.00	-0.00	0.01	1.00
Sex	0.34*	0.08	1.40	0.34*	0.08	1.40	0.34*	0.08	1.41	0.34*	0.08	1.41
Grades in class 9	1.53*	0.05	4.61	1.53*	0.05	4.61	1.54*	0.05	4.68	1.54*	0.05	4.67
Reasoning	0.08*	0.02	1.09	0.09*	0.02	1.09	0.06*	0.02	1.06	0.06*	0.02	1.06
Pseudo-R^2	0.41			0.41			0.41			0.41		
	Strategy 13			Strategy 14			Strategy 15			Strategy 16		
	B	*(SE)*	OR	*B*	*(SE)*	OR	*B*	*(SE)*	OR	*B*	*(SE)*	OR
Gaming time: linear	-0.12*	0.04	0.89	-0.11*	0.05	0.90	-0.11*	0.04	0.89	-0.10*	0.05	0.91
Gaming time: quadratic	0.01	0.00	1.01	0.00	0.01	1.00	0.01	0.00	1.01	0.00	0.01	1.00
Sex	0.35*	0.08	1.42	0.35*	0.08	1.42	0.35*	0.08	1.43	0.35*	0.08	1.42
Grades in class 9	1.53*	0.05	4.60	1.53*	0.05	4.60	1.54*	0.05	4.67	1.54*	0.05	4.66
Reasoning	0.09*	0.02	1.09	0.09*	0.02	1.09	0.06*	0.02	1.06	0.06*	0.02	1.06
Pseudo-R^2	0.41			0.41			0.41			0.41		

Note. Ordinal logistic regressions with robust standard errors. Sex was dummy coded with 0 for girls and 1 for boys. *B* = Regression weight, *SE* = Standard error for *B*, OR = Odds ratio, Pseudo-R^2 = Nagelkerke R^2. The analyses strategies are summarized in Table 1.

* $p < .05$, $^{+}$ $p < .10$

Table S3.

Estimated Coefficients of Regression Models for Grades in German Measured in Class 11 for Different Analyses Strategies

	Strategy 1			Strategy 2			Strategy 3			Strategy 4		
	B	*(SE)*	OR	*B*	*(SE)*	OR	*B*	*(SE)*	OR	*B*	*(SE)*	OR
Gaming time: linear	-0.12*	0.04	0.89	-0.06	0.05	0.94	-0.12*	0.04	0.89	-0.06	0.05	0.94
Gaming time: quadratic	0.00	0.01	1.00	-0.01	0.01	0.99	0.00	0.01	1.00	-0.01	0.01	0.99
Sex	-0.67*	0.08	0.51	-0.68*	0.08	0.51	-0.67*	0.08	0.51	-0.68*	0.08	0.51
Reasoning												
Pseudo-R^2	0.07			0.07			0.07			0.07		
	Strategy 5			Strategy 6			Strategy 7			Strategy 8		
	B	*(SE)*	OR	*B*	*(SE)*	OR	*B*	*(SE)*	OR	*B*	*(SE)*	OR
Gaming time: linear	-0.18*	0.04	0.84	-0.13*	0.05	0.88	-0.18*	0.04	0.84	-0.13*	0.05	0.88
Gaming time: quadratic	0.01^{+}	0.00	1.01	0.00	0.01	1.00	0.01^{+}	0.00	1.01	0.00	0.01	1.00
Sex	-0.66*	0.08	0.52	-0.67*	0.08	0.51	-0.66*	0.08	0.52	-0.67*	0.08	0.51
Reasoning												
Pseudo-R^2	0.07			0.07			0.07			0.07		
	Strategy 9			Strategy 10			Strategy 11			Strategy 12		
	B	*(SE)*	OR	*B*	*(SE)*	OR	*B*	*(SE)*	OR	*B*	*(SE)*	OR
Gaming time: linear	-0.13*	0.05	0.88	-0.07	0.05	0.93	-0.13*	0.04	0.88	-0.07	0.05	0.93
Gaming time: quadratic	0.00	0.01	1.00	-0.01	0.01	0.99	0.00	0.01	1.00	-0.01	0.01	0.99
Sex	-0.68*	0.08	0.51	-0.68*	0.08	0.51	-0.68*	0.08	0.50	-0.69*	0.09	0.50
Reasoning	0.07*	0.02	1.07	0.07*	0.02	1.07	0.08*	0.02	1.08	0.08*	0.02	1.08
Pseudo-R^2	0.07			0.07			0.07			0.07		
	Strategy 13			Strategy 14			Strategy 15			Strategy 16		
	B	*(SE)*	OR	*B*	*(SE)*	OR	*B*	*(SE)*	OR	*B*	*(SE)*	OR
Gaming time: linear	-0.19*	0.04	0.83	-0.14*	0.05	0.87	-0.18*	0.04	0.83	-0.13*	0.05	0.88
Gaming time: quadratic	0.01*	0.01	1.01	0.00	0.01	1.00	0.01*	0.00	1.01	0.00	0.01	1.00
Sex	-0.67*	0.08	0.51	-0.68*	0.08	0.51	-0.67*	0.08	0.51	-0.68*	0.09	0.50
Reasoning	0.07*	0.02	1.07	0.07*	0.02	1.07	0.07*	0.02	1.08	0.07*	0.02	1.08
Pseudo-R^2	0.07			0.07			0.07			0.07		

Note. Ordinal logistic regressions with robust standard errors. Sex was dummy coded with 0 for girls and 1 for boys. *B* = Regression weight, *SE* = Standard error for *B*, OR = Odds ratio, Pseudo-R^2 = Nagelkerke R^2. The analyses strategies are summarized in Table 1.

* $p < .05$, $^{+}$ $p < .10$

Table S4.

Estimated Coefficients of Regression Models for Changes in Grades in German Measured in Class 11 for Different Analyses Strategies

	Strategy 1			Strategy 2			Strategy 3			Strategy 4		
	B	*(SE)*	OR	*B*	*(SE)*	OR	*B*	*(SE)*	OR	*B*	*(SE)*	OR
Gaming time: linear	-0.08^{+}	0.04	0.93	-0.04	0.05	0.96	-0.08^{+}	0.04	0.93	-0.04	0.05	0.96
Gaming time: quadratic	0.00	0.00	1.00	-0.01	0.01	0.99	0.00	0.00	1.00	-0.01	0.01	0.99
Sex	-0.38^{*}	0.09	0.68	-0.38^{*}	0.09	0.68	-0.38^{*}	0.09	0.68	-0.38^{*}	0.09	0.68
Grades in class 9	1.65^{*}	0.05	5.18	1.64^{*}	0.05	5.14	1.65^{*}	0.05	5.18	1.64^{*}	0.05	5.14
Reasoning												
Pseudo-R^2	0.37			0.37			0.37			0.37		

	Strategy 5			Strategy 6			Strategy 7			Strategy 8		
	B	*(SE)*	OR	*B*	*(SE)*	OR	*B*	*(SE)*	OR	*B*	*(SE)*	OR
Gaming time: linear	-0.12^{*}	0.04	0.89	-0.07	0.05	0.93	-0.12^{*}	0.04	0.89	-0.07	0.05	0.93
Gaming time: quadratic	0.01	0.00	1.01	-0.00	0.01	1.00	0.01	0.00	1.01	-0.00	0.01	1.00
Sex	-0.37^{*}	0.09	0.69	-0.38^{*}	0.09	0.68	-0.37^{*}	0.09	0.69	-0.38^{*}	0.09	0.68
Grades in class 9	1.64^{*}	0.06	5.15	1.64^{*}	0.06	5.14	1.64^{*}	0.06	5.15	1.64^{*}	0.06	5.14
Reasoning												
Pseudo-R^2	0.37			0.37			0.37			0.37		

	Strategy 9			Strategy 10			Strategy 11			Strategy 12		
	B	*(SE)*	OR	*B*	*(SE)*	OR	*B*	*(SE)*	OR	*B*	*(SE)*	OR
Gaming time: linear	-0.08^{*}	0.04	0.92	-0.05	0.05	0.96	-0.08^{*}	0.04	0.92	-0.04	0.05	0.96
Gaming time: quadratic	0.00	0.00	1.00	-0.01	0.01	0.99	0.00	0.00	1.00	-0.01	0.01	0.99
Sex	-0.39^{*}	0.09	0.68	-0.38^{*}	0.09	0.68	-0.39^{*}	0.09	0.68	-0.39^{*}	0.09	0.68
Grades in class 9	1.64^{*}	0.05	5.16	1.63^{*}	0.05	5.12	1.64^{*}	0.05	5.15	1.63^{*}	0.05	5.11
Reasoning	0.03	0.02	1.03	0.03	0.02	1.03	0.05^{*}	0.02	1.05	0.05^{*}	0.02	1.05
Pseudo-R^2	0.37			0.37			0.37			0.37		

	Strategy 13			Strategy 14			Strategy 15			Strategy 16		
	B	*(SE)*	OR	*B*	*(SE)*	OR	*B*	*(SE)*	OR	*B*	*(SE)*	OR
Gaming time: linear	-0.12^{*}	0.04	0.89	-0.08	0.05	0.92	-0.12^{*}	0.04	0.89	-0.08	0.05	0.93
Gaming time: quadratic	0.01	0.00	1.01	-0.00	0.01	1.00	0.01	0.00	1.01	-0.00	0.01	1.00
Sex	-0.37^{*}	0.09	0.69	-0.39^{*}	0.09	0.68	-0.37^{*}	0.09	0.69	-0.39^{*}	0.09	0.67
Grades in class 9	1.64^{*}	0.06	5.13	1.63^{*}	0.05	5.12	1.63^{*}	0.06	5.12	1.63^{*}	0.05	5.11
Reasoning	0.03	0.02	1.03	0.03	0.02	1.03	0.05^{*}	0.02	1.05	0.05^{*}	0.02	1.05
Pseudo-R^2	0.37			0.37			0.37			0.37		

Note. Ordinal logistic regressions with robust standard errors. Sex was dummy coded with 0 for girls and 1 for boys. *B* = Regression weight, *SE* = Standard error for *B*, OR = Odds ratio, Pseudo-R^2 = Nagelkerke R^2. The analyses strategies are summarized in Table 1.

* $p < .05$, $^{+}$ $p < .10$

Table S5.

Estimated Coefficients of Regression Models for Mathematical Competences Measured in Class 11 for Different Analyses Strategies

	Strategy 1			Strategy 2			Strategy 3			Strategy 4		
	B	*(SE)*	β	*B*	*(SE)*	β	*B*	*(SE)*	β	*B*	*(SE)*	β
Gaming time: linear	0.03	0.02	0.06	0.05*	0.03	0.10	0.05*	0.02	0.11	0.06*	0.02	0.12
Gaming time: quadratic	-0.01*	0.00	-0.12	-0.01*	0.00	-0.15	-0.01*	0.00	-0.16	-0.01*	0.00	-0.17
Sex	0.68*	0.05	0.31	0.67*	0.05	0.31	0.64*	0.04	0.35	0.64*	0.04	0.36
Reasoning												
R^2	0.10			0.10			0.13			0.13		
	Strategy 5			Strategy 6			Strategy 7			Strategy 8		
	B	*(SE)*	β	*B*	*(SE)*	β	*B*	*(SE)*	β	*B*	*(SE)*	β
Gaming time: linear	-0.03	0.02	-0.05	-0.01	0.03	-0.01	-0.02	0.02	-0.04	0.01	0.02	0.01
Gaming time: quadratic	-0.00	0.00	-0.03	-0.01+	0.00	-0.07	-0.00	0.00	-0.05	-0.01*	0.00	-0.10
Sex	0.73*	0.05	0.33	0.72*	0.05	0.33	0.68*	0.04	0.38	0.68*	0.04	0.37
Reasoning												
R^2	0.10			0.10			0.13			0.13		
	Strategy 9			Strategy 10			Strategy 11			Strategy 12		
	B	*(SE)*	β	*B*	*(SE)*	β	*B*	*(SE)*	β	*B*	*(SE)*	β
Gaming time: linear	0.00	0.02	0.00	0.03	0.02	0.05	0.04+	0.02	0.09	0.05*	0.02	0.10
Gaming time: quadratic	-0.00	0.00	-0.07	-0.01*	0.00	-0.11	-0.01*	0.00	-0.14	-0.01*	0.00	-0.16
Sex	0.67*	0.04	0.31	0.66*	0.04	0.30	0.63*	0.04	0.35	0.64*	0.04	0.35
Reasoning	0.19*	0.01	0.30	0.19*	0.01	0.30	0.11*	0.01	0.23	0.11*	0.01	0.23
R^2	0.19			0.19			0.18			0.18		
	Strategy 13			Strategy 14			Strategy 15			Strategy 16		
	B	*(SE)*	β	*B*	*(SE)*	β	*B*	*(SE)*	β	*B*	*(SE)*	β
Gaming time: linear	-0.05*	0.02	-0.09	-0.03	0.02	-0.05	-0.02	0.02	-0.05	0.00	0.02	0.01
Gaming time: quadratic	0.00	0.00	0.00	-0.00	0.00	-0.04	-0.00	0.00	-0.04	-0.01*	0.00	-0.09
Sex	0.70*	0.04	0.32	0.69*	0.04	0.32	0.67*	0.04	0.37	0.66*	0.04	0.37
Reasoning	0.19*	0.01	0.30	0.19*	0.01	0.31	0.11*	0.01	0.23	0.11*	0.01	0.23
R^2	0.19			0.19			0.18			0.18		

Note. Ordinary least square regressions with robust standard errors. Sex was dummy coded with 0 for girls and 1 for boys. *B* = Regression weight, *SE* = Standard error for *B*, β = Standardized *B*. The analyses strategies are summarized in Table 1.

* $p < .05$, + $p < .10$

Table S6.

Estimated Coefficients of Regression Models for Changes in Mathematical Competences Measured in Class 11 for Different Analyses Strategies

	Strategy 1			Strategy 2			Strategy 3			Strategy 4		
	B	*(SE)*	β	*B*	*(SE)*	β	*B*	*(SE)*	β	*B*	*(SE)*	β
Gaming time: linear	0.01	0.02	0.03	0.03	0.02	0.06	0.02	0.01	0.05	0.03^{+}	0.02	0.07
Gaming time: quadratic	-0.00	0.00	-0.06	-0.01^{*}	0.00	-0.08	-0.00^{+}	0.00	-0.06	-0.01^{*}	0.00	-0.08
Sex	0.31^{*}	0.04	0.14	0.30^{*}	0.04	0.14	0.20^{*}	0.03	0.11	0.20^{*}	0.03	0.11
Competences in class 9	0.58^{*}	0.01	0.63	0.58^{*}	0.01	0.63	0.68^{*}	0.01	0.78	0.68^{*}	0.01	0.78
Reasoning												
R^2	0.47			0.47			0.67			0.68		
	Strategy 5			Strategy 6			Strategy 7			Strategy 8		
	B	*(SE)*	β	*B*	*(SE)*	β	*B*	*(SE)*	β	*B*	*(SE)*	β
Gaming time: linear	-0.01	0.02	-0.02	0.00	0.02	0.01	-0.01	0.02	-0.01	0.01	0.02	0.01
Gaming time: quadratic	-0.00	0.00	-0.02	-0.00	0.00	-0.05	-0.00	0.00	-0.01	-0.00	0.00	-0.04
Sex	0.33^{*}	0.04	0.15	0.32^{*}	0.04	0.15	0.22^{*}	0.03	0.12	0.22^{*}	0.03	0.12
Competences in class 9	0.58^{*}	0.01	0.63	0.58^{*}	0.01	0.63	0.68^{*}	0.01	0.78	0.68^{*}	0.01	0.78
Reasoning												
R^2	0.47			0.47			0.67			0.67		
	Strategy 9			Strategy 10			Strategy 11			Strategy 12		
	B	*(SE)*	β	*B*	*(SE)*	β	*B*	*(SE)*	β	*B*	*(SE)*	β
Gaming time: linear	0.01	0.02	0.01	0.02	0.02	0.04	0.02	0.01	0.05	0.03^{+}	0.02	0.06
Gaming time: quadratic	-0.00	0.00	-0.05	-0.01^{*}	0.00	-0.08	-0.00^{+}	0.00	-0.06	-0.01^{*}	0.00	-0.08
Sex	0.32^{*}	0.03	0.15	0.32^{*}	0.04	0.15	0.20^{*}	0.03	0.11	0.21^{*}	0.03	0.11
Competences in class 9	0.55^{*}	0.01	0.60	0.55^{*}	0.01	0.60	0.67^{*}	0.01	0.77	0.68^{*}	0.01	0.77
Reasoning	0.06^{*}	0.01	0.10	0.06^{*}	0.01	0.10	0.02^{*}	0.01	0.04	0.02^{*}	0.01	0.04
R^2	0.48			0.48			0.67			0.68		
	Strategy 13			Strategy 14			Strategy 15			Strategy 16		
	B	*(SE)*	β	*B*	*(SE)*	β	*B*	*(SE)*	β	*B*	*(SE)*	β
Gaming time: linear	-0.02	0.02	-0.04	-0.00	0.02	-0.01	-0.01	0.02	-0.02	0.01	0.02	0.01
Gaming time: quadratic	-0.00	0.00	-0.01	-0.00	0.00	-0.04	-0.00	0.00	-0.01	-0.00	0.00	-0.04
Sex	0.34^{*}	0.03	0.16	0.34^{*}	0.04	0.15	0.23^{*}	0.03	0.13	0.22^{*}	0.03	0.12
Competences in class 9	0.55^{*}	0.01	0.59	0.55^{*}	0.01	0.59	0.67^{*}	0.01	0.77	0.67^{*}	0.01	0.77
Reasoning	0.06^{*}	0.01	0.10	0.06^{*}	0.01	0.10	0.02^{*}	0.01	0.04	0.02^{*}	0.01	0.04
R^2	0.48			0.48			0.67			0.68		

Note. Ordinary least square regressions with robust standard errors. Sex was dummy coded with 0 for girls and 1 for boys. *B* = Regression weight, *SE* = Standard error for *B*, β = Standardized *B*. The analyses strategies are summarized in Table 1.

* $p < .05$, $^{+}$ $p < .10$

Table S7.

Estimated Coefficients of Regression Models for Reading Competences Measured in Class 11 for Different Analyses Strategies

	Strategy 1			Strategy 2			Strategy 3			Strategy 4		
	B	*(SE)*	β	*B*	*(SE)*	β	*B*	*(SE)*	β	*B*	*(SE)*	β
Gaming time: linear	0.03^{+}	0.02	0.08	0.03	0.02	0.06	0.05*	0.02	0.13	0.03	0.02	0.07
Gaming time: quadratic	-0.01*	0.00	-0.11	-0.00	0.00	-0.07	-0.01*	0.00	-0.15	-0.01^{+}	0.00	-0.08
Sex	-0.18*	0.04	-0.10	-0.18*	0.04	-0.10	-0.20*	0.04	-0.13	-0.20*	0.04	-0.13
Reasoning												
R^2	0.01			0.01			0.02			0.02		

	Strategy 5			Strategy 6			Strategy 7			Strategy 8		
	B	*(SE)*	β	*B*	*(SE)*	β	*B*	*(SE)*	β	*B*	*(SE)*	β
Gaming time: linear	0.01	0.02	0.01	-0.00	0.02	-0.00	0.01	0.02	0.03	0.00	0.02	0.01
Gaming time: quadratic	-0.00	0.00	-0.06	-0.00	0.00	-0.02	-0.00^{+}	0.00	-0.08	-0.00	0.00	-0.04
Sex	-0.16*	0.04	-0.09	-0.16*	0.04	-0.09	-0.17*	0.04	-0.11	-0.18*	0.04	-0.12
Reasoning												
R^2	0.01			0.01			0.02			0.02		

	Strategy 9			Strategy 10			Strategy 11			Strategy 12		
	B	*(SE)*	β	*B*	*(SE)*	β	*B*	*(SE)*	β	*B*	*(SE)*	β
Gaming time: linear	0.02	0.02	0.04	0.01	0.02	0.03	0.04*	0.02	0.11	0.02	0.02	0.06
Gaming time: quadratic	-0.00	0.00	-0.07	-0.00	0.00	-0.04	-0.01*	0.00	-0.13	-0.00	0.00	-0.07
Sex	-0.19*	0.04	-0.11	-0.19*	0.04	-0.11	-0.20*	0.04	-0.13	-0.21*	0.04	-0.13
Reasoning	0.11*	0.01	0.22	0.11*	0.01	0.22	0.08*	0.01	0.21	0.08*	0.01	0.21
R^2	0.06			0.06			0.06			0.06		

	Strategy 13			Strategy 14			Strategy 15			Strategy 16		
	B	*(SE)*	β	*B*	*(SE)*	β	*B*	*(SE)*	β	*B*	*(SE)*	β
Gaming time: linear	-0.01	0.02	-0.02	-0.02	0.02	-0.03	0.01	0.02	0.02	0.00	0.02	0.00
Gaming time: quadratic	-0.00	0.00	-0.03	0.00	0.00	0.00	-0.00	0.00	-0.07	-0.00	0.00	-0.03
Sex	-0.17*	0.04	-0.10	-0.18*	0.04	-0.10	-0.18*	0.04	-0.11	-0.19*	0.04	-0.12
Reasoning	0.11*	0.01	0.22	0.11*	0.01	0.22	0.08*	0.01	0.21	0.08*	0.01	0.21
R^2	0.06			0.06			0.06			0.06		

Note. Ordinary least square regressions with robust standard errors. Sex was dummy coded with 0 for girls and 1 for boys. *B* = Regression weight, *SE* = Standard error for *B*, β = Standardized *B*. The analyses strategies are summarized in Table 1.

* $p < .05$, $^{+}$ $p < .10$

Table S8.

Estimated Coefficients of Regression Models for Changes in Reading Competences Measured in Class 11 for Different Analyses Strategies

	Strategy 1			Strategy 2			Strategy 3			Strategy 4		
	B	*(SE)*	β	*B*	*(SE)*	β	*B*	*(SE)*	β	*B*	*(SE)*	β
Gaming time: linear	-0.00	0.02	-0.01	-0.01	0.02	-0.01	0.00	0.02	0.00	-0.02	0.02	-0.04
Gaming time: quadratic	-0.00	0.00	-0.03	-0.00	0.00	-0.02	-0.00	0.00	-0.03	-0.00	0.00	-0.00
Sex	-0.05$^+$	0.03	-0.03	-0.05$^+$	0.03	-0.03	-0.04	0.03	-0.02	-0.03	0.03	-0.02
Competences in class 9	0.41*	0.01	0.50	0.41*	0.01	0.50	0.52*	0.01	0.64	0.53*	0.01	0.64
Reasoning												
R^2	0.26			0.26			0.42			0.42		
	Strategy 5			Strategy 6			Strategy 7			Strategy 8		
	B	*(SE)*	β	*B*	*(SE)*	β	*B*	*(SE)*	β	*B*	*(SE)*	β
Gaming time: linear	-0.02	0.02	-0.05	-0.03	0.02	-0.06	-0.02	0.01	-0.04	-0.01	0.02	-0.03
Gaming time: quadratic	-0.00	0.00	-0.00	0.00	0.00	0.02	-0.00	0.00	-0.00	0.00	0.00	0.00
Sex	-0.04	0.03	-0.02	-0.04	0.03	-0.03	-0.02	0.03	-0.01	-0.04	0.03	-0.02
Competences in class 9	0.41*	0.01	0.50	0.41*	0.01	0.50	0.52*	0.01	0.64	0.53*	0.01	0.64
Reasoning												
R^2	0.26			0.26			0.42			0.42		
	Strategy 9			Strategy 10			Strategy 11			Strategy 12		
	B	*(SE)*	β	*B*	*(SE)*	β	*B*	*(SE)*	β	*B*	*(SE)*	β
Gaming time: linear	-0.01	0.02	-0.02	-0.01	0.02	-0.03	-0.00	0.01	-0.01	-0.02	0.02	-0.05
Gaming time: quadratic	-0.00	0.00	-0.02	-0.00	0.00	-0.01	-0.00	0.00	-0.02	0.00	0.00	0.01
Sex	-0.06*	0.03	-0.04	-0.06*	0.03	-0.04	-0.04	0.03	-0.03	-0.04	0.03	-0.02
Competences in class 9	0.39*	0.01	0.48	0.39*	0.01	0.48	0.51*	0.01	0.63	0.52*	0.01	0.63
Reasoning	0.05*	0.01	0.10	0.05*	0.01	0.10	0.06*	0.01	0.15	0.06*	0.01	0.15
R^2	0.27			0.27			0.44			0.45		
	Strategy 13			Strategy 14			Strategy 15			Strategy 16		
	B	*(SE)*	β	*B*	*(SE)*	β	*B*	*(SE)*	β	*B*	*(SE)*	β
Gaming time: linear	-0.02	0.02	-0.06	-0.03	0.02	-0.07	-0.02	0.01	-0.05	-0.02	0.02	-0.04
Gaming time: quadratic	0.00	0.00	0.01	0.00	0.00	0.03	0.00	0.00	0.01	0.00	0.00	0.01
Sex	-0.05$^+$	0.03	-0.03	-0.06$^+$	0.03	-0.03	-0.03	0.03	-0.02	-0.05	0.03	-0.03
Competences in class 9	0.39*	0.01	0.48	0.39*	0.01	0.48	0.51*	0.01	0.63	0.52*	0.01	0.63
Reasoning	0.05*	0.01	0.10	0.05*	0.01	0.10	0.06*	0.01	0.15	0.06*	0.01	0.15
R^2	0.27			0.27			0.45			0.45		

Note. Ordinary least square regressions with robust standard errors. Sex was dummy coded with 0 for girls and 1 for boys. *B* = Regression weight, *SE* = Standard error for *B*, β = Standardized *B*. The analyses strategies are summarized in Table 1.

* $p < .05$, $^+$ $p < .10$