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Analyzing the associations between motivation and academic performance via the mediator variables of specific mathematic cognitive learning strategies in different subject domains of higher education

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Abstract

Background There are different teaching methods and learning content in the academic field of mathematics between school and university. Many students fail in their studies when the proportion of mathematics is high. Additionally, dropout rates, due to mathematical performance, are high. However, there are different strategies used to improve mathematical skills. Based on the process model of self-regulated learning, an analysis of the association between motivational aspects in the pre-action phase as well as seven special cognitive learning strategies for mathematics in the action phase was conducted. The variables were compared with student performance. The study drew on data from 548 retrospective interviews of cooperative students, using a cross-sectional research design.

Results The analysis via structural equation modeling shows a direct association between motivational aspects, such as academic self-concept and curiosity, and the seven learning strategies in mathematics. Furthermore, there is a direct effect of academic self-concept on performance. However, the learning strategy of practicing was the only variable with associations to performance. Additionally, the indirect effect of curiosity on performance via practicing is analyzed.

Conclusion It can be seen, that curiosity on its own is not enough to ensure a good level of performance in mathematics. The findings suggest student learning strategies focusing on harnessing their curiosity and on practicing. A high academic self-concept is also relevant to the performance level achieved. Lecturers should create a learning environment to support such student behavior.

Introduction

Mathematics is a central element in many study programs at university, such as engineering or economics (Faulkner et al., 2019; Green et al., 2009; Neumann et al., 2021). This is a challenge, especially for first-year students. There is an unresolved discussion on the association between academic performance in mathematics and high dropout rates, with regard to cognitive factors,

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motivation, self-beliefs, personality traits, and self-regulated learning (Pepin et al., 2021; Theobald, 2021). As a consequence, the search for guidelines for academic success, as often debated by educational researchers and politicians over the last few decades, must be analyzed in more depth (Dent & Koenka, 2016).

This article addresses the research question of how motivation and learning strategies are associated with academic performance. The study focused on the motivational aspects of curiosity (Kashdan et al., 2020) and academic self-concept (Kadir & Yeung, 2016), as well as seven specific learning strategies, specific to mathematics in higher education (Liebendörfer et al., 2021). The direct and indirect effects on academic performance in mathematics from motivation were analyzed, using mathematics-specific learning strategies. Self-regulated learning and the situated expectancy-value theory was used to develop the theoretical framework (Boekaerts, 1999; Eccles & Wigfield, 2020).

Existing empirical research in STEM (science, technology, engineering and mathematics) education indicates associations between mathematic achievement and motivation (Taylor et al., 2014; Van Soom & Donche, 2014; Wang et al., 2022) as well as between mathematic achievement and learning strategies (Jackson, 2018; Pinxten et al., 2019). Berger and Karabenick (2011) show in a longitudinal study, that motivation affects learning strategies and not vice versa. Related research on cooperative education students show that, in general, the learning strategy "repeating" is most significant in the academic major of economics (Wild, 2000). In addition, Derr (2018) was able to demonstrate that cognitive variables have the greatest influence on the mathematical achievement of cooperative education students.

In this study, research gaps were analyzed that are embedded in the following backgrounds and are hardly discussed. Environmental changes are dramatic, e.g. knowledge is growing exponentially, technology is developing rapidly and the availability of information is rising. Therefore, new procedures for using data are necessary, as well as new techniques to make learning more efficient (Dignath et al., 2008). At the same time, it is recognized that previous research on learning strategies and curiosity lacks depth and must be more domain-specific (Liebendörfer et al., 2021; Pekrun, 2019). Researchers postulated that primarily learning processes should be analyzed, e.g. in the context of motivation research (Schiefele et al., 2018; Xu et al., 2021). Self-regulated learning is becoming more important as a contributor to academic achievement, in advanced education systems, because (1) it is developed during adolescence and (2) it must be improved, in order to face the environmental changes mentioned above, for solving complex tasks (Dent & Koenka, 2016). A special focus on cooperative education students is necessary, as their numbers are increasing in Germany (Federal Institute for Vocational Education and Training, 2021).

Theoretical framework and empirical results

The research focused on the concept of self-regulated learning (Boekaerts, 1999). There is evidence to suggest that self-regulated learning is a central ability, contributing to lifelong learning (Dent & Koenka, 2016; Theobald, 2021). Many researchers agree that motivation, as well as learning strategies, are central aspects in developing self-regulated learning skills (Credé & Phillips, 2011; Jansen et al., 2019).

Process model of self-regulated learning

Self-regulation models can be used to describe the learning behavior of students. According to Pintrich (2000), self-regulated learning is seen as an "active, constructive process whereby students set goals for their learning and then attempt to monitor, regulate, and control their cognition, motivation, and behavior, guided and constrained by their goals and the contextual features of their environment" (p. 453). Schmitz (2001) and Zimmerman (2000) propose a process model based on three phases: (1) pre-action phase, (2) action phase and (3) post-action phase. Figure 1 presents a visualized overview of this model. The assumption is that each phase influences the following phase.

The starting point in the *pre-action phase* is the examination of a task in a specific situation (Schmitz, 2001). For example, students have to consider if a task is so easy that it can be solved with automated routines. In such situations, self-regulation is not necessary. If the difficulty of the task increases, students have to check their resources. In this situation, students will start setting goals and develop a method for solving the task (Schmitz & Perels, 2011). Affect and motivation are further factors. The study drew on the motivation framework of situated expectancy-value theory by Eccles and Wigfield (2020). Self-efficacy beliefs also play an important role (Schmitz & Perels, 2011). Specific variables influence the action phase (Schmitz, 2001).

The situated expectancy-value theory of learning and achievement motivation suggests that student motivation can be characterized by students' expectancy of success and by four different components of task values that predict namely "task" and "activity choice", "performance", and "engagement" in the chosen activities (Eccles & Wigfield, 2020). Student expectancy of success can be defined as their "[…] beliefs about how well they will do on upcoming tasks" (Wigfield & Eccles, 2000, p. 70). The four task values encompass (1) enjoying a task (intrinsic

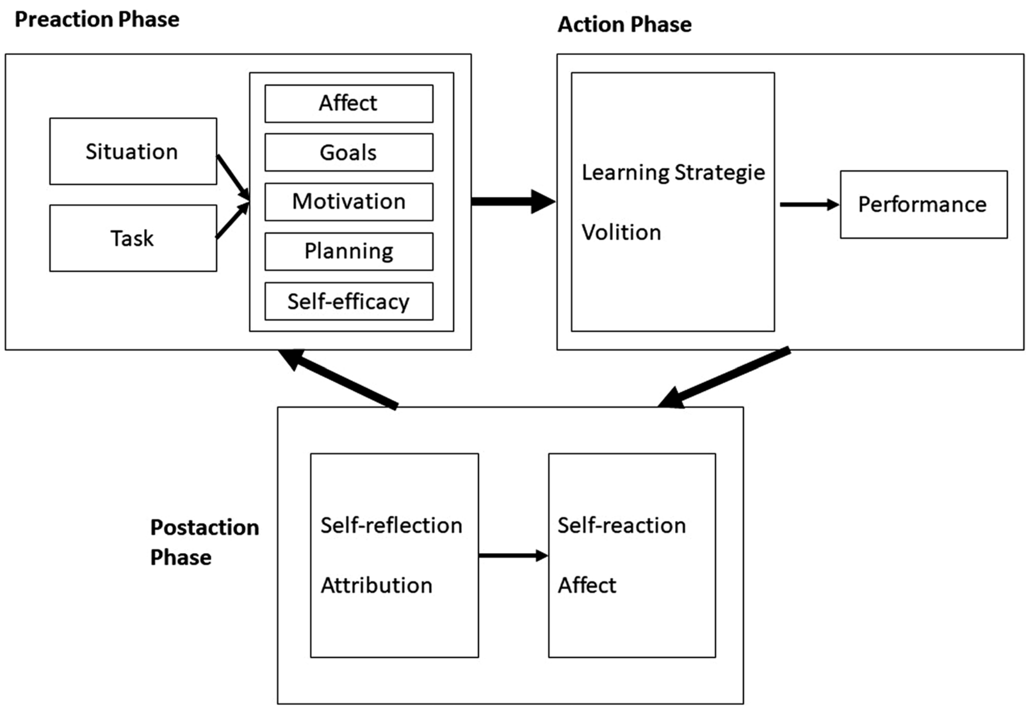

Fig. 1 Self-regulation model (adapted from Schmitz & Perels, 2011, p. 258)

value), that (2) the task is important for one's self (attainment value), and that (3) consequences of doing the task are useful for other goals (utility value) (Eccles & Wigfield, 2020). Cost (4), entails all negative consequences of tasks, such as effort, emotional/psychological cost, or opportunity cost (Eccles & Wigfield, 2020; Flake et al., 2015).

The *action phase* describes the actual work on a particular task. A person can expect a successful learning outcome, if they use the learning time efficiently and employ volitional learning strategies (Schmitz, 2001). According to Corno (1994), volition is seen "as the tendency to maintain focus and effort toward goals despite potential distractions" (p. 229). In the general discussion about learning strategies (see McKeachie et al., 1990; Perels et al., 2005; Vrugt & Oort, 2008), there exist three accepted forms of learning strategies: cognitive, metacognitive and resource-management strategies. The research underpinning this article focused on cognitive strategies.

The *post-action phase* comprises of self-reflection and self-reaction. In the beginning, the learning outcome is evaluated. More specifically, self-reflection is self-judgement by comparing one's behavior with the achieved results. Positive or negative effects are possible outcomes of self-reflection. In case of behavior modification, consequences will be applied to the next learning episode, e.g. changing learning goals or adjusting strategies. These changes are called self-reaction (Schmitz & Perels, 2011).

Research regarding self-regulated learning can be classified in two research fields. On the one hand, associations between self-regulated learning and academic performance, and on the other hand, the relationship between supporting elements and self-regulated learning (Otto et al., 2015). The focus of this research is on associations between self-regulated learning and academic performance. Meta-analyses and a review of existing articles show associations between self-regulated learning (based on individual learning strategies and motivational beliefs) and academic achievement. However, the effects are small, vary, are based on cross-sectional studies, and the variables used are measured in a very general way (Broadbent & Poon, 2015; Dent & Koenka, 2016; Li et al., 2018; Otto et al., 2015; Schneider & Preckel, 2017). Further meta-analyses show that training to support self-regulated learning also has an impact on academic performance (Jansen et al., 2019; Theobald, 2021). It is postulated, that domain-specific views should form part of the research on self-regulated learning (Otto et al., 2015).

Relevance of academic self-concept and curiosity for learning strategies on academic performance

Student motivation to learn and achieve are central components for academic success (Richardson et al., 2012; Schneider & Preckel, 2017). Referring to the expectancy-value theory, by Eccles and Wigfield (2020), student academic self-concept is understood as an expectation that is the "mental representations of one's abilities in academic domains" (Brunner et al., 2010, p. 964). Additionally, curiosity as an intrinsic value is seen from an epistemic view as "seeking information, knowledge acquisition, learning, and thinking" in terms of its importance in the workplace (Mussel et al., 2012, p. 109).

It is assumed that academic self-concept remains stable over a relatively long period, but the latest research discusses the view of a trait and state perspective, due to fluctuations in the short-term state perspective, e.g. from one academic situation to another (Hausen et al., 2022). Therefore, a trait perspective was used in this research. Researchers argue that curiosity should be seen from a domain perspective, because without a domain-specific conceptualization of curiosity, it is difficult to differentiate between interest and curiosity (Peterson & Cohen, 2019). In addition, it is assumed that curiosity can also be seen as a trait or state phenomenon (Pekrun, 2019; Wagstaff et al., 2021). The research used a domain-specific perspective trait for curiosity, in terms of solving new problems, developing strategies, or fostering innovations in the workplace (Mussel et al., 2012).

Empirical research underlines the reciprocal relation between academic self-concept and performance in education (Marsh & Martin, 2011; Niepel et al., 2014; Wu et al., 2021). According to Steinmayr et. al. (2019), self-concept is "the most important motivational predictor of students' grades above and beyond differences in their intelligence and prior grades, even when all predictors were assessed domain-specifically" (Steinmayr et al., 2019, p. 9), a view supported by the meta-analysis conducted by Richardson et. al. (2012). Further empirical research highlights the relationship between curiosity and performance (Hardy et al., 2017; Reio & Wiswell, 2000; von Stumm et al., 2011; Wavo, 2004). Some research sheds light on the association between motivation and learning strategies (Berger & Karabenick, 2011; Kulakow, 2020), but the theoretical constructs are measured in a general way and the domain-specific focus on mathematics is not deep enough.

Reciprocal effect between learning strategies and academic performance

It is argued, that the procedure of acquiring, organizing or transforming information to succeed in an education program is defined as a learning strategy (Alexander et al., 1998; Neroni et al., 2019). There are various taxonomies and classifications regarding learning strategies (Hattie & Donoghue, 2016; McCombs, 2017). A widely-used learning strategy differentiation is classified, as follows: (1) cognitive strategies, (2) metacognitive strategies, and (3) resource management strategies (Barak et al., 2016; Broadbent, 2017; Credé & Phillips, 2011; Duncan & McKeachie, 2005), which refers to the instrument Motivated Strategies for Learning Questionnaire (MSLQ) by Pintrich et. al. (1991). Neroni et. al. (2019) conclude that cognitive strategies are directly applicable to a certain task or course, like rehearsal or the organization around solving a problem. Thoughts of students about their own thinking, like planning, monitoring their own understanding, and modifying one's own mental processes are metacognitive strategies. Resource management strategies investigate the pattern of non-cognitive strategies, e.g. effort regulation, organizing time and place to study, searching for help from the lecturer or peers, and cooperation with other persons.

Empirical research indicates an association between learning strategies and performance. A meta-analysis for performance in higher education by Schneider and Preckel (2017) shows small to medium-large effects for several cognitive and metacognitive strategies, as well as medium-large effects for resource management strategies. However, these effects do not consider specific domains or study forms. Research in teacher education identifies the effect of cognitive learning strategies, metacognitive learning strategies and resource management strategies to pre-service teachers' performance in professional education (Derilo, 2019). There are indications that metacognitive learning strategies and resource management strategies have a positive effect and the use of cognitive strategies have a negative effect on exam scores (Vrugt & Oort, 2008), regarding first-year psychology students in the course "Introduction to Psychology". Research on undergraduate medical students shows an effect on the cognitive strategies of elaboration as well as from the resource management of time/study environment and effort regulation on academic performance (Cheema et al., 2018). A longitudinal study on distance learning in the Netherlands describes a positive effect from the management of time and effort, as well as the use of a complex cognitive strategy on academic performance (Neroni et al., 2019).

Learning strategies in mathematics in higher education

Looking at mathematics and learning strategies in higher education, there are two main topics in focus. Firstly, teaching aspects are based on the learning content, like proofs and the deductive structure of the curriculum, where prior knowledge has an important role. Secondly, the approach to learning the course content (Liebendörfer et al., 2021). Following the arguments of Liebendörfer et. al. (2021), cognitive learning strategies are critically important in mathematics, however, existing measurement instruments for learning strategies, like MSLQ (Pintrich et al., 1991) or LIST (Berger

& Karabenick, 2011; Wild & Schiefele, 1994), are limited. The reason for this limitation is the general point of view and the missing detailed focus on mathematics.

Liebendörfer et. al. (2021) underline, referring to the meta-analysis by Dent and Koenka (2016) that the relationship between metacognitive learning strategies and performance in mathematics can be compared to other subject domains, but differs regarding cognitive learning strategies and performance. Further analyses show that there is no correlation between non-domain specific cognitive learning strategies and performance in mathematics (e.g. Cho & Heron, 2015; Dent & Koenka, 2016; Griese, 2017). While there is a positive correlation between domain-specific learning strategies and performance in mathematics, and between elaboration and performance as well, there is a negative correlation between performance in mathematics and rehearsal (Kolter et al., 2018). However, Liebendörfer et. al. (2022) present results in mathematics, that suggest practicing, as a cognitive learning strategy, predicts performance. Alternatively, Schiefele et. al. (2003) show for students in different academic fields that effort is the only aspect in learning behavior that plays an important role, besides university entrance qualification grades, for explaining effects on performance in higher education. Nonetheless, cognitive learning strategies in mathematics are very important for the analysis of successful learning, because they can use domain-specific content and environment. Cognitive learning strategies can also be linked to existing results, such as positive correlations between mathematics performance and elaboration as well as negative correlations between mathematics performance and repetition (Liebendörfer et al., 2021).

The present study

The purpose of this study is to research the influencing factors in mathematics-related studies in higher education, related to motivation, more specifically, academic self-concept and curiosity, based on the situated expectancy-value theory by Eccles and Wigfield (2020), and cognitive learning strategies on academic performance. The study analyzed what motivational factors, as well as cognitive learning strategies are relevant to increasing academic performance. A further aim is to model a process in self-regulated learning, based on the approach of Schmitz (2001). The authors test the following hypotheses.

Hypothesis 1 Higher motivation, specifically academic self-concept and curiosity, is associated with academic performance.

Hypothesis 2 Higher motivation, specifically academic self-concept and curiosity, is associated with the use of cognitive learning strategies.

Hypothesis 3 The extensive use of cognitive learning strategies is associated with academic performance.

Hypothesis 4 Higher motivation, specifically academic self-concept and curiosity is associated with academic performance via cognitive learning strategies.

The university entrance qualification grade is used as a control variable in the analysis. Current research supports this approach, because previous performance, such as high school Grade Point Average (GPA), has a significant effect on performance in higher education (Richardson et al., 2012; Schneider & Preckel, 2017). Figure 2 presents a visualized overview of the four hypotheses.

Method

Participants and design

The data is derived from a complementary follow-up study originating from the panel study entitled "Study Process—Crossroads, Determinants of Success and Barriers while Studying at the DHBW" (Deuer & Meyer, 2020) with a cross-sectional design and convenience sampling in April 2022, by the heads of the research groups. The study was conducted in accordance with the Declaration of Helsinki. It was approved by the Baden-Wuerttemberg Cooperative State University (8th July 2015) and the local heads of the research groups for ethical standards. Before the participants responded, informed consent was obtained, and the anonymity of responses ensured. Students are enrolled at the Baden-Wuerttemberg Cooperative State University Ravensburg (DHBW). The data was collected with a paper-and-pen questionnaire during lectures by the heads of the respective departments. Survey participants were asked retrospectively about their motivation (16 items), learning strategies (24 items), and subsequent performance (two items). Furthermore, there exist items in the questionnaire concerning another project on "Pro-environmental behavior" (46 items) and demographic variables (22 items). The survey took participants about 15 min to respond to the 110 questions.

The $N = 548$ cooperative students in the sample had an average age of $M = 21.22$ years ($SD = 2.01$) comprising of 427 male (78.8%), 112 female (20.7%) and three diverse (0.6%) students. 44 per cent have at least one parent with a university degree. The faculty distribution shows that 150 participants belong to the faculty of business administration (27.4%; study field: Industrial Management and Business Informatics) and 398 are engineering students

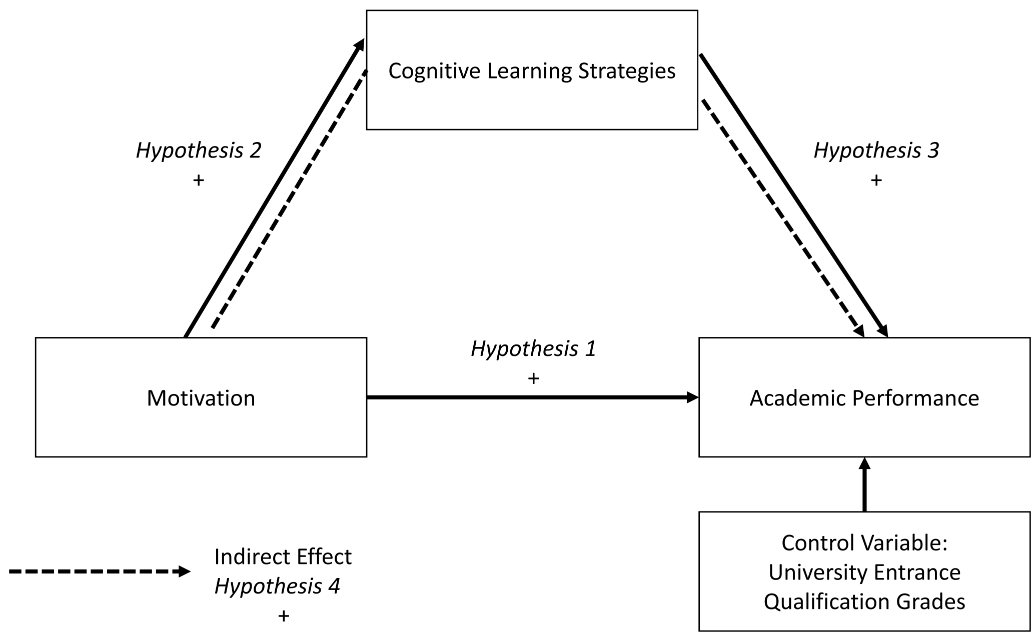

Fig. 2 Hypothesized model

(72.6%; study field: Electrical Engineering, Mechanical Engineering and Embedded Systems).

Depending on the type of educational program, cooperative students rotate every 3 or 6 months between academic learning, based on the theoretical framework of their university, and practical experience in their companies. The students are recruited by their companies and have an employment contract with their company. Due to the intensive nature of the degree programs, including a high proportion of practice, the 3-year bachelor programs attract 210 credits according to the European Credit Transfer System (Wild & Neef, 2019).

Measures

McDonald's omega was used to estimate the reliability in the sample (McDonald, 1999). A value of $\omega \geq 0.70$ is considered as acceptable (Viladrich et al., 2017). The scales for motivation and cognitive learning strategies use items with a 5-point Likert scale, ranging from 1 (strongly disagree) to 5 (strongly agree).

Motivation

Motivation was measured, in terms of academic self-concept and curiosity. We used an adjusted instrument by Dickhäuser et. al. (2002), measuring "academic self-concept" with three items and a good level reliability ($\omega = 0.87$; sample item: Learning something new is easier for me than other students). "Curiosity" is measured by an adjusted instrument from Mussel et. al. (2012) with five items and a good level of reliability ($\omega = 0.71$; sample item: I am inquisitive). This scale was judged as adequate for measuring the curiosity of cooperative students in the working context, because of their rotation between university and working in their companies every 3 or 6 months. Furthermore, the students could explore their specific domain of work, address deficits and satisfy their need for cognition.

Cognitive learning strategies

Seven shortened scales from the measurement instrument "LimSt—A questionnaire for learning strategies in mathematics related studies" by Liebendörfer et. al. (2021) are used to measure cognitive learning strategies for exam preparation in previous mathematics modules. The scales show a good level of reliability. Rehearsal was measured with "repeating" ($\omega = 0.77$; sample item: So that I don't forget important content, I go over it again and again) and "practicing" ($\omega = 0.78$; sample item: I go through calculation paths again and again to get a routine). Elaboration is measured by "building connections" ($\omega = 0.78$; sample item: I try to relate new terms and concepts to terms and concepts I already know), "using examples" ($\omega = 0.72$; sample item: I test statements using examples), and "connecting to practice" ($\omega = 0.74$; sample item: With new content, I think about what it means in the real world). For measuring organization, we used the scales "using proof" ($\omega = 0.83$; sample item: For proofs, I try to follow the logical argument step by step) and "simplifying" ($\omega = 0.72$; sample item: In order to be able to remember content in a better way, I reduce it to its essentials). Every scale is measured with two items, except the scale "using examples", which is measured with three items.

Academic performance

Academic performance is measured by the "grade" attained in the previous mathematics module. This grade, as well as the university entrance qualification grade, were reported by participants. In the German university system and also in the study presented in this paper, grades range between the highest score of 1 (equivalent to a grade A in Great Britain and the United States) and the lowest score of 5 (equivalent to a grade E and F in Great Britain or F in the United States). In the German education system, "university entrance qualification grades" range between the highest score of 1 and the lowest score of 4 (equivalent to a grade D in Great Britain and the United States). In the analysis, measurements were recoded, with higher scores indicating a better performance.

Finally, an analysis was conducted of measurement invariance for motivation and cognitive learning strategies, in order to assess the (psychometric) equivalence of constructs across groups for performance by median-split—and to check that a construct has the same meaning in those groups—by following four steps outlined by Putnick and Bornstein (2016):

(1) configural, equivalence of model form; (2) metric (weak factorial), equivalence of factor loadings; (3) scalar (strong factorial), equivalence of item intercepts or thresholds; and finally (4) residual (strict or invariant uniqueness), equivalence of items' residuals or unique variances (p. 2).

To examine if differences in model fit were significant, the cut-off values for model fit suggested by Chen (2007) were used and interpreting a decline of Comparative Fit Index (CFI) ≥ 0.010 and Root Mean Square Error of Approximation ($RMSEA$) ≥ 0.015 or Standardized Root Mean Square Residual ($SRMR$) ≥ 0.010 as an indication of non-invariance (for metric invariance: $SRMR \geq 0.030$). The results confirmed strict measurement invariance for participants with low performance, compared with participants with high performance, because the model fits of CFI, $RMSEA$ and $SRMR$ in Table 1 have no higher deviation between configural invariance, metric invariance, scalar invariance and strict invariance than 0.005 (see last three columns in Table 1).

Data analyses and missing values

This study used SPSS (Version 28) to explore the data presented in the section, preliminary analysis. Pearson's r, a product-moment correlation coefficient that is most frequently used in linear associations between two variables, ranges between +1 (both variables increase together) and −1 (one variable increases while the other variable decreases) (Tabachnick & Fidell, 2013). It is seen as small from 0.10 to 0.29, as medium between 0.30 to 0.49, and as large ≥0.50 according to Cohen (1988). Although these interpretations are highly disputed (e. g. Gignac & Szodorai, 2016), they are still considered a standard approach (Field, 2018). Skewness and Kurtosis values falling outside the range of −1 to +1 are seen as problematic, like normal distribution (Hair et al., 2014). In the data analysis, the p-value is seen as statistically significant, if it is less or equal than 0.05 (two-tailed).

Structural Equation Modelling (SEM; Ullman, 2013) and the package "lavaan" by Rosseel (2012) in the software R was employed for testing the hypotheses. The criteria by Hu and Bentler (1999) with $RMSEA \leq 0.06$, $CFI \geq 0.95$, $TLI \geq 0.95$ and $SRMR \leq 0.08$ are judged as a good model fit. For testing Hypotheses 1 to 3, direct effects are used. The results of this analysis were standardized coefficients. Drawing on the methods of Hayes (2018), the mediator effect (Hypothesis 4) was tested, by estimating bootstrapped conditional indirect effects (using 5000 replications). For this analysis, non-standardized effects were used. The zero hypothesis of a non-indirect effect is rejected in this approach, when the confidence interval does not integrate the value zero.

The sample of 548 participants has missing values, with a range for the variables between 0.4 and 7.04% ($M = 1.25$; $SD = 1.40$). For 492 participants (90% of the sample) no missing values exist. The missing data was replaced, using a multiple imputation by chained equations of the R package "mice" with 20 imputations (van Buuren & Groothuis-Oudshoorn, 2011).

Table 1 Results of measurement invariance testing between motivation, learning strategies and the persons in group low and high performance separated by median split ($N = 548$)

	df	χ^2	χ^2/df	*CFI*	*TLI*	*RMSEA*	*SRMR*	Δ *CFI*	Δ *RMSEA*	Δ *SRMR*
Configural invariance	432	642.83	1.49	0.949	0.934	0.042	0.046			
Metric invariance	447	666.80	1.49	0.946	0.934	0.042	0.048	0.003	0.000	0.002
Scalar invariance	462	695.15	1.51	0.943	0.932	0.043	0.050	0.003	0.002	0.002
Strict invariance	486	714.91	1.47	0.944	0.937	0.041	0.050	0.001	0.005	0.000

Results

Preliminary analysis

Table 2 presents the descriptive information and correlations (r) of the variables in the research. It is noticeable that there is a left-skewed distribution for all variables. The kurtosis of learning strategy "building connections" is 1.12 and the kurtosis of "curiosity" is 1.19, which is seen as slightly problematic, in order to maintain the normal distribution assumption.

The correlations between the learning strategies "repeating" and "practicing" are large ($r=0.59$). Medium correlations exist between "curiosity" and "building connections" ($r=0.39$) as well as between "curiosity" and "connecting to practice" ($r=0.31$). Furthermore, the learning strategies "using examples" and "connecting to practice" ($r=0.33$) as well as "using examples" and "using proofs" ($r=0.30$) have medium correlations, too. "University entrance qualification grades" and "performance" are correlated ($r=0.35$), as was expected from the meta-analysis by Richardson et. al. (2012).

Results on the hypotheses

For analyzing the hypotheses, the researchers used the Structural Equation Modelling technique. Indices of the estimation show an adequate fit ($\chi^2=466.977$; $df=255$; $\chi^2/df=1.831$; $p\leq 0.001$; $CFI=0.951$; $TLI=0.938$; $RMSEA=0.039$; $SRMR=0.046$). The results indicate that the theoretical model represents the research data in a reasonable way (see Fig. 3) and only $TLI=0.938$ is below the cutoff criteria by Hu and Bentler (1999). However, Hair et. al. (2014, p. 582) discuss situations when a cutoff criteria is not met and summarize that "no single "magic" value always distinguishes good models from bad models".

The results in Fig. 3 show that a positive relationship exists between "academic self-concept" and "performance" ($\beta=0.38$; $p\leq 0.001$) (Hypothesis 1). According to Hypothesis 2, academic self-concept is negatively associated with the cognitive learning strategies "connecting to practice" ($\beta=-0.13$; $p=0.016$) and "simplifying" ($\beta=-0.13$; $p=0.021$). Furthermore, "curiosity" is positively associated with the cognitive learning strategies "repeating" ($\beta=0.34$; $p\leq 0.001$), "practicing" ($\beta=0.32$; $p\leq 0.001$), "building connections" ($\beta=0.54$; $p\leq 0.001$), "using examples" ($\beta=0.34$; $p\leq 0.001$), "connecting to practice" ($\beta=0.44$; $p\leq 0.001$) and "using proofs" ($\beta=0.38$; $p\leq 0.001$). In line with Hypothesis 3, the cognitive learning strategy of "practicing" is positively related to "performance" ($\beta=0.21$; $p=0.014$). An indirect effect is the transfer of "curiosity" to "performance" via "practicing" ($\beta=0.07$; $p=0.014$) (Hypothesis 4).

Further analysis of the 95%-confidence intervals for the indirect effects confirmed the mediation (Hypothesis 4). Practicing mediates the effect of curiosity on performance ($b=0.13$, 95% CI $=[0.001; 0.257]$). The study reported non-standardized parameters on this point. This result means that "curiosity" leads only to better "performance" when persons "practice". Curiosity on its own is not enough to attain a good performance.

Discussion

Previous work has indicated that learning strategies in STEM have an impact on achievement (Pinxten et al., 2019). However, the learning strategies that have been assessed are only general in nature and the results cannot be applied to domain-specific learning strategies

Table 2 Descriptive statistics and bivariate correlations ($N=548$)

	M	*SD*	*Skew*	*Kurtosis*	1	2	3	4	5	6	7	8	9	10	11
1. Academic self-concept	2.86	0.90	−0.09	−0.17	–										
2. Curiosity	3.91	0.58	−0.69	1.19	0.20	–									
3. Repeating	3.59	0.95	−0.28	−0.60	−0.01	0.23	–								
4. Practicing	3.55	0.97	−0.33	−0.44	0.02	0.22	0.59	–							
5. Building connections	4.01	0.74	−0.80	1.12	0.03	0.39	0.12	0.07	–						
6. Using examples	3.70	0.76	−0.37	−0.05	−0.01	0.23	0.19	0.19	0.19	–					
7. Connecting to practice	3.68	0.88	−0.46	−0.25	−0.02	0.31	0.08	0.09	0.21	0.33	–				
8. Using proofs	3.38	1.02	−0.33	−0.47	0.11	0.29	0.14	0.13	0.17	0.30	0.24	–			
9. Simplifying	3.97	0.84	−0.83	0.47	−0.09	0.04	0.24	0.20	0.18	0.24	0.16	−0.01	–		
10. UEQG	4.01	0.54	−0.38	−0.06	0.22	0.11	−0.01	0.06	0.13	−0.07	0.03	0.09	−0.02	–	
11. Performance	3.70	0.89	−0.81	0.28	0.20	0.13	0.03	0.12	0.08	−0.04	0.04	0.07	−0.01	0.35	–

Scales ranging from 1 (= strongly disagree) to 5 (= strongly agree). UEQG ranging from 2 (= lowest performance) to 5 (= best performance). Performance ranging from 1 (= lowest performance) to 5 (= best performance). Correlation (r) is shown below the diagonal

UEQG University entrance qualification grades

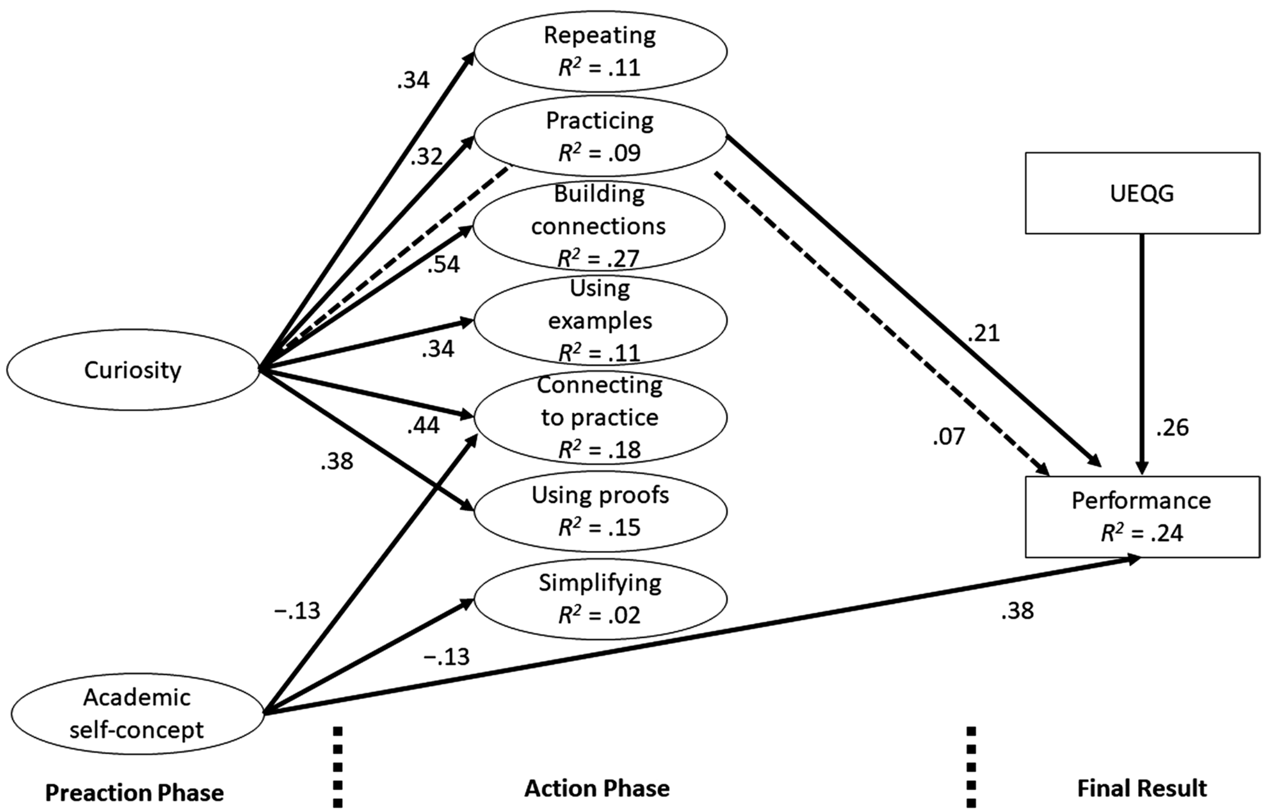

Fig. 3 Model for the direct and indirect effect of motivation on grades through learning strategies ($N = 548$). Solid lines are direct effects that are significant at the significance level of $p \leq 0.05$. The indirect effects at the significance level of $p \leq 0.05$ are presented with dashed lines. Coefficients are standardized beta weights. *UEQG* University entrance qualification grades

for mathematics. Furthermore, motivational variables explain performance, with self-concept being a good predictor and intrinsic components seen as less important (Steinmayr et al., 2019). Research about topics in STEM in the area of cooperative higher education is rare.

The findings expand on existing research, by using domain-specific measurement instruments for learning strategies in mathematics, such as LimSt by Liebendörfer et. al. (2021). On the other hand, there are numerous overlaps with the current state of research. While academic self-concept influences performance, curiosity does not (Hypothesis 1). The latter fits to the lesser importance of intrinsic components regarding performance, as referred to above, but it is not in line with empirical research, which highlights the relationship between curiosity and performance (Hardy et al., 2017; Reio & Wiswell, 2000; von Stumm et al., 2011; Wavo, 2004). The results related to academic self-concept confirms the findings of the study, outlined in this paper (Marsh & Martin, 2011; Niepel et al., 2014; Wu et al., 2021) and shows that these findings are also valid for mathematics. Furthermore, there is a correlation between motivational aspects and learning strategies, which confirms Hypothesis 2. Remarkable are the various relations between curiosity and different learning strategies in mathematics. The narrow connection between curiosity and the learning strategies “building connections” and “connecting to practice” shows that curiosity, which is defined as the acquisition, combining and connecting of knowledge, is reflected in the empirical results.

The learning strategy “practicing” affects performance, which is also reported in Liebendörfer et. al. (2022) and confirms Hypothesis 3. Nevertheless only the learning strategy “practicing” is associated with academic performance. A possible explanation in the context of mathematics is that practicing is the most important strategy for achieving good results, as opposed to other learning strategies, such as “using examples” or “connecting to practice” that are more likely to be used in other study areas, e.g. economics. On the one hand, regarding the strength of the association between the learning strategy “practicing” and the resulting performance, the study is aligned with results of the meta-analysis conducted by Schneider and Preckel (2017), which shows small to medium-large effects for cognitive learning theories regarding performance. On the other hand, a generalized opinion that cognitive learning strategies are critically important in mathematics (Liebendörfer et al., 2021) cannot be made as only one learning strategy is linked to academic performance. The author's research demonstrates the indirect effect of curiosity on performance via the learning strategy "practicing", which is in line with Hypothesis 4.

The results of this paper strengthen existing theories. The assumptions forming the basis of the process model of self-regulated learning by Schmitz (2001) and Zimmerman (2000), were correlated with the research outlined in this paper. The pre-action phase (phase 1) and the action phase (phase 2) were aligned with the aspects of motivation and learning strategies, linked to Hypothesis 2. The aspects of learning strategies and performance, linked to Hypothesis 3, were also aligned to the action phase. Based on the empirical results, several theoretical assumptions can be confirmed (Fig. 1). In addition, the confirmed indirect effect of Hypothesis 4 of motivation on performance via learning strategies is of particular importance, as this is an important assumption in the process model. The post-action phase (phase 3) and the subsequent feedback to the pre-action phase (phase 1) are not considered in the present research, although it would be interesting to find out whether changes or adjustments result from possible reflections in the course of a further process.

The situated expectancy-value theory (Eccles & Wigfield, 2020) is an important part in the research. Several of the associated theoretical assumptions could be validated by the empirical results. This is seen through the confirmation of the direct effect of motivation on performance, expressed by academic self-concept (Hypothesis 1). One explanation could be that curiosity is only one of four different components of the task values, whereas academic self-concept is a factor on its own. Additionally, the assumptions of the situated expectancy-value theory could be successfully demonstrated in the context of the process model of self-regulated learning. This is shown by the fact that the intrinsic value of curiosity has an indirect effect on performance via learning strategies (Hypothesis 4).

There are several practical implications that can be derived from the research. Meta-analyses show the effect of training on self-regulated learning on university students' academic performance, by training them to improve various (meta-) cognitive and resource management strategies (Theobald, 2021). Another possibility would be to expand the preparatory courses that dispose students for mathematics at universities and whose effects has been demonstrated (Bahr, 2008; Bettinger & Long, 2009; Wood, 2001). A third way to keep the student motivation at a high level, throughout the entirety of their study programs is through self-assessment, which can be deployed before the study program starts, e.g. to clarify the expectations of the students (Ćukušić et al., 2014). The quality of instruction is linked to the level of motivation to achieve and self-regulated learning (Hernesniemi et al., 2020; Sogunro, 2017). Consequently, efforts should be made to improve the instruction quality of lecturers, in order to enhance the teaching and learning environment. Advanced training, concentrating in particular on teaching and methodology, could be one of the answers. Additionally, work shadowing during lectures, with an integrated debriefing, should be considered in order to strengthen the quality of lecturing. For students, the results showed the importance of practicing. To support the ability to practice, it would be helpful to offer special courses to students at the university. The simple message is: curiosity is not enough—you have to practice!

The strengths of this study are the measurement of domain-specific cognitive learning strategies in mathematics. The results shed light into the association between motivation and cognitive learning strategies and academic performance. Furthermore, the research was conducted on the growing student population of cooperative students in Germany, which nearly doubled to 108,000 students in the last decade (Federal Institute for Vocational Education and Training, 2021). The good model fit with the data indicates that the theory used is suitable. The results in this research are much in line with former research.

There are limitations to the research conducted. Unfortunately, performance data could not be obtained from the university administration. Therefore, measurement errors, due to social bias, cannot be avoided. The generalization of the research to all students is problematic, because cooperative students are recruited by their companies, which could lead to a possible selection bias (Kupfer, 2013; Wild & Neef, 2019). The level of measurement could be improved, as most reliability was $\omega < 0.80$. Furthermore, the research was based on a cross sectional design and longitudinal research is needed to develop a more exact modelling process. Additionally, the method of convenience sampling is discussed in the research. A criticism of this sampling method is that the results are difficult to generalize (Andrade, 2021). Mahboobi et. al. (2014) emphasize the existence of some missing values using this method. In the exploring phase, and when little is known about a population, convenience sampling is done (Chawla & Sodhi, 2011). However, replication of the results from convenience sampling is a huge challenge (Warner, 2013).

Based on the framework of situated expectancy-value theory, it must be emphasized that attainment value, utility value and costs (Eccles & Wigfield, 2020) should be integrated into the research. However, the low variance in terms of performance of nearly 24% in the structural equal model indicates that there are further variables that have an influence on performance, e.g. personality, which needs to be investigated (Richardson et al., 2012; Schneider & Preckel, 2017). Overall, performance seems to be affected by different factors and this study is only one small step to develop a better understanding of academic performance.

The multivariate analysis using the structural equation model shows a deeper analysis of learning strategies in mathematics, where to date mostly general learning strategies were analyzed. In addition, the research contributes to the analysis of construct curiosity, which is rarely explored. The integration of the framework from situated expectancy-value theory in the concept of self-regulated learning is a further highlight of this research. Furthermore, research was conducted on an increasingly large population, cooperative students, and tests theories in this population for robustness.

Conclusion

The work emanating from the study advances research on the role of motivational aspects, as well as domain-specific cognitive learning strategies on performance, in mathematics-related study programs. The results suggest that academic self-concept, as well as curiosity via the learning strategy of practicing, is associated with performance. Empirical results support the framework of the process model of self-regulated learning by Schmitz (2001) and Zimmerman (2000) as well as the situated expectancy-value theory by Eccles and Wigfield (2020). Further research is needed to explore other factors, such as costs, instead of the intrinsic value of curiosity (Flake et al., 2015), which is likely to explain the process of performance in more detail.

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Data availability
Data is available. Please contact the corresponding author.

Code availability
Syntax is available. Please contact the corresponding author.

Declarations

Ethics approval and consent to participate
The study was conducted in accordance with the Declaration of Helsinki. It was approved by Baden-Wuerttemberg Cooperative State University (8th July 2015) and local heads of the research group for ethical standards. Before the participants responded, informed consent was obtained and the anonymity of responses ensured.

Consent for publication
Not applicable.

Competing interests
Authors of this study declare that they have no conflicts of interest to disclose.

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