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What do we Actually Know About Math Learning Strategies?

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WHAT DO WE ACTUALLY KNOW ABOUT MATH LEARNING STRATEGIES?

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Abstract: Various studies investigate the effects of learning strategies on students' (math) performance. However, particularly in math, one can see a mixed pattern of the impact of learning strategies on performance. This is probably because of different methodological approaches, leading to different results. This study investigates the effect of learning strategies on math performance within different statistical and methodological approaches using a sample of 299 undergraduate students enrolled in Economics and Business Administration at a midsized German university and compares the different outcomes. On the one hand, the results suggest that most studies probably report biased estimations, which are not trustworthy. On the other hand, those learning strategies might not be as important as educational researchers and practitioners think.

Keywords: math performance, learning strategies, omitted variables, higher education

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Various studies investigate the effects of learning strategies on students' (math) performance. However, particularly in math, one can see a mixed pattern of the impact of learning strategies on performance. This is probably because of different methodological approaches, leading to different results. This study investigates the effect of learning strategies on math performance within different statistical and methodological approaches using a sample of 299 undergraduate students enrolled in Economics and Business Administration at a midsized German university and compares the different outcomes. On the one hand, the results suggest that most studies probably report biased estimations, which are not trustworthy. On the other hand, those learning strategies might not be as important as educational researchers and practitioners think.

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1. Introduction

Mathematics in higher education is one of the most challenging subjects, particularly in study programs with service mathematics like economics or engineering. Furthermore, many students (in Germany) drop out because of performance issues (Heublein 2014). Notably, the transition to higher education challenges students in two ways. Firstly, structural changes from secondary school to higher education (e. g., formal teaching authority vs. self-regulated learning), and secondly, math-related changes (e. g., proof schemes) might be challenging (Geudet 2008, Luk 2005).

This transition, however, most likely leads to changes according to students' use of learning strategies (Coertjens 2017, Donche 2010). The presented study uses these naturally occurring changes and investigates the effect of different learning strategies on students' math performance and learning growth. Furthermore, this study compares different and highly used methodological and statistical approaches when examining the effect of learning strategies.

2. Theoretical background

2.1 Literature Review

2.1.1 The influence of learning strategies on academic achievement

A wide variety of studies investigate the influence of learning strategies on academic achievement from primary to higher and adult education. Cho (2021), for instance, reports positive effects of self-regulated strategies, functioning as a mediator variable between adaptive beliefs and the performance of international students. Magen-Nagar and Cohen (2017) also found mediating effects of learning strategies, and their results imply that different learning strategies mediate the positive influence of motivation on academic achievement. Dabas et al. (2021) report that higher-skilled students (utilizing exam grades) have more robust metacognitive self-regulation and elaboration. Further recent studies (Diseth et al., 2021; Weisskirch, 2018) report similar results of significant positive correlations between strategic learning approaches, quality of learning, and effort with course grades. Particularly in medicine, learning strategies positively influence academic achievement (Nabzadeh, 2019; Hayat et al., 2020). Further research approaches are interventions in the form of metacognitive training for teachers or students. Olson (2012) performed an experimental study on secondary school teachers and found that teacher training on cognitive strategies used during lessons increases students' reading and writing. Similar results were reported by Ulstad et al. (2018).

Most of the reported studies focus on particular courses or study programs (such as English, Math, or Medicine) or overall academic achievement (e. g. GPA) at single schools or universities. A meta-analysis, however, uses this variety and combines the effects of these studies with limited external validity. Credé et al. (2011), for instance, reviewed studies using the MSLQ (Motivated Strategies for Learning Questionnaire) and found positive but mostly weak correlations between elaboration, organization, as well as meta-cognitive self-regulation, and general academic achievement (GPA). De Boer et al. (2018) report a similar influence of these learning constructs on students' achievement, investigating studies focusing on student strategy instruction interventions. The meta-analysis of Richardson et al. (2012) reveals, among others, a significant positive influence of metacognition, elaboration, and deep learning on students' GPA, while surface learning correlates negatively. However, learning approaches and the effect on academic achievement might differ in different subjects or educational settings. Therefore, it seems necessary to review the literature on the impact of learning strategies on mathematic achievement separately in the next section.

2.1.2 The influence of learning strategies on math achievement

The studies focusing on mathematics subjects find somewhat mixed results and cannot fully replicate the clear findings of the previous section. With a view to studies investigating the relationship between learning strategies and secondary school math performance, research finds a positive influence of higher metacognitive strategies (Chiu et al. 2007) and deep learning strategies (McInerney et al. 2012; Murayama et al. 2013) on students' math performance. High use of surface learning (McInerney et al. 2012; Murayama et al. 2013) or memorizing strategies (Chiu et al. 2007) negatively influences math achievement. A further study (Fadlelmule et al., 2015) does not find any significant correlation between students' math performance and organizational or metacognitive strategies, while robust elaboration strategies correlate positively (Murayama et al., 2013).

Regarding studies investigating college students' performance, the picture gets even fuzzier. For instance, Cho and Heron (2015) do not find any significant influence of college students' metacognitive strategies on math achievement. Laging and Voßkamp (2017) reported similar results, and Liston and O'Donogue (2009) did not find any significant effects of memorizing strategies, surface learning, elaboration strategies, or deep learning. Liebendörfer et al. (2022) report a positive impact of practicing and frustration resistance and adverse effects of repeating on students' math achievement. This picture gets even more differentiated when focusing on the point of time students' learning strategies, and math achievement was measured. Roick and Ringeisen (2018) find positive effects of strong metacognitive learning strategies on performance when measured at the beginning of the semester and adverse effects of the same strategies before the final exam.

This mixed pattern leads to various methodological problems when investigating the influence of learning strategies on math achievement. On the one hand, the point of time the learning strategies and math achievement are measured seems essential, since at the beginning of tertiary education, "the variables map the learning behaviour the students applied at school "(Laging and Voßkamp 2017, p. 132). On the other hand, the reviewed literature on the influence of learning strategies on math performance cannot provide a clear picture, which might be due to the studies' different methodological approaches. In the next section, we give a brief overview of the various methodological approaches and the problems regarding internal validity. However, we focus on practical examples rather than technical, mathematical, or statistical explanations[1].

1 Readers interested in more technical approaches are refered to Antonakis (2010) and Sajons (2020).

2.2 Methodological approaches and issues

Focusing on the methodological approaches and statistical analysis of the above-reviewed studies, one finds analysis with cross-sectional and longitudinal data, correlative or experimental studies, and different statistical techniques, like correlation analysis, regression analysis (OLS), and structural equation modeling (SEM). However, most of the studies cannot provide any causally interpretable results. The different statistical approaches, which also depend on the methodological setting (e. g. cross-sectional vs. longitudinal data), limit the results. Furthermore, only about half of the studies mention limitations regarding the causation of their results.

The problem is often summarized as "endogeneity", which is a threat to one of the conditions of causal effects, namely, that other causes must not explain the relationship between two variables (Kenny 1979). In the case of endogeneity, there is a correlation (covariance (COV)) between the independent variable (e. g., particular learning strategy (LS)) and the error term of the dependent variable (e. g., math achievement (MA), see Figure 1).

[Figure 1 near here]

This (unwanted) correlation, however, leads to an inconsistent (biased) estimator (e. g., Sajons 2020). Literature (Antonakis et al. 2010; Antonakis et al. 2014) refers to different validity threats that result in biased estimations. In this study's focus, omitted variables are the most crucial threat. Omitting variables means (among others) not including important control variables or not knowing about the control variables. Then, the estimation will be inconsistent, as shown by Antonakis et al. (2010). One can identify groups of often used statistical approaches, which all suffer (at different levels) from problems regarding the internal validity of the results, which are presented next.

2.2.1 Correlation analysis and group differences

Studies that focus solely on correlations form the first group. For instance, Liston and O'Donoghue (2009) perform separate correlation analyses to investigate the influence of learning strategies on math performance. Studies investigating and comparing differences in learning strategies for higher-skilled and lower-skilled students (e. g., Dabas et al. 2021, Thiessen and Blasius 2008), or perform cluster analysis (e. g., Malcolm and Meyer 2004), are also correlative. The issue with solely correlative results in cross-sectional and non-randomized data is that one cannot interpret it causally because of omitted variables.

[Figure 2 near here]

Correlation analysis is performed isolated (for each learning strategy separately). Therefore, the estimated correlation between different learning strategies and math achievement is likely biased (see Figure 2). For instance, given an accurate model (A1), where a second learning strategy (LS_2) is correlated with both the first learning strategy (LS_1) and the math achievement (MA), isolating the second learning strategy from the model, which is the case for separated correlation analysis (A2), would lead to omitted variable bias. In a non-randomized setting, one can nearly always find such a third variable, affecting both the independent and dependent variables. Therefore, most studies do not rely on separate correlation analysis but rather use statistical models, where one can implement more variables.

2.2.2 OLS and SEM in cross-sectional data

Therefore, the second group clusters studies that perform multiple regression analysis (OLS) or structure equation modeling (SEM). The main difference between these two approaches and the separated correlation analysis is that one can implement more than one dependent variable and control different variables. However, the studies in this group use cross-sectional data. From the above-reviewed studies Cho (2021), Diseth (2010), Fadlelmula et al. (2015), Magen-Nagar & Cohen (2017), Nabizadeh et al. (2019), Hayat et al. (2020), McInerney (2012) use SEM, while Weisskirch (2018), Chiu et al. (2007), and Cho and Heron (2015) use OLS to identify the influence of learning strategies on math achievement. However, when it comes to omitted variable bias, both methods suffer from the same methodological issue (see Figure 3).

[Figure 3 near here]

Assuming an accurate multiple regression model (B1.1) with motivation (MOT) as a control variable correlating with the set of learning strategies (LS_i) and math achievement (MA), the estimations β_{1i} are consistent. Excluding motivation from the model, when, for instance, student data for motivation is not available, the estimates of β_{1i} get inconsistent because the variable motivation now acts as an omitted variable, and the variables LS_i directly correlate with the error term of math achievement (B 1.2). SEM behaves very similarly to omitted variables. Example B2.1 shows a valid model with a consistent β_1 estimator; not controlling for motivation as a control variable results in an inconsistent estimation of β_1 (B2.2).

2.2.3 OLS and SEM in "quasi-panel-data"

In the next step, to overcome the issue of omitted variables, some studies make use of longitudinal data (Laging and Voßkamp (2017), Roick and Ringeisen (2018), Liebendörfer et al. (2022)). While longitudinal data can help reduce estimation bias (students' characteristics and confounding variables might be constant over time), these studies either miss crucial information or do not follow acceptable methods to make use of the time-series data. We refer to this type of data as "quasi-panel-data". For instance, Roick and Ringeisen (2018) measured learning strategies at two points in time, the beginning of the semester and later, before the final exam. Math achievement, however, was only measured once at the second point in time. On the contrary, Liebendörfer et al. (2022) measured math achievement twice but learning strategies only once. Therefore, these studies cannot use statistical methods of panel analysis since crucial information on independent or dependent variables is unavailable at both points. However, these studies have an advantage compared to studies using cross-sectional data. They can implement prior math achievement (at the beginning) as a control variable and predictor for the later math achievement measured at the second point. Controlling for students' prior math achievement should combine various control variables and underly the consistency of the estimation, but it remains unclear whether it completely solves omitted variable bias (see Figure 4).

[Figure 4 near here]

One could assume an accurate model (C1), where the math achievement at the second point in time (MA_{T2}) depends on learning strategies (LS_i), math achievement at the first point in time (MA_{T1}), and, for instance, students' prior high school GPA (pGPA). Not including the pGPA, which, in this model, correlates with both MA_{T1} and MA_{T2}, will result in biased estimations (C2), even if the correlation between LS_i and the error term remains zero, which is unlikely. In this case, the bias might get through the correlations of MA_{T1} with the error term (see also Antonakis et al. 2010). Consequently, controlling for prior math achievement leads to a more consistent estimation than analysis with cross-sectional data; however, it is not enough to claim causation.

2.2.4 Methods for more consistent estimations

One can fall back on various experimental or quasi-experimental designs to counter endogeneity. There are, for instance, methods like propensity score matching (PSM), difference-in-difference (DID), regression-discontinuity (RD), and instrumental variable (IV), which are very common in research fields of economics, but relatively unknown in social sciences or management research (Antonakis et al. 2010). These are approaches for quasi-experimental settings and evaluations of interventions where randomized manipulation is impossible. However, to examine the influence of learning strategies on academic achievement, these approaches seem (except IV or DID) complicated and not suitable. Therefore, we propagate two possible approaches to minimize endogeneity bias: first-best and second-best options.

The first best option is randomization within an experimental setting. Students could be randomly assigned to an experimental and control group. Studies have shown, that educational interventions might influence students' strategy use (Dignath et al. 2008, Biwer et al. 2020). Therefore, interventions could foster, for instance, deep learning strategies of the students in the experimental group, and omitted variables would be addressed because of the randomization. Olson (2012) and Ulstad et al. (2018) investigate randomized metacognitive interventions for teachers and report a positive effect on students' academic achievement. However, randomization is not always possible, and even if one conducts a randomized experiment, results might still be biased if an IV approach is not performed (see Sajons 2020).

[Figure 5 near here]

The illustrated research design in Figure 5 uses a randomized intervention to estimate the effect of a learning strategy (LS_1) on math achievement (MA). In the first setting (D1), experimental studies measure the causal effect of the intervention on the learning strategy (β_1). However, the learning strategy acts as a mediator between the intervention and math achievement. Therefore, there is a second correlation between the learning strategy and math achievement, which is, in most cases, not separately analyzed. If only the direct effect (intervention → math achievement ($\beta_1 * \beta_2$)) is reported, this effect could still be biased if the estimator of β_2 is inconsistent. Therefore, Sajons (2020) suggests an instrumental variable approach. Using the randomization of the intervention as an exogenous variation (instrumental variable), one can also estimate a consistent estimator for β_2. However, experimental designs, particularly in higher education, are laborious, costly, and hardly controllable.

Therefore, the second-best option for analyzing learning strategy effects is a time-series panel design, in which students' academic achievement and learning strategies are measured at least twice. Roick and Ringeisen (2018) state that "collecting data on the mathematics performance prior to course participation would have enabled […] a measure of relative change in mathematics achievement" (p. 156). The advantage of time-series data is that baseline information on learning strategy use, and academic achievement is available. Therefore, one can measure students' changes in the use of learning strategies between (at least) two points in time and estimate the influence of these changes on learning growth over the same time (see e. g. Murayama et al. (2013)). Panel analysis (e. g., fixed effects models (FE)) controls for unobserved heterogeneity and therefore omitted variables when heterogeneity is constant over time. This means that students' time-invariant characteristics that affect academic achievement the first time just the same as the second point in time are controlled (see section 3.3). However, time-dependent heterogeneity has to be controlled by including crucial variables. Additionally, panel analysis reduces measurement errors[2] since the same students are surveyed at different times, expecting individual measurement errors for learning strategy scales to remain the same over time.

2 Measurement errors are, as well as omitted variables, a threat to internal validity (Antonakis et al. 2020).

2.2.5 Changes in students' use of learning strategies

Problematic seems that, at first, one has to observe changes in the use of learning strategies over time when measuring the effects on academic achievement. But how and when does the use of learning strategies change? Change can be fostered with educational interventions (first best option) or naturally expected; for instance, the transition to higher education changes the students' learning approaches (Hussey 2010).

Some studies investigate the change in general learning strategies (not math-related) used in secondary school and higher education; however, naturally occurring changes in learning strategy use seem relatively rare in secondary schooling. For instance, Leutwyler (2009) could not find a development in metacognitive learning strategies during upper secondary education. A possible reason could be the formal teaching authority, which leads to more stable learning approaches (Lietz and Matthews 2010). Contrary, a study by Veenman et al. (2004) reports a development of metacognitive learning strategies, particularly over the lifespan. Studies investigating changes in students' use of learning strategies, particularly during the first year of college, find some developments (Coertjens 2017, Donche 2010). Therefore, research analyzing learning strategies should focus on the transition from secondary to higher education, which seems empirically more consistent. Because of the structural, educational and individual changes during the college transition, changes in the use of students' learning strategies can be naturally expected. This study investigates the effect of learning strategies in a higher education math course for economics using time-series data of first-year students transitioning to higher education.

3. Empirical background

3.1 Sample

Since the winter semester of 2012, students enrolled in the study program of economics and business administration were asked to take an anonymous math skill test and accompanying questionnaire in the first lecture of "mathematics for economics "– a first-year course – at a German midsized university. The data was raised entirely anonymously, and students knew the gathered data would be used for research studies. While the math skill test remained the same over time, the questions asked in the questionnaire slightly changed according to the lecturer's research interests and limitations in the length of the questionnaire. Data on learning strategies were mainly gathered in the winter semesters of 2012 and 2013. Additionally, students in these semesters participated in an anonymous skill test in the middle of the semester. Altogether, complete information of 299 students who took part in both skill tests at the beginning (T_1) and middle of the semester (T_2) in the winter semester of 2012 and 2013 is available. At both points, data on students' math skills and the use of different learning strategies was gathered. Consequently, there is information on the students' change in math skills and the change in using different learning strategies during their first semester.

3.2 Variables, measurement, and descriptive statistics

3.2.1 Variables

Two different but comparable skill tests (see also Laging & Voßkamp 2017) measured the students' math skills at the beginning (T_1) and the middle of the semester (T_2). Each skill test consists of 30 tasks, and students could score 30 points (one point per task). The skill tests were developed for students enrolled in economics and similar study programs and focused on secondary school math (arithmetic, algebra, functions, calculus).

Besides the math skill, data on students' use of learning strategies, learning goal orientation, and control strategies was gathered, once at the beginning of the semester (T_1) and again in the middle of the semester (T_2). Information on learning and concept strategies was raised via proven scales (see e. g., Laging & Voßkamp 2017; Büchele 2020). At both points in time, we measured the students' use of memorizing strategies (MS), elaboration strategies (ES), learning goal orientation (LGO), control strategies (CS) while learning math, and math self-concept (MSC). For better readability, all scales are referred to as learning strategies.

Additionally, at T_2 only, we raised information on students' persistence (LP) and regularity (LR) in learning math, which are variables that only affect math achievement in the middle of the semester (at T_2). The original items of the learning strategy scales are in German and, therefore, not reported in detail[3]. Table 1 gives a brief overview with item examples (translated from German).

[Table 1 near here]

3.2.2 Descriptive statistics

Table 2 gives an overview of the variables mentioned above' descriptive statistics. We report both values of each variable (at T_1 and T_2) separately and the differences between the two points in time.

[Table 2 near here]

Firstly, the student's math skill (scores on both tests) is relatively low. Students, on average, only gained 8.3 points (nearly 30 %) in the first and about 11.5 points

[3] However, one can find a sufficient overview in Laging & Voßkamp (2017).

(almost 40 %) in the second skill test. However, the students performed better over time and increased their math skills by about 3.3 points. Secondly, one can find information on the different learning strategies measured. Except for memorizing strategies (Cronbach's alpha of .69 and .71, respectively), the scales show good reliability values. Furthermore, students show a relatively high learning regularity (4.78) and learning persistence (4.01) over the semester.

As mentioned in section 2.2.5, one could expect changes and adjustments in student learning over the transition into higher education. As summarized in Table 2, however, the average changes that occur to the use of the given learning strategies are relatively small or non-existent. Although t-statistics show that the use in MS ($t=5.09$, $p<.01$), LGO ($t=3.48$, $p<.01$), CS ($t=6.99$, $p<.01$), and MSC ($t=6.13$, $p<.01$) declined statistically significant, the size of the changes is small. ES, for instance, did not change at all over time. These relatively minor changes, however, came with a high standard deviation (compared to the mean difference). And although there are no significant average differences in the shift of ES, the individual variation is relatively high. For each variable, at least half of the sample show individual changes above 0.5 scale units (scale from 1 to 6). This change is normally distributed, which results in minor average differences. However, for the statistical analysis in this study, average differences do not matter since individual changes are regressed on individual achievement differences over time (see next section).

3.3 Different statistical approaches

As mentioned in section 2.2, research in learning strategies usually falls back on typical statistical approaches. This study will pick up and compare the results of three of these approaches with the exact same sample, namely: separated correlation (simple OLS), multiple OLS, and "quasi-panel" OLS (with math skill baseline information).

Furthermore, since information on students' math skills and the use of learning strategies at two points is available, we will run a fixed-effects regression (FE), isolating changes in the use of learning strategies. All models were estimated in Stata with robust standard errors to counter heteroskedasticity, and for better comparability, all models were estimated with math achievement at T2 as the dependent variable.

3.3.1 Simple OLS (Model 1)

The first model estimates the separate correlations of each learning strategy with math achievement at T_2. We used simple regression analysis instead of Pearson correlations for better comparability with the other models. Therefore, we can refer to non-standardized coefficients like models 2 to 4. Consequently, we ran the regression seven times for the seven learning scales. Equation (1) shows the estimation with α as the constant, β_i as the estimator for learning strategy i at time T_1 (LS_{1i}), and the error term ϵ.

$$MA_{T2} = \alpha + \beta_i * LS_{1i} + \epsilon \quad (1)$$

3.3.2 Multiple OLS (Model 2)

In the second model (see equation 2), we run only one multiple regression with information only available at T_1, representing a typical cross-sectional study design (except for MA_{T2}, which is taken as the dependent variable for comparability). Therefore, we simultaneously include the five learning scales MS, ES, LGO, CS, and MSC.

$$MA_{T2} = \alpha + \sum_{i=1}^{5} \beta_i * LS_{1i} + \epsilon \quad (2)$$

3.3.3 "Quasi-panel" OLS (Models 3.1 and 3.2)

Models 3.1 and 3.2 take advantage of the aforementioned "quasi-panel", with the additional information on students' baseline math skills at T_1. Therefore, the math achievement at T_1 is taken into the model (MA_{T1}) as an independent variable. Furthermore, variables are included in two steps to compare the models with models 1 and 2. First, the five learning scales as in model 2 (equation 3.1), and second, the additional scales LP and LR, which influence the math achievement at T2 only (equation 3.2).

$$MA_{T2} = \alpha + \gamma * MA_{T1} + \sum_{i=1}^{5} \beta_i * LS_{1i} + \epsilon \quad (3.1)$$

$$MA_{T2} = \alpha + \gamma * MA_{T1} + \sum_{i=1}^{7} \beta_i * LS_{1i} + \epsilon \quad (3.2)$$

3.3.4 Fixed-effects (Models 4.1 and 4.2)

In the fourth model, we estimate a fixed-effects model, isolating changes in the use of learning strategies over time and regressing these changes on the skill differences over the same time. As in models 3.1 and 3.2, variables are implemented in two steps; first, the variables affecting the math achievement at T_1 and T_2 (equation 4.1), and second, including the variables affecting math achievement at T_2 only (equation 4.2).

The fixed-effects regression can be estimated with various time-periods (T) and the individuals (j), as in equations 4.1 (FE) and 4.2 (FE), where, for instance, $\overline{MA_J} = \frac{\sum_1^t MA_{jt}}{T}$. The major advantage in contrast to multiple regression analysis is that a_j describes unobserved and time-invariant individual effects (like gender, age, etc.). Since these variables are time-invariant a_j equals $\overline{a_J}$ and the effect adds up to zero (see equations 4.1 and 4.2). Consequently, the fixed effects model controls for time-invariant unobserved variables. However, estimation bias due to omitted variables is not automatically controlled since only time-invariant but not time-variant unobserved individual effects are eliminated. Since the students' use of learning scales changes over time, these variables are time-variant, and these changes (difference between LS_{jti} and $\overline{LS_{Jl}}$) can be implemented as control variables.

$$MA_{jt} - \overline{MA_J} = (a_j - \overline{a}_J) + \sum_{i=1}^{5}(\beta_i(LS_{jti} - \overline{LS_{J\iota}})) + (\epsilon_{jt} - \overline{\epsilon}_J) \quad (4.1 \text{ (FE)})$$

$$MA_{jt} - \overline{MA_J} = (a_j - \overline{a}_J) + \sum_{i=1}^{7}(\beta_i(LS_{jti} - \overline{LS_{J\iota}})) + (\epsilon_{jt} - \overline{\epsilon}_J) \quad (4.2 \text{ (FE)})$$

However, in the case of two measurement points – like in this study – the fixed-effects estimation (FE) is equivalent to the first difference estimation (FD), which is more compact. The differences between the learning scales ($\Delta LS_i = LS_{2i} - LS_{1i}$) can be regressed on the differences in math achievement ($\Delta MA = MA_{T2} - MA_{T1}$):

$$\Delta MA = \sum_{i=1}^{5}(\beta_i * \Delta LS_i) + \Delta\epsilon \quad (4.1 \text{ (FD)})$$

$$\Delta MA = \sum_{i=1}^{7}(\beta_i * \Delta LS_i) + \Delta\epsilon \quad (4.2 \text{ (FD)})$$

4. Results

In this section, we will only present the results of our statistical analysis. For a better readability and overview, the discussion of these results (changes and interpretation of statistical significance or effect sizes and comparability analysis) is shifted to the next section. Table 3 provides the coefficients of the models described above, and the sample and variables remained the same for each model. For better comparability between the models, the coefficients are not standardized. Analysis was performed in Stata with robust standard errors.

[Table 3 near here]

With a view on the first model (column 2), we find significant correlations between math achievement at T_2 and all given learning strategies. The non-standardized coefficients are easy to interpret. Therefore, one additional point in the skill test at T_1 (math achievement T_1) leads to .87 points in the second skill test. Furthermore, one extra point on the scales (from 1 - 6) leads to a higher score from about 1.3 points for ES, 1.8 points for LGO, 2.4 points for CS, 3.5 points for MSC, 2 points for LP, and 1.6

points for LR. Higher use of memorizing strategies (MS) results in a decreasing score of about 1.2 points per unit on the scale.

In the second model (column 3), the influence of learning strategies is measured simultaneously, which clears parts of the interdependence between the independent variables. In the second model, only LGO and MSC correlate significantly with math achievement. One additional point on the LGO scale leads to about 0.7 (extra) points in the skill test and 3.3 points (MSC), respectively.

Model 3 use the baseline information of students' math skill at the beginning of the semester (math achievement T_1). For better comparability, the first step (model 3.1) is estimated without the semester-dependent variables LP and LR. In this model, prior math achievement (MA_{T1}) and MSC correlates significantly with later math achievement. Including LP and LR in the model leads to a slightly reduced effect size of MSC and a significant and positive influence of LR on math achievement.

Model 4 estimates a fixed-effects regression, and again, the semester-dependent variables (LP and LR) are implemented in a second step (model 4.2). Because the dependent variable is now the individual differences in math achievement, the model includes the baseline, and no values for prior math achievement can be reported. In model 4.1, we find two significant influences of learning strategies on math achievement. First, MS is negatively correlated with math achievement. More precisely, the increase of MS uses during the semester by one unit on the scale results in an average decrease in math achievement of about 1.5 points. Second, the rise of ES uses during the semester by one unit on the scale results in an average increase in math achievement of about 0.9 points over the semester. However, including learning habits (LP and LR) in model 4.2, these effects dissolve, and the scales of LP and LR now positively correlate with the differences in math achievement.

5. Discussion

One can see that, although the sample always remains the same, the statistical significance and effect sizes change depending on the used model. Therefore, using different models leads to different coefficients, results, and implications. The discussion of these results is divided into one methodological part, where we compare the models, and one educational part, where we further analyze and put perspective on the particular influences and outcomes on math achievement.

5.1 Discussion of the Results

5.1.1 Methodological Discussion

At first, we discuss the methodological results of the different statistical approaches. Not surprisingly, the separately performed analysis in model 1 shows highly significant and large effect sizes of the given learning attributes on math achievement. However, as mentioned above (see section 2.2.1), statistical significance typically does not easily match causation. Since these variables and correlations with math achievement are interdependent and correlate simultaneously with math achievement, the effect sizes are not trustworthy and overestimated. In the transition to the second model, which also imitates a cross-sectional design, one can see that the coefficients mostly lose their effect size and significance. Only the coefficients for LGO and MSC remained statistically significant, but the effect size for LGO decreased by more than half, while MSC nearly remained the same. In this model, the learning strategies are included simultaneously, which results in a more accurate estimation.

Model 3.1 additionally controls for baseline math skills, and the coefficients from model 2 change again. Firstly, the coefficient of LGO loses statistical significance and its effect size, and secondly, the MSC's effect size is halved. Similarly, one can see that model 2 overestimated the effect of LGO and MSC because of omitted variables. This picture intensifies in transition to model 3.2, where we additionally control for the time-variant variables LP and LR. However, the effect of prior on later math achievement seems relatively consistent. We can only observe minor changes from model 1 to model 3.

Finally, models 4.1 and 4.2 estimates the coefficients via a first-difference regression. The effect sizes change again and are, in some cases, similar to the first model. We can report comparable positive effects of ES and adverse effects of MS on math achievement in model 4.1. As mentioned above, fixed effects analysis only controls for time-invariant heterogeneity. Therefore, die estimations are more trustworthy than, for example, model 1 or 2, but time variant heterogeneity might still bias the effect sizes. This is the case for model 4.1; In the transition to model 4.2, we include the variables LP and LR. However, the effect sizes of ES and MS disappear, which indicates that Model 4.1 also overestimates the effects of ES and MS, although we control for time-invariant heterogeneity. Consequently, fixed-effects models might still be biased if the information on crucial confounding and time-dependent variables is rare. However, it is still more consistent than models 1 to 3.

Altogether, it gets clear that different models estimate different coefficients, although the sample and data remain the same. This is a major issue when interpreting the effect of learning strategies on math achievement since different studies are not comparable and might report different results because of misspecified models.

5.1.2 Educational discussion

The results suggest different factors influencing the students' math achievements. At first, one can see that prior (math) knowledge positively correlates with the student's math skills in the middle of the semester. This is not surprising, and many studies find a strong correlation between prior knowledge, academic achievement, and learning growth (e.g., Liebendörfer et al. 2022, Laging & Voßkamp 2017).

From an educational view, the results of Model 4 are more interesting. The fixed-effects analysis in Model 4.1 shows a positive influence of the high use of elaboration strategies and a negative effect of memorizing strategies on math learning growth. This, in particular, is not surprising since theory and empirical evidence underlying the advantage of elaboration strategies and deep learning (see section 2.1). However, the transition to Model 4.2 shows that the variables LR and LP act as mediators between ES, MS, and students' math achievement, indicating that it is essential for students to show regular engagement and high persistence when it comes to learning math. In other words: the results suggest that it does not matter how but if students learn regularly.

5.2 Implications and limitations

The study showed that different methodological approaches lead to different outcomes when analyzing the effect of learning strategies. This is mainly because of missing information on students learning growth since many studies only use cross-sectional data. However, this problem cannot be easily solved, even with panel data and information on students' math skills and learning habits over various periods. One can control for time-independent but not for time-dependent heterogeneity with panel data. We gave some evidence that panel data analyses (as demanded by multiple researchers) seem more trustworthy than other methods, but cannot solely fix the issue of omitted variable bias. Therefore, we recommend instrumental variable and experimental designs to estimate learning strategies' effect for future research.

This study also showed that learning strategies might not be that important. Learning regularity and persistence mainly determine students' math achievement in higher education, and this has also been demonstrated most recently by Liebendöfer et al. (2022). The research did not sufficiently investigate these mediating effects yet. For educational practice, we suggest that students are animated to learn regularly and are provided with educational offers that help to foster persistence. Concrete measures could be different assessments distributed over the semester, mandatory exercises, or math support centers, which have become very popular over the last decade (Schürmann et al. 2020, Lawson et al. 2019).

This study has some limitations. Most importantly, the sample only consists of students enrolled in the Economics and Business Administration study program. Therefore, the educational analysis must be limited and not generalized since the topics of, e. g. mathematical study programs are more technical. Particularly in mathematical proof schemes, elaboration strategies might be more critical. Furthermore, the skill tests mainly cover topics of secondary math schooling, which is sufficient for the first semester of math for Economics but not for other study programs. From the methodological view, we have to point out that the effects are still not causally interpretable. Even though using panel data and a fixed-effects model lead to more trustworthy coefficients, we cannot assure that further time-dependent omitted variables might bias the results.

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Table 1: Item examples of learning strategy scales

Scale	Examples
Memorizing strategy	• When I am learning math, I try to memorize as much as possible • I calculate some tasks so often that I can solve them while sleeping
Elaboration strategy	• When solving tasks in math, I often think about new solving strategies • When learning math, I try to find links to topics I already know
Learning goal orientation	• I prefer challenging tasks so that I can learn new skills • I am happy with my study when the lecture is thought-provoking
Control strategy	• When I want to perform well in math, I can do so
Learning persistence	• When I am stuck solving a task, I try another way • I do not give up, even when a task is challenging
Learning regularity	• I solve the exercise sheets every week

Table 2: Overview of descriptive statistics

Variable (short)	Value	Items (CA^4_{T1} / CA_{T2})	Mean (SD) T_1	Mean (SD) T_2	Differences (SD)
Math achievement	0 – 30	30	8.30 (4.78)	11.61 (5.80)	3.31 (4.08)
Memorizing strategies (MS)	1 (lowest) - 6 (highest)	5 (.69 / .71)	3.60 (.95)	3.35 (.96)	-.25 (.84)
Elaboration strategies (ES)	1 (lowest) - 6 (highest)	7 (.78 / .84)	3.06 (.87)	3.07 (.95)	.01 (.78)
Learning goal orientation (LGO)	1 (lowest) - 6 (highest)	5 (.86 / .88)	3.61 (.91)	3.46 (.96)	-.15 (.74)
Control strategies (CS)	1 (lowest) - 6 (highest)	5 (.89 / .90)	4.17 (.99)	3.88 (.96)	-.29 (.71)

[4] Cronbach's alpha at T_1 and T_2

Math self-concept (MSC)	1 (lowest) - 6 (highest)	3 (.90 / .89)	3.65 (.93)	3.42 (.99)	-.23 (.64)
Learning regularity (LR)	1 (lowest) - 6 (highest)	3 (- / .83)		4.78 (1.15)	
Learning persistence (LP)	1 (lowest) - 6 (highest)	4 (- / .83)		4.01 (1.08)	
Number of cases (N)	299				

Table 3: Overview of estimations in different statistical approaches

Variable	OLS - simple (Model 1)	OLS - multiple (Model 2)	OLS – mutliple „quasi panel“ (Models 3.1 / 3.2)		Fixed-effects (first difference) (Models 4.1 / 4.2)	
	Coefficient (robust SE)	Coefficient (robust SE)	Coefficient (robust SE)		Coefficient (robust SE)	
Constant		-.21 (1.82)	.25 (1.40)	-2.21 (1.44)		
Math achievement (T_1)	.87** (.04)		.68** (.05)	.68** (.05)		
Memorizing strategies (MS)	-1.15** (.37)	-.22 (.33)	-.13 (.27)	-.33 (.25)	-1.47** (.36)	-.39 (.30)
Elaboration strategies (ES)	1.32** (.34)	-.19 (.32)	.03 (.25)	-.12 (.25)	.87* (.37)	.20 (.30)
Learning goal orientation (LGO)	1.85** (.35)	.72* (.32)	.22 (.24)	-.04 (.24)	-.58 (.42)	-.32 (.33)
Control strategies	2.38** (.34)	-.17 (.39)	-.09 (.29)	-.07 (.29)	-.69 (.41)	.31 (.35)

(CS)						
Math self-concept (MSC)	3.45** (.26)	3.31** (.36)	1.65** (.29)	1.28** (.30)	-.68 (.45)	.37 (.36)
Persistence (LP)	2.03** (.26)			.41 (.27)		.47* (21)
Learning regularity (LR)	1.64** (.27)			.83** (.21)		.53** (.17)
Dependent Variable	Math achievement (T_2)				Math achievement differences (ΔMA)	
N	299	299	299		598	
R^2		.355	.579	.615	.112 (within R^2)	.466 (within R^2)

**p<.01 *p<.05

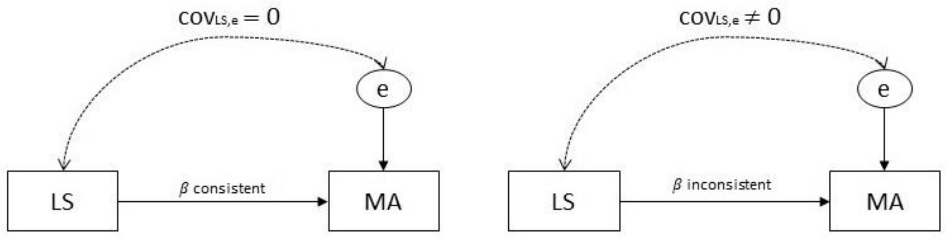

Figure 1: The issue of endogeneity (adapted from Antonakis et al. 2010)

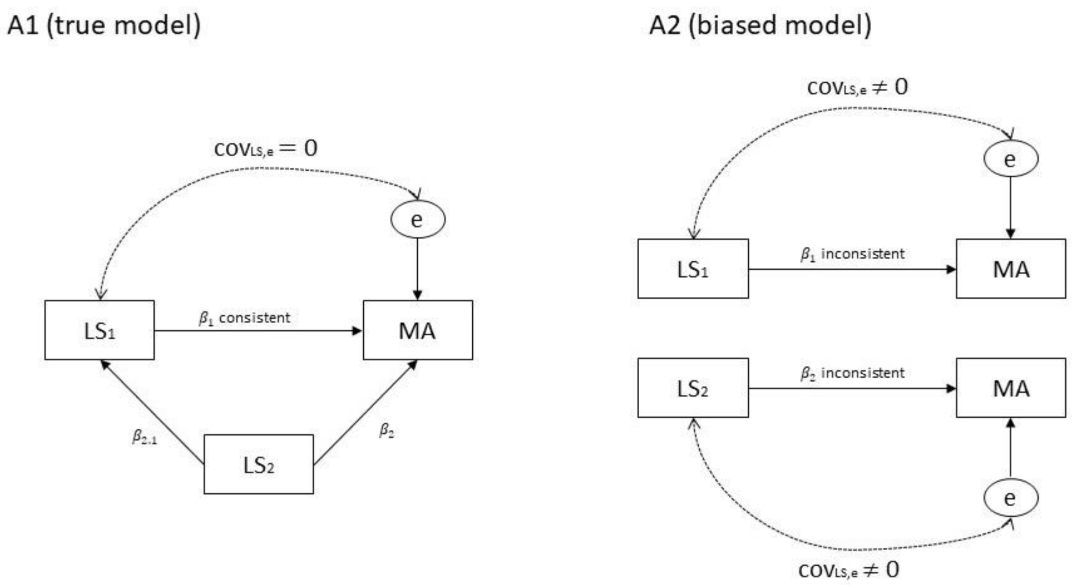

Figure 2: Endogeneity in correlation analysis

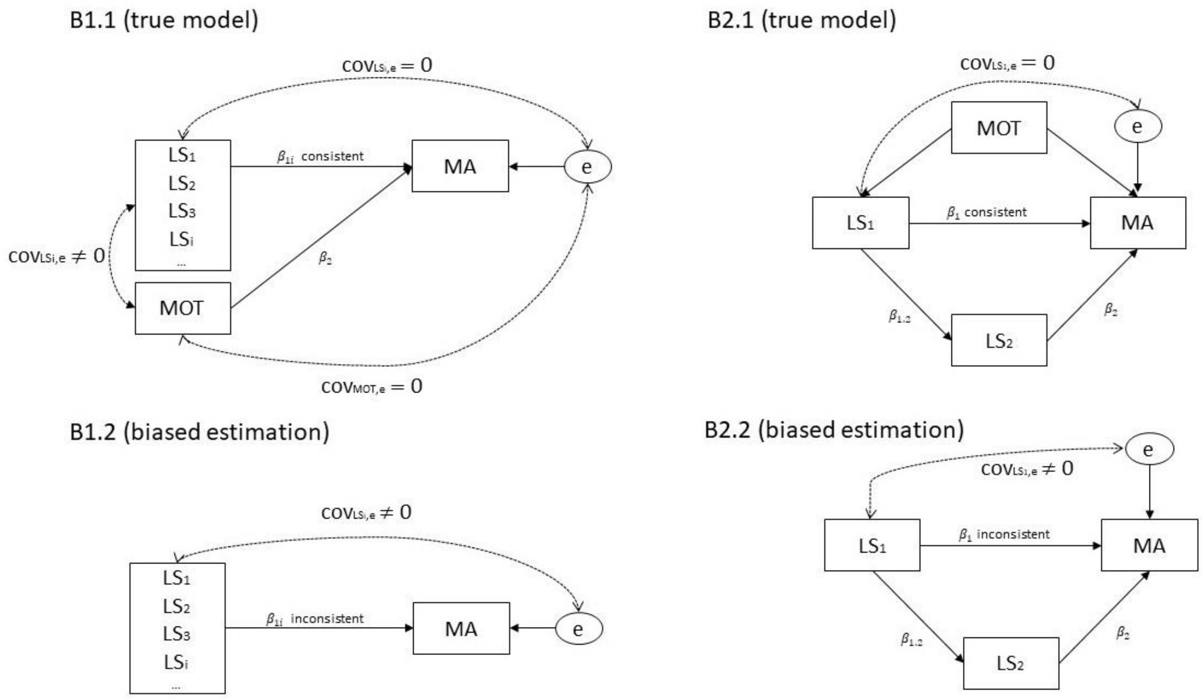

Figure 3: Endogeneity in multivariate models

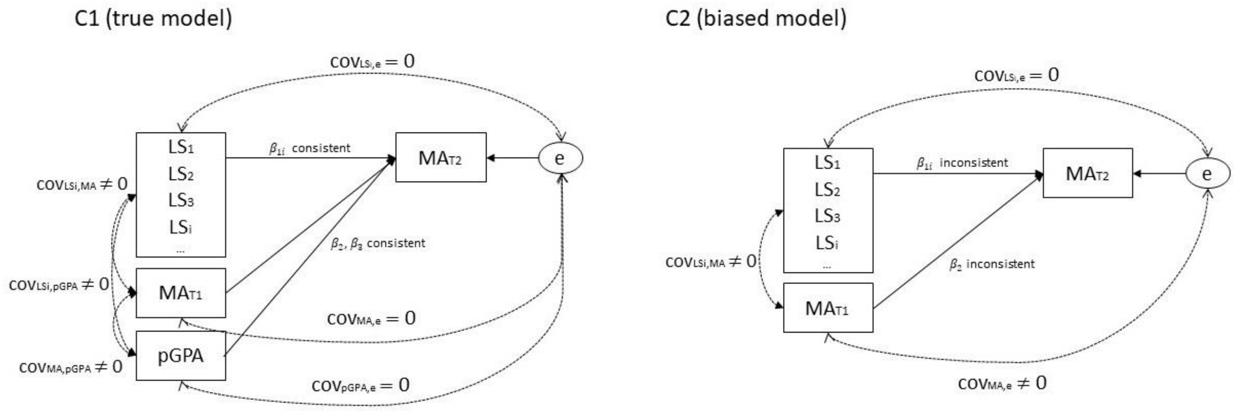

Figure 4: Endogeneity in "quasi-panel" models

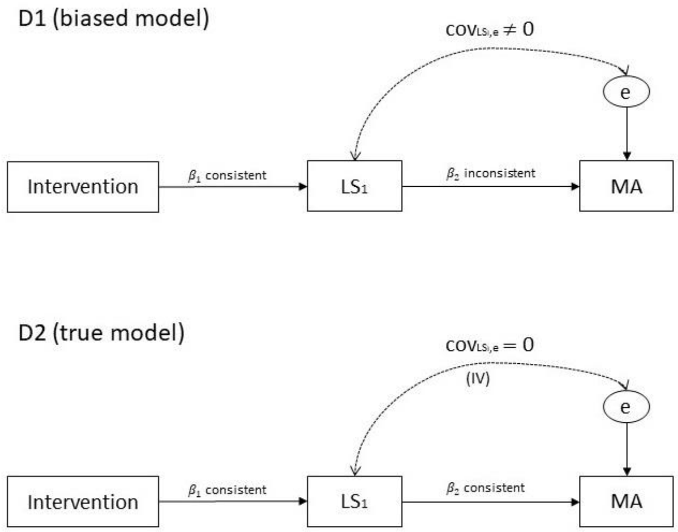

Figure 5: Endogeneity in randomized interventions (adapted from Sajons 2020)