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Performance increases in mathematics during COVID-19 pandemic distance learning in Austria: Evidence from an intelligent tutoring system for mathematics

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ABSTRACT

Background: In 2020, school closures during the COVID-19 pandemic forced students all over the world to promptly alter their learning routines from in-person to distance learning. However, so far, only a limited number of studies from a few countries investigated whether school closures affected students' performance within intelligent tutoring system—such as intelligent tutoring systems.
Method: In this study, we investigated the effect of school closures in Austria by evaluating data (n = 168 students) derived from an intelligent tutoring system for learning mathematics, which students used before and during the first period of school closures.
Results: We found that students' performance increased in mathematics in the intelligent tutoring system during the period of school closures compared to the same period in previous years.
Conclusion: Our results indicate that intelligent tutoring systems were a valuable tool for continuing education and maintaining student learning during school closures in Austria.

1. Introduction

The COVID-19 pandemic led to the abrupt closure of schools in many countries all over the world, including Austria, where schools were first closed on March 16th, 2020 [1,2]. Consequently, students were required to rapidly shift to distance learning scenarios [3–8], relying on digital learning software—such as intelligent tutoring systems[1]—for distance learning, in lieu of traditional in-person schooling [9,10]. While the devastating impact of school closures on students' performance has been studied excessively with data from large-scale assessments [11–18], with most studies reporting performance losses during school closures [19–21], only a limited number of studies have thus far evaluated the effect of school closures on students' performance within intelligent tutoring systems [10,22–25]. Therefore, we looked at students from Austria who studied mathematics using the intelligent tutoring system *Bettermarks,* with the aim to evaluate their longitudinal performance changes during school closures compared to before.

Previous studies evaluating performance changes within intelligent tutoring systems during school closures due to COVID-19 regulations yielded mixed results, with one study from Switzerland indicating decreasing performance [24], while four other studies considering Dutch [22,23] and German students [10,25] indicated performance to increase. For instance, evidence that school closures negatively affected students' performance in mathematics in an intelligent tutoring system comes from Tomasik et al. (2020). They compared the performance of students who used the intelligent tutoring system *Mindsteps* during the first eight weeks of school closures in Switzerland with another cohort of students who used the software eight weeks before school closures in Switzerland and observed performance decreases in particular for younger students (aged 9 to 13 years) during the first period of school

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[1] We refer to intelligent tutoring system as the overall term which includes intelligent tutoring systems, while we use the term intelligent tutoring system for intelligent tutoring system where specific features are implemented (e.g., adapting learning content towards students' needs) and documented in the literature.

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closures in Switzerland, while they observed no effect of school closures for older students (aged 13 to 16 years).

In contrast, other studies that also considered data obtained from intelligent tutoring systems reported performance increases [10,22,23,25]. For instance, Meeter (2021) evaluated data from a sample of Dutch students (aged 7 to 11 years) who used the intelligent tutoring system *Snappet* for mathematics in the school year 2018/19 with another sample of students who used the intelligent tutoring system in the school year 2019/20 in which school were closed for some time. Meeter (2021) observed significant performance increases in the cohort using the intelligent tutoring system during school closures compared to the other cohort that used the intelligent tutoring system the previous school year (2018/19). In another study, comparing the performance of students during school closures with the performance of another cohort of students during the same time one year earlier, Van der Velde (2021) investigated another sample of Dutch students (aged 7 to 10 years) who studied French within the intelligent tutoring system *SlimStampen*. Interestingly, they also observed significant performance increases during school closures compared to the cohort who used the learning software during the same time period in 2019.

Furthermore, Spitzer and Musslick (2021) followed a cohort of German students who learned mathematics using the intelligent tutoring system *Bettermarks* longitudinally. This allowed to compare the performance of the same students during school closures in Germany with their performance during the same period in the year before when there were no school closures. Their findings indicated that the students' performance increases made significantly during school closures relative to the previous year. Moreover, Spitzer and Musslick (2021) observed that students who performed below average demonstrated particular increases in their performance within the intelligent tutoring system during school closures.

In summary, the impact of school closures on student performance within intelligent tutoring systems has been studied in only a limited number of countries thus far. Therefore, additional evidence from a broader range of countries, such as Austria, is required to obtain a more comprehensive understanding of the use of intelligent tutoring systems during school closures amidst the COVID-19 pandemic. As evidenced by the aforementioned studies, the data on the effects of school closures on students' performance in intelligent tutoring systems has been gathered from various systems and studies conducted across different countries. Nevertheless, to date, no study has utilized data from the same intelligent tutoring system employed in multiple countries.

Against this background, in this study, we investigated the effect of school closures due to COVID-19 regulations on students' performance when studying mathematics in the intelligent tutoring system *Bettermarks*. Therefore, we analyzed data from students ($n = 168$ students; $n = 6992$ mathematical problem sets) who used *Bettermarks* in Austria to learn mathematics (as compared to Germany in Spitzer & Musslick, 2021). Our analysis considered students ($n = 168$ students; $n = 6992$ mathematical problem sets) who used *Bettermarks* in Austria before *and* during the first period of school closures due to COVID-19 regulations to evaluate performance changes longitudinally. As previous studies reported differential effects for low- vs. high-performing students, we were especially interested in comparing students performing below-average with those performing above-average to evaluate whether such differential effects generalize across countries.

Based on previous research reporting performance increases during school closures within the intelligent tutoring system *Bettermarks* (but also in *Snappet* and *SlimStampen*), we expected to observe performance increases during the time when schools were closed in Austria as compared to before.

2. Methods

2.1. The intelligent tutoring system

2.1.1. Background

The present study is based on data gathered from *Bettermarks*, an intelligent tutoring system designed for learning mathematics, which has been implemented in several schools in Austria but also in other countries such as Germany, the Netherlands, Uruguay and South Africa. *Bettermarks* covers the mathematics curriculum for students in grades 4 through 12, spanning an age range from 9 to 18 years, and includes over 100 books that cover a broad range of mathematical concepts such as fractions, algebra, and percentages [26,27]. Importantly, each book within *Bettermarks* includes numerous problem sets that are based on the curriculum of the respective country.

2.1.2. Usage

The intelligent tutoring system can be used by students and teachers in school or at home. It enables teachers to assign problem sets to students and as such allows interactions between teachers and students. Teachers can assign problem sets to be completed by their students and the platform provides immediate feedback to students and teachers on completed assignments. However, students may also use the intelligent tutoring system on their own. That is, without assignments from their teachers but by assigning problem sets to themselves. In this case, only students receive feedback but their teachers do not receive feedback. The intelligent tutoring system enables students to repeat worked through problem sets. However, when a problem set is repeated, the parameterization of the problems within the problem set changes with each new attempt. This means that memorization of previous results is of limited use. The intelligent tutoring system identifies knowledge gaps in case students make specific errors and it suggests problem sets to students based on these errors.

2.1.3. Data collection and privacy

The data collected for this study included error rates on problem sets, problem IDs, and the date and time of completion. The data is fully anonymized and no demographic information about students is available.

2.2. Current dataset

We defined the following inclusion criteria to obtain our sample prior to data analysis. We considered data from students who used *Bettermarks* during the dates when schools were closed in Austria (March 16th until May 18th, 2020) and for the same dates in the previous three years (2017 to 2019). Importantly, we conducted a within-student analysis and thus only considered students who used Bettermarks during school closures *and* during the same time in the previous three years. This allowed us to analyze longitudinal performance changes within the same students. In addition, we only included students who computed at least 5 problem sets before and during school closures.[2] As students are able to repeat problem sets, we only considered students' best result on each problem set as a proxi for their performance. The best result was akin to previous studies that assessed students' performance within *Bettermarks* [10,25,28]. Finally, we only considered problem sets that were assigned by teachers as previous research showed differences in performance effects based on the assignment type within *Bettermarks* [25]. After applying these inclusion criteria, the dataset comprised 168 students who completed 6992 problem sets.

[2] We also re-ran the analysis with students who completed at least 1 or 2 problem sets after we completed the intial analysis and replicated the results with these inclusion criteria.

2.3. Dependent and independent variables

As in Spitzer and Musslick (2021), we computed the *relative error rate* of students as the dependent variable to quantify students' performance, with negative relative error rates indicating below-average performance and positive relative error rates indicating above-average performance. Relative error rates were computed by subtracting the *absolute error rate* for a problem set for each student from the *average error rate* of the respective problem set (the average error rate of a problem set was first computed based on all students who worked through this problem set). For example, consider a problem set with an average error rate of the cohort of 20%. A specific student computes this problem set and achieves an absolute error rate on this problem set of 10%. The relative error rate is now: 20% - 10% = +10%. We also carried out analyses reporting the absolute error rate of students as well as the average error rate of problem sets as a proxy for problem set difficulty to show how changes in relative error rates evolved from changes in absolute error rates and average error rates.

The first independent variable was the year in which the data was obtained which we labeled as the *year* variable. We pooled performance measures of students from years 2017 to 2019 as an estimate of their performance before school closures and contrasted this against their performance in 2020. Thus, the year variable was a binary variable (before, i.e., 2017 to 2019 vs. during, i.e., 2020, school closures).[3]

The second independent variable—a *group* variable—reflected two groups of students performing below versus above average. This variable was computed based on students' performance before school closures. In particular, we split students into two groups with students with a relative error rate of 0 or above (before school closures) forming the above-average performing group and students with a relative error rate below 0 (before school closures) forming the below-average performing group. This allowed us to investigate whether school closures affected below-average performance students differently than above-average students, reflected in the interaction between the two variables year and group.

2.4. Data analysis

The statistical software R (R Core Team, 2013) was used to analyze the data. We ran three separate hierarchical regression models, each of which had the identical model structure, with variables *year* and *group* as independent variables including both main effects and the interaction between the two variables and a random intercept for each student. The three regression models varied with respect to the dependent variable (i.e., relative error rate, absolute error rate, and average error rate). We investigated changes in performance during school closures as compared to before for each group of students separately with two further post-hoc regressions (for each dependent variable, respectively) only considering data for either above-average students or below-average students to report changes in performance over time for each group.

3. Results

The results are illustrated in Fig. 1. The regression results are listed in Table 1 and the results of post-poc tests for each group of students are reported in the text below.

3.1. Relative error rate

The regression results indicated a significant main effect of year

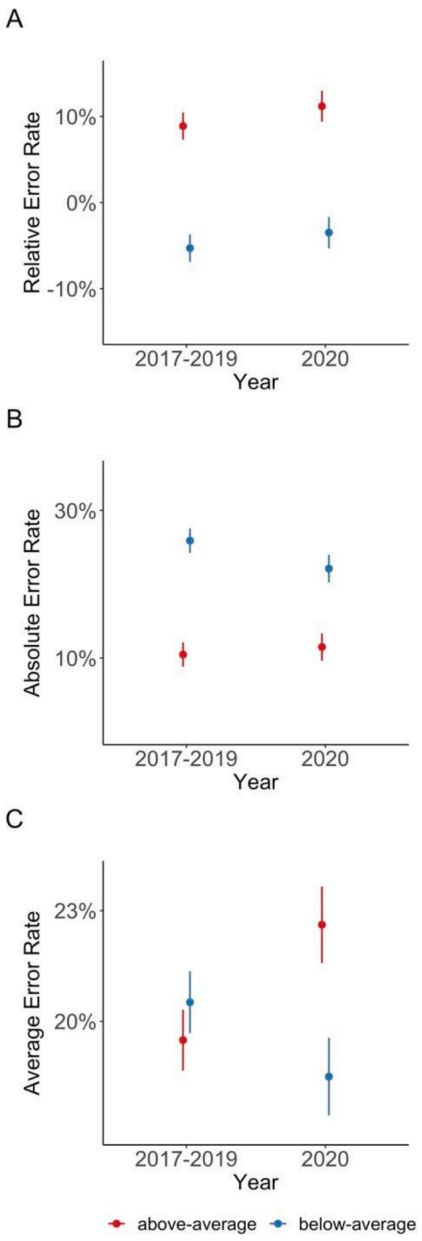

Fig. 1. Relative error rate (A), absolute error rate (B), and average error rate (C) as a function of year and group (below-average vs. above-average). A: Relative error rates increased during school closures in 2020, as compared to the same months in the previous three years, for both below-average and above-average students. **B:** Absolute accuracy rates decreased significantly for below-average students while no significant changes were observed for above-average students. **C:** Average error rates (i.e., the difficulty of the assigned problems) decreased for below-average students, while average error rates increased for above-average students. Each point indicates the regression estimate. Error bars reflect 1 standard error of the mean. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

indicating that students had higher relative error rates (suggesting increased performance) during school closures in 2020 compared to the previous three years (see Fig. 1A and Table 1). We also observed a significant main effect for group (see Fig. 1A and Table 1), suggesting that below-average students performed worse than above-average students. Finally, the interaction between year and group was not significant (see Fig. 1A and Table 1), suggesting no significant differences in performance changes from before school closures to times during school

[3] Note that all students used bettermarks in 2019 and 2020 and results were virtually identical when only considering the data from 2019 (before school closures) contrasted against the data from 2020 (during school closures).

Table 1
Regression results (estimates, t-values; and p-values indicated with asterix) of each hierarchical linear regression model.

Coefficient	Relative error rate				Absolute error rate				Average error rate			
	b	*SE*	*t-Value*	*p*	*b*	*SE*	*t-Value*	*p*	*b*	*SE*	*t-Value*	*p*
(Intercept)	0.03	0.01	5.16	**<0.001**	0.17	0.01	30.68	**<0.001**	0.20	<0.01	73.46	**<0.001**
Year	0.01	<0.01	3.68	**<0.001**	−0.01	<0.01	−2.47	**0.014**	<0.01	<0.01	1.40	0.162
Group	0.07	0.01	13.21	**<0.001**	−0.07	0.01	−11.42	**<0.001**	0.01	<0.01	2.80	**0.005**
Year x Group	<0.01	<0.01	0.45	0.655	0.01	<0.01	4.28	**<0.001**	0.01	<0.01	6.48	**<0.001**
$N_{students}$	168				168				168			
$N_{problem\ set}$	6992				6992				6992			

closures for students performing below or above average. Further post-hoc regression analyses for each group separately indicated significant performance increases for both groups, respectively (below-average: $b = 0.009$; $t = 2.09$; $p = .036$; above-average: $b = 0.011$; $t = 3.23$; $p = .001$)

3.2. Absolute error rate

The results of the regression analysis reflected a significant main effect of year indicating that students had higher absolute error rates (suggesting increased performance) during school closures in 2020 compared to the previous three years (see Fig. 1B and Table 1). We also observed a main effect for group suggesting that absolute error rates of below-average students were higher compared to those for above-average students (see Fig. 1B and Table 1). Finally, the interaction between year and group was significant. This indicated that the difference in absolute error rates between below-average students and above-average students was reduced in 2020 compared to 2017–2019 (see Fig. 1B and Table 1). As in the previous analysis, we conducted separate post-hoc regression analyses for each group of students. Results showed significant decreases in absolute error rates for below-average students but not for above-average students (below-average: $b = -0.018$; $t = -3.96$; $p < .001$; above-average: $b = 0.004$; $t = 1.63$; $p = .10$). This indicates that below-average students had significantly lower absolute error rates during school closures as during the same time in the years before.

3.3. Average error rate

The average error rate reflects the difficulty of the problem sets students computed, with higher values indicating that the computed problem sets were more difficult. The regression results indicated no significant main effect for year, but a significant main effect for group, suggesting that below-average performing students generally computed less difficult problems compared to above-average performing students (see Fig. 1C and Table 1). Finally, the interaction between year and group was significant and reflected that below-average students computed less difficult problems during school closures as compared to before, while above-average computed more difficult problems during school closures as compared to before (see Fig. 1C and Table 1). Further post-hoc analyses for each group of students showed that the average error rate significantly increased for above-average students ($b = 0.015$; $t = 5.55$; $p < .001$), while it significantly decreased for below-average students ($b = -0.010$; $t = -3.54$; $p < .001$).

4. Discussion

In this study, we examined longitudinal performance changes of Austrian students who learned mathematics using the intelligent tutoring system *Bettermarks* before and during the first period of school closures during the COVID-19 pandemic in 2020. Evaluating the data of 168 students who worked through over 6000 problem sets, we observed that students' performance within the intelligent tutoring system increased during school closures compared to the previous three years. These increases were observed for both below-average and above-average performing students. In contrast to a previous study considering data from the same intelligent tutoring system used in Germany, our results provided no evidence for a differential effect indicating significantly more pronounced performance gains in below-average performing students compared to above-average performing students. Together, our results contribute an important piece of evidence substantiating that intelligent tutoring systems are valuable tools for students during times of distance learning. In addition, this study provides evidence for this positive effect not only considering data from students who worked with an intelligent tutoring system in another country (i.e., Austria) but also finding these positive effects within the same intelligent tutoring system to generalize across countries (Germany and Austria).

Previous research considering the impact of school closures during the COVID-19 pandemic on students from Austria investigated other important variables obtained via questionnaires, such as self-rated measures of students' abilities to learn independently, the amount of parental aid received, intrinsic motivation, perceived stress, perceived competence, or self-rated achievement [29–34]. For instance, Helm and Huber (2022) found that students' intrinsic motivation and their ability to self-organize best predicted students' self-rated achievement. Pelikan et al. (2021) observed a positive relationship between students who rated themselves as highly competent used more self-regulated learning strategies than students who rated themselves as less competent. In another study, Weiss et al. (2022) found that females experienced more stress than males during the COVID-19 pandemic. Yet, potential influences of school closures on explicit performance measures from mathematics learning within an intelligent tutoring system have thus far not been evaluated for students in Austria. Thus, this study is—to the best of our knowledge—the first to provide evidence on how students from Austria who studied mathematics using an intelligent tutoring system were affected by school closures during the COVID-19 pandemic.

While the aim of this study was to evaluate whether students' performance within an intelligent tutoring system used in Austria was affected (positively or negatively) by school closures, future studies may look into the specific mechanisms on *why* this study, as well as others, observed performance increases during school closures as compared to before. One potential hypothesis is that students may experience less math anxiety (i.e., worry or fear about performing mathematics; [35–40]) when learning at home in absence of their teachers, which in turn may affect their performance positively. Another possible explanation is that teachers may have increased incentives for students' performance within the intelligent tutoring system, which may have motivated students to perform better during distance learning in 2020 as compared to before.

Another important future avenue may be to investigate whether the obtained results generalize to other countries. So far, only evidence from four European countries (Germany, Switzerland, the Netherlands, and Austria) on the effect of school closures on students' performance within intelligent tutoring systems exist—to the best of our knowledge. Thus, more studies from other countries on the impact of school closures within intelligent tutoring systems are needed.

There are some limitations to be considered when interpreting the results of this study. First, our study is limited by the anonymity of the data. That is, we evaluated data from an intelligent tutoring system that is fully anonymized. Thus, demographic data was not available as well

as other additional information regarding our sample. This does not allow us to control for other variables such as age or gender which may affect mathematics performance as well [41]. Second, this study comprised relatively few students compared to previous studies that obtained data from the same intelligent tutoring system. This resulted from our strict inclusion criteria which only considered students that used the intelligent tutoring system in Austria during both time periods—before and during the first school closures in Austria.

To conclude, our study is the first to investigate performance changes within an intelligent tutoring system used in Austria. Our results indicated that students' performance increased during school closures as compared to the same time period in previous years. Furthermore, these increases were observed for below-average as well as above-average performing students. As such, our study provides valuable evidence for future research on how school closures during the COVID-19 pandemic affected students' performance within intelligent tutoring systems and how to best learn from distance.

Declaration of Competing Interest

There are no known conflicts of interest associated with this publication.

Ethical statement

In this study, we are reporting a retrospective study of archived data which was fully anonymized before data analysis. Thus, it is not possible to track the data back to any software user.

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References

[1] UNESCO, Education: from disruption to recovery. School clusures caused by Coronavirus (Covid-19), (2020).
[2] J.P. Azevedo, A. Hasan, D. Goldemberg, S. Aroob, I. Koen Geven, Simulating the Potential Impacts of COVID-19 School Closures on Schooling and Learning Outcomes: a Set of Global Estimates, 2020. http://www.worldbank.org/prwp.%0Ahttp://pubdocs.worldbank.org/en/798061592482682799/covid-and-education-June17-r6.pdf.
[3] M. Spitzer, Open schools! Weighing the effects of viruses and lockdowns on children, Trends Neurosci. Educ. 22 (2021), 100151, https://doi.org/10.1016/j.tine.2021.100151.
[4] M. Poletti, Hey teachers! Do not leave them kids alone! Envisioning schools during and after the coronavirus (COVID-19) pandemic, Trends Neurosci. Educ. 20 (2020), 100140, https://doi.org/10.1016/j.tine.2020.100140.
[5] O. Trabelsi, M.A. Souissi, S. Scharenberg, M. Mrayeh, A. Gharbi, YouTube as a complementary learning tool in times of COVID-19: self-reports from sports science students, Trends Neurosci. Educ. 29 (2022), 100186, https://doi.org/10.1016/j.tine.2022.100186.
[6] S. Flegr, J. Kuhn, K. Scheiter, How to foster STEM learning during Covid-19 remote schooling: combining virtual and video experiments, Learn. Instr. 86 (2023), 101778, https://doi.org/10.1016/j.learninstruc.2023.101778.
[7] T. Fütterer, E. Hoch, A. Lachner, K. Scheiter, K. Stürmer, High-quality digital distance teaching during COVID-19 school closures: does familiarity with technology matter? Comput. Educ. 199 (2023) https://doi.org/10.1016/j.compedu.2023.104788. Article 104788.
[8] A.K. Jaekel, K. Scheiter, R. Göllner, Distance teaching during the COVID-19 crisis: social connectedness matters most for teaching quality and students' learning, AERA Open 7 (2021) 1–14, https://doi.org/10.1177/23328584211052050.
[9] M.W.H. Spitzer, R. Gutsfeld, M. Wirzberger, K. Moeller, Evaluating students ' engagement with an online learning environment during and after COVID-19 related school closures : a survival analysis approach, Trends Neurosci. Educ. 25 (2021), 100168.
[10] M.W.H. Spitzer, S. Musslick, Academic performance of K-12 students in an online-learning environment for mathematics increased during the shutdown of schools in wake of the Covid-19, PLoS ONE 16 (2021) 1–16, https://doi.org/10.1371/journal.pone.0255629.
[11] K. Zierer, Effects of pandemic-related school closures on pupils' performance and learning in selected countries: a rapid review, Educ. Sci. 11 (2021), https://doi.org/10.3390/educsci11060252.
[12] E. Panagouli, A. Stavridou, C. Savvidi, A. Kourti, T. Psaltopoulou, T.N. Sergentanis, A. Tsitsika, School performance among children and adolescents during covid-19 pandemic: a systematic review, Children 8 (2021) 1–12, https://doi.org/10.3390/children8121134.
[13] G. Molnár, Z. Hermann, Short- and long-term effects of COVID-related kindergarten and school closures on first- to eighth-grade students' school readiness skills and mathematics, reading and science learning, Learn. Instr. 83 (2023), https://doi.org/10.1016/j.learninstruc.2022.101706.
[14] I. May, S. Awad, M.S. May, A. Ziegler, Parental stress provoked by short-term school closures during the second COVID-19 lockdown, J. Fam. Issues. 44 (2023) 25–45, https://doi.org/10.1177/0192513X211041987.
[15] P. Engzell, A. Frey, M.D. Verhagen, Learning loss due to school closures during the COVID-19 pandemic, Proc. Natl. Acad. Sci. U. S. A. (2021) 118, https://doi.org/10.1073/PNAS.2022376118.
[16] J. Schult, N. Mahler, B. Fauth, M.A. Lindner, Long-term consequences of repeated school closures during the COVID-19 pandemic for reading and mathematics competencies, Front. Educ. 13 (2022) 1–13, https://doi.org/10.3389/feduc.2022.867316.
[17] J. Schult, N. Mahler, B. Fauth, M.A. Lindner, Did students learn less during the COVID-19 pandemic? Reading and mathematics competencies before and after the first pandemic wave, Sch. Eff. Sch. Improv. 33 (2022) 544–563, https://doi.org/10.1080/09243453.2022.2061014.
[18] J.F. Birkelund, K.B. Karlson, No evidence of a major learning slide 14 months into the COVID-19 pandemic in Denmark, Eur. Soc. (2022) 1–21, https://doi.org/10.1080/14616696.2022.2129085.
[19] B.A. Betthäuser, A.M. Bach-Mortensen, P. Engzell, A systematic review and meta-analysis of the evidence on learning during the COVID-19 pandemic, Nat. Hum. Behav. 2023 (2023) 1–11, https://doi.org/10.1038/s41562-022-01506-4.
[20] G. Di Pietro, The impact of Covid-19 on student achievement : evidence from a, Educ. Res. Rev. 39 (2023), 100530, https://doi.org/10.1016/j.edurev.2023.100530.
[21] S. Hammerstein, C. König, T. Dreisörner, A. Frey, Effects of COVID-19-related school closures on student achievement-a systematic review, Front. Psychol. 12 (2021) 1–8, https://doi.org/10.3389/fpsyg.2021.746289.
[22] M. Meeter, Primary school mathematics during Covid-19: no evidence of learning gaps in adaptive practicing results, Trends Neurosci. Educ. 25 (2021), 100163, https://doi.org/10.1016/j.tine.2021.100163.
[23] M. van der Velde, F. Sense, R. Spijkers, M. Meeter, H. van Rijn, Lockdown learning: changes in online foreign-language study activity and performance of dutch secondary school students during the COVID-19 pandemic, Front. Educ. 6 (2021) 1–8, https://doi.org/10.3389/feduc.2021.712987.
[24] M.J. Tomasik, L.A. Helbling, U. Moser, Educational gains of in-person vs. distance learning in primary and secondary schools: a natural experiment during the COVID-19 pandemic school closures in Switzerland, Int. J. Psychol. 56 (2020) 566–576, https://doi.org/10.1002/ijop.12728.
[25] M.W.H. Spitzer, K. Moeller, S. Musslick, Assignment strategies modulate students' academic performance in an online learning environment during the first and second COVID-19 related school closures, PLoS ONE (2023).
[26] M.W.H. Spitzer, Just do it! Study time increases mathematical achievement scores for grade 4-10 students in a large longitudinal cross-country study, Eur. J. Psychol. Educ. 37 (2022) 39–53, https://doi.org/10.1007/s10212-021-00546-0.
[27] M.W.H. Spitzer, K. Moeller, Predicting fraction and algebra achievements online: a large-scale longitudinal study using data from an online learning environment, J. Comput. Assist. Learn. (2022) 1–10, https://doi.org/10.1111/jcal.12721.
[28] M.W.H. Spitzer, K. Moeller, Predicting fraction and algebra achievements online: a large-scale longitudinal study using data from an online learning environment, J. Comput. Assist. Learn. (2022), https://doi.org/10.31234/osf.io/rw6b9.
[29] E.R. Pelikan, M. Lüftenegger, J. Holzer, S. Korlat, C. Spiel, B. Schober, Learning during COVID-19: the role of self-regulated learning, motivation, and procrastination for perceived competence, Z. Erziehungswiss 24 (2021) 393–418, https://doi.org/10.1007/s11618-021-01002-x.
[30] C. Helm, S.G. Huber, Predictors of central student learning outcomes in times of COVID-19: students', Parents', and Teachers' perspectives during school closure in 2020—A multiple informant relative weight analysis, Front. Educ. 7 (2022) 1–22, https://doi.org/10.3389/feduc.2022.743770.
[31] E.M. Weiss, L. Kaufmann, M. Ninaus, M. Canazei, Belastungen durch Fernlehre und psychische Gesundheit von Studierenden während der COVID-19-Pandemie, Lernen. Lernstörungen. (2022).
[32] K. Resch, G. Alnahdi, S. Schwab, Exploring the effects of the COVID-19 emergency remote education on students' social and academic integration in higher education in Austria, High. Educ. Res. Dev. 42 (2023) 215–229, https://doi.org/10.1080/07294360.2022.2040446.
[33] F. Berger, C. Schreiner, W. Hagleitner, L. Jesacher-Rößler, S. Roßnagl, C. Kraler, Predicting coping with self-regulated distance learning in times of COVID-19: evidence from a longitudinal study, Front. Psychol. 12 (2021), https://doi.org/10.3389/fpsyg.2021.701255.
[34] S.G. Huber, C. Helm, Huber-Helm2020_Article_COVID-19AndSchoolingEvaluation.pdf, (2020) 237–270.
[35] M. Stella, Network psychometrics and cognitive network science open new ways for understanding math anxiety as a complex system, J. Complex Netw. 10 (2022) 5–8, https://doi.org/10.1093/comnet/cnac022.
[36] M.H. Ashcraft, J. Krause, Working memory, math performance, and math anxiety, Psychon. Bull. Rev. 14 (2007) 243–248. http://personal.psu.edu/users/s/a/sap246/spaul_HCOMPworkshop_CHI11.pdf%5Cnpapers3://publication/uuid/32ECD18C-4D33-42EB-802D-D2EAEA9FEA2E.
[37] M.H. Ashcraft, E.P. Kirk, The relationships among working memory, math anxiety, and performance, J. Exp. Psychol. Gen. 130 (2001) 224–237, https://doi.org/10.1037/0096-3445.130.2.224.

[38] S. Caviola, E. Toffalini, D. Giofrè, J.M. Ruiz, D. Szűcs, I.C. Mammarella, Math performance and academic anxiety forms, from sociodemographic to cognitive aspects: a meta-analysis on 906,311 participants, 2022. https://doi.org/10.1007/s10648-021-09618-5.

[39] E. Carey, A. Devine, F. Hill, D. Szucs, Differentiating anxiety forms and their role in academic performance from primary to secondary school, PLoS ONE 12 (2017) 1–20, https://doi.org/10.1371/journal.pone.0174418.

[40] A. Devine, F. Hill, E. Carey, D. Szűcs, A. Devine, Cognitive and emotional math problems largely dissociate: prevalence of developmental dyscalculia and mathematics anxiety, J. Educ. Psychol. 110 (2016) 431–444. https://www.airipa.it/wp-content/uploads/2019/03/devine_etal2018.pdf.

[41] N.C. Jordan, N. Hansen, L.S. Fuchs, R.S. Siegler, R. Gersten, D. Micklos, Developmental predictors of fraction concepts and procedures, J. Exp. Child Psychol. 116 (2013) 45–58, https://doi.org/10.1016/j.jecp.2013.02.001.