- Need for Cognition and Ability Self-Concepts as Predictors of Changes in School Grades
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13 Abstract

14 ...

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16 Modeling, Longitudinal

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Need for Cognition and Ability Self-Concepts as Predictors of Changes in School Grades

Over the past decades, a large body of research has examined variables predicting 19 performance in school. Comprehensive meta-analytic findings demonstrated intelligence to 20 be the strongest predictor for academic achievement (e.g., Deary, Strand, Smith, & 21 Fernandes, 2007; Kriegbaum, Becker, & Spinath, 2018), but motivational variables have consistently been found to have predictive value for school performance, too (e.g., 23 Kriegbaum et al., 2018; Steinmayr, Weidinger, Schwinger, & Spinath, 2019). In this context, motivational concepts like ability self-concept, hope for success and fear of failure, 25 interest and values are well known and equally established indicators (Wigfield & Cambria, 2010; e.g., Wigfield & Eccles, 2000) that are subsumed under the umbrella term of 27 achievement motivation (Steinmayr et al., 2019).

Over the last years, an additional predictor of academic performance came into the 29 focus of researchers in this field of research: Need for Cognition (NFC), the stable intrinsic 30 motivation of an individual to engage in and enjoy challenging intellectual activity 31 (Cacioppo, Petty, Feinstein, & Jarvis, 1996). According to the Investment Theory 32 (Ackerman & Heggestad, 1997), traits such as NFC determine how individuals invest their 33 cognitive resources and how they deal with cognitively challenging material. Studies could show that NFC is related to academic performance in different stages of academic life (e.g., 35 Ginet & Pv. 2000; Grass, Strobel, & Strobel, 2017; Luong et al., 2017; Preckel, 2014; for a meta-analytical review see von Stumm & Ackerman, 2013) as well as to behaviour 37 associated with success in learning. As examples, NFC was found to be related to ability self-concept (e.g., Dickhäuser & Reinhard, 2010; Luong et al., 2017), to interest in school (e.g., Preckel, 2014) or to deeper processing while learning (Evans, Kirby, & Fabrigar, 2003; Luong et al., 2017).

Diseth and Martinsen (2003)

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43 Methods

We report how we determined our sample size, all data exclusions, all manipulations, and all measures in the study (cf. Simmons, Nelson, & Simonsohn, 2012). All data and materials for reproducing our analyses are permanently and openly accessible at ... The study was not preregistered.

48 Participants

Sample size was determined by pragmatic considerations, i.e., to collect as many participants given existing time constraints and the longitudinal nature of the project. We eventually managed to recruit a sample of N=277 participants (60% women) at the first measurement occasion (T1) of which N=251 participants (61% women) also took part at the second measurement occasion (T2) that took place 53-59 weeks later. Age range was 14-19 years (median = 17 years) at T1 and 15-20 years (median = 18 years) at T2. With the sample size accomplished at T2, we were able to detect correlations of $r \ge .18$ at $\alpha =$.05 (two-sided) and $1-\beta = .80$. Yet, we tried to impute missing values to raise power (see below, Statistical analyses).

58 Material

We used the following self-report measures to assess the measures of interest for the present study.

School Grades in general, i.e., Grade Point Average (GPA), and grades in German, math, chemistry, and physics were assessed via self-report. In Germany, school grades range from 1 (excellent) to 6 (insufficient). For better interpretability, we reversed this coding via 6 – grade, so the values we used for statistical analyses ranged from 0 (insufficient) to 5 (excellent). Need for Cognition (NFC) was assessed with the 16-item short version of the German NFC scale (Bless, Wänke, Bohner, Fellhauer, & Schwarz, 1994). Responses to each item (e.g., "Thinking is not my idea of fun", recoded) were recorded on a four-point scale ranging from -3 (completely disagree) to +3 (completely agree) and were summed to the total NFC score. The scale has a comparably high internal consistency, Cronbach's $\alpha > .80$ (Bless et al., 1994; Fleischhauer et al., 2010), and retest reliability, $r_{tt} = .83$ across 8 to 18 weeks (Fleischhauer, Strobel, & Strobel, 2015).

Hope for Successs and Fear of Failure were assessed using the Achievement Motive Scales (Gjesme & Nygard, 2006; German version: Göttert & Kuhl, 1980). For the present study, we used a short form measuring each construct with seven items. All items were answered on a four-point scale ranging from 1 (does not apply at all) to 4 (fully applies). Example items for the two scales are "Difficult problems appeal to me" and "Matters that are slightly difficult disconcert me". Both scales exhibit high internal consistencies, Cronbach's $\alpha \geq .85$ (Steinmayr & Spinath, 2009).

The Ability Self-Concept in school in general and in the four subjects German, math,
physics, and chemistry were assessed with four items per domain using the Scales for the
Assessment of Academic Self-Concept (Schöne, Dickhäuser, Spinath, & Stiensmeier-Pelster,
2002) (example item: "I can do well in ... (school, math, German, physics, chemistry).").
Items were answered on a 5-point scale ranging from 1 () to 5 (). The scales' internal
consistency, Cronbach's $\alpha \geq .80$, and retest reliability, $r_{tt} \geq .59$ across six months, can be
considered as high.

Interest in school in general and in the above four subjects were measured using
Interest subscales of the Scales for the Assessment of Subjective Values in School
(Steinmayr & Spinath, 2010). Answers to three items per domain (example item: "How
much do you like . . . (school, math, German, physics, chemistry).") were recorded on a
5-point scale ranging from 1 () to 5 (). The scales have high internal consistency,

Cronbach's $\alpha \geq .89$, and retest reliability, $r_{tt} = .72$ across six months (Steinmayr & Spinath, 2010).

94 Procedure

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96 Statistical analysis

We used RStudio [Version 2021.9.0.351; RStudio Team (2016)] with R (Version 4.1.1; 97 R Core Team, 2018) and the R-packages lavaan (Version 0.6.10; Rosseel, 2012), psych (Version 2.1.9; Revelle, 2018), and pwr (Version 1.3.0; Champely, 2018). This manuscript 99 was created using RMarkdown with the packages papaja [Version 0.1.0.9997; Aust and 100 Barth (2018), knitr [Version 1.37; Xie (2015)], and shape [Version 1.4.6; Soetaert (2021)]. 101 First the variables were separated into four sets, each containing the T1 and T2 102 measurements of the variables Hope for Success (HfS), Fear of Failure (FoF), and Need for 103 Cognition (NFC) as well as either GPA, overall ability self-concept regarding school, and 104 general interest in school, or domain-specific grades, ability self-concept and interest in 105 German, math, physics, and chemistry. All measures were initially analyzed with regard to 106 descriptive statistics, reliability (retest-reliability r_{tt} as well as Cronbach's α), and possible 107 deviation from univariate and multivariate normality. Almost all relevant variables 108 deviated from univariate normality as determined using Shapiro-Wilks tests with a 109 threshold of $\alpha=.20,$ all $p\leq.089$ except for NFC at T2, p=.461. Also, there was 110 deviation from multivariate normality as determined using Mardia tests, all p_{skew} and 111 $p_{kurtosis} < .001$. Therefore, we used more robust variants for the statistical tests to be 112 performed, i.e., Spearman rank correlations (r_s) for correlation analyses and Robust 113 Maximum Likelihood (MLR) for regression analyses and latent change score modeling. 114

Possible differences between the measurement occasions T1 and T2 were descriptively

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assessed via boxplots, with overlapping notches—that can roughly be interpreted as 95\% 116 confidence intervals of a given median—pointing to noteworthy differences. Otherwise 117 differences between time points were not considered further given the scope of the present 118 report. Correlation analyses were performed separately for the five sets of data (see Table 1 119 and Supplementary Tables S1 to S4). Where appropriate, evaluation of statistical 120 significance was based on 95% confidence intervals (CI) that did not include zero. 121 Evaluation of effect sizes of correlations was based on the empirically derived guidelines for 122 personality and social psychology research provided by Gignac and Szodorai (2016), i.e., 123 correlations were regarded as small for r < .20, as medium for $.20 \le r \le .30$, and as large 124 for r > .30. 125

To examine which variables measured at T1 would be significant predictors of school 126 grades at T2, we ran a five regression analyses with the GPA and the four subject-specific 127 grades as criterion and used the results of the first regression analysis (with the 128 domain-general Ability Self-Concept, Interest in School, Hope for Success and Fear of 129 failure, and NFC measured at T1 as predictors and GPA at T2 as criterion) to select the 130 variables for latent change score modeling. Significant predictors in this model were used 131 for all latent change score models even if for certain subjects, the predictors were not significant in the respective regression models. Regression models were fitted via lavaan, using MLR as estimation technique and the Full-Information Maximum Likelihood (FIML) 134 approach to impute missing values. Due to missing patterns, this resulted in an effective 135 sample size of N=271-276. To asses whether a model that included NFC was superior to 136 a model that included established predictors of academic achievement, we (1) evaluated the 137 fit of the respective models based on the recommendations by Hu and Bentler (1999), with 138 values of CFI \geq .95, RMSEA \leq .06, and SRMR \leq 0.08 indicating good model fit, and (2) 139 performed χ^2 -difference tests between the former and the latter model (and all other 140 variables' loadings fixed to zero). 141

In the final step, latent change score modeling was applied. In this approach (see

Kievit et al., 2018), one can examine (1) whether true change in a variable has occurred via 143 a latent change score that is modeled from the respective measurements of this variable at 144 different measurement occasions, here T1 and T2, (2) to what extent the change in a 145 variable is a function of the measurement of the same variable at T1 (self-feedback) and (3) 146 to what extent the change in this variable is a function of the measurement of other 147 variables in the model at T1 (cross-domain coupling). Thereby, cross-domain effects, i.e., 148 whether the change in one domain (e.g., school grades) is a function of the baseline score of 149 another (e.g., NFC) and vice versa could be examined. In addition, correlated change in 150 the variables of interest can be examined, i.e., to what extent does the change in one 151 variable correlate with the change in another variable. Again, MLR estimation and 152 imputation of missing values via FIML was employed. 153

154 Results

155 Domain-general grades

Table 1 gives the descriptive statistics and intercorrelations of the variables of interest 156 in this analysis step, i.e., the T1 and T2 measurements of GPA, domain-general ability 157 self-concept, and general interest in school as well as the variables Hope for Success, Fear of 158 Failure, and NFC. As can be seen in the diagonal and the upper right of the correlation 159 table, all variables exhibited good internal consistency, Cronbach's $\alpha \geq .83$, and retest 160 reliability, $r_{tt} \geq .56$. Among the predictors at T1, GPA at T1 showed the strongest relation 161 to GPA at T2, $r_s = .75$, followed by the domain-general ability self-concept, $r_s = .53$, and 162 NFC at T1, $r_s = .46$, all p < .001. The other variables at T1 showed significant correlations 163 with GPA at T2 as well, $|r_s| \ge .20$, $p \le .004$. 164

A multiple regression analysis involving all measures at T1 (see Table 2) showed that apart from GPA at T1, B = 0.61, 95% CI [0.49, 0.73], p < .001, the only significant predictors were the domain-general ability self-concept, B = 0.12, 95% CI [0.01, 0.22],

p=.031, and NFC, B=0.09, 95% CI [0.01, 0.17], p=.024. Model fit was better for a model that included GPA, the ability self-concept, and NFC at T1 (while all other predictors were set to zero), $\chi^2(3)=3.68$, p.299, CFI = 1.00, RMSEA = .03 with 90% CI [0.00, 0.11], SRMR = .01, than a model that included GPA and the ability self-concept only, $\chi^2(4)=10.91$, p.028, CFI = 0.96, RMSEA = .08 with 90% CI [0.02, 0.14], SRMR = .02, and a χ^2 -difference test supported the superiority of the former compared to the latter model, $\chi^2(1)=6.34$, p=.012.

We therefore further examined a trivariate latent change score model involving school 175 grades, the ability self-concept, and NFC. Figure 1B gives the results of the latent change score modeling with regard to the prediction of change and correlated change in overall 177 school grades, i.e., GPA. While the best predictor of change on GPA was GPA at T1 (i.e., 178 self-feedback), B = -0.37, 95% CI [-0.48, -0.25], p < .001, $\beta = -.55$, there was also evidence 179 for cross-domain coupling, as the overall ability self-concept and NFC at T1 also 180 significantly predicted change in GPA, B = 0.13, 95% CI [0.02, 0.24], p = .020, $\beta = .19$, 181 and B = 0.08, 95% CI [0.02, 0.15], $p = .009, \beta = .19$, respectively. Correlated change was 182 observed for GPA and the ability self-concept, B = 0.03, 95% CI [0.01, 0.05], p = .001, $\beta = .001$ 183 .22, and the ability self-concept and NFC, B = 0.05, 95% CI [0.02, 0.08], $p.001, \beta = .22$, 184 while the correlated changes in GPA and NFC did not reach significance, B = 0.03, 95% CI 185 $[0.00, 0.05], p = .053, \beta = .14.$ 186

187 Domain-specific grades

For the four subjects examined, i.e., German, math, physics, and chemistry, similar results were obtained with regard to correlation analyses (see Supplementary Tables Sx to Sy). As regards multiple regression analyses (see Supplementary Table Sz), for all subjects, grades at T2 were significant predictors of grades at T2, p < .001. The subject-specific ability self concept at T1 was a significant predictor of grades at T2 in German only, B = 0.29, 95% CI [0.15, 0.43], p < .001. NFC at T1 was a significant predictor of T2 grades in

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German, B = 0.18, 95% CI [0.05, 0.32], p = .007 and physics, B = 0.22, 95% CI [0.07, 0.37], p = .004.
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As regards the latent change score models, there was evidence for significant 196 self-feedback for all subjects, all p < .001. With regard to the subject-specific ability 197 self-concept, cross-domain coupling with changes in grades was observed for German, B =198 0.28, 95% CI [0.16, 0.40], $p < .001, \beta = .36$, and chemistry, B = 0.09, 95% CI [0.00, 0.18], 199 $p = .042, \beta = .14$. NFC at T1 showed cross-domain coupling with grades at T2 for 200 German, B = 0.13, 95% CI [0.04, 0.21], p = .005, $\beta = .17$, physics, B = 0.23, 95% CI [0.13, 201 0.33], p < .001, $\beta = .24$, and chemistry, B = 0.10, 95% CI [0.00, 0.20], p = .047, $\beta = .13$. 202 Correlated change between grades and the subject-specific ability self-concept was observed for all subjects, while correlated change between grades and NFC was observed for 204 German, math, and physics only (see Fig. 1C-F). 205

206 Discussion

The present study was conducted in order to ...

208 Subheading 1

Our result show that ...

210 Subheading 2

211 ...

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Conclusion

Taken together, the present study provides evidence that ...

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Table 1
Spearman correlations and descriptive statistics of the variables in the analyses on overall school grades

	GRD1	ASC1	INT1	HFS1	FOF1	NFC1	GRD2	ASC2	INT2	HFS2	FOF2	NFC2
GRD1	_	.58	.38	.34	24	.44	.75	.52	.34	.40	23	.49
ASC1		.83	.49	.37	27	.38	.50	.60	.32	.34	18	.26
INT1			.88	.32	09	.35	.44	.47	.65	.31	05	.26
HFS1				.86	30	.62	.32	.38	.26	.57	17	.50
FOF1					.88	42	17	28	14	29	.59	43
NFC1						.89	.46	.43	.25	.62	32	.71
GRD2							_	.53	.34	.41	18	.48
ASC2								.84	.53	.45	25	.46
INT2									.88	.31	05	.34
HFS2										.87	28	.66
FOF2											.90	39
NFC2												.89
Mean	3.30	3.55	3.25	2.92	1.86	4.46	3.46	3.62	3.41	2.72	1.71	4.69
SD	0.55	0.54	0.83	0.57	0.61	0.84	0.52	0.56	0.82	0.56	0.61	0.87
Min	2.00	1.75	1.00	1.14	1.00	2.19	2.10	2.25	1.00	1.00	1.00	2.50
Max	5.00	5.00	5.00	4.00	4.00	6.94	5.00	5.00	5.00	4.00	3.71	6.88
Skew	0.17	0.09	-0.27	-0.23	0.45	0.16	0.31	0.33	-0.21	-0.02	0.89	0.07
Kurtosis	-0.09	0.24	-0.37	-0.07	-0.34	0.14	-0.11	-0.14	-0.42	0.17	0.47	-0.45

Note. N=193-259 due to missings; p<.05 for $|r_s|>.18$; coefficients in the diagonal are Cronbach's α , bold-faced coefficients give the 53-59 week retest reliability; GRD = Grade Point Average, ASC = Overall Ability Self-Concept, INT = Overall Interest in School, HFS = Hope for Success, FOF = Fear of Failure, NFC = Need for Cognition at measurement occasion 1, and 2, respectively

Table 2 $Results\ of\ the\ multiple\ regression\ of\ school\ grades\ measured\ at\ T2\ on$ $predictors\ measured\ at\ T1$

	В	SE	CI.LB	CI.UB	β	p
Intercept	0.488	0.231	0.034	0.941	.906	.035
GPA	0.606	0.061	0.485	0.726	.616	< .001
Ability Self-Concept	0.116	0.054	0.010	0.222	.117	.031
Interest	0.057	0.031	-0.005	0.118	.087	.072
Hope for Success	-0.028	0.050	-0.126	0.070	029	.578
Fear of Failure	0.013	0.039	-0.063	0.089	.015	.733
Need for Cognition	0.089	0.040	0.012	0.167	.140	.024

Note. N=276; coefficients are unstandardized slopes B with their standard errors SE and 95% confidence intervals (CI.LB= lower bound, CI.UB= upper bound), β is the standardized slope and p the respective p-vealues

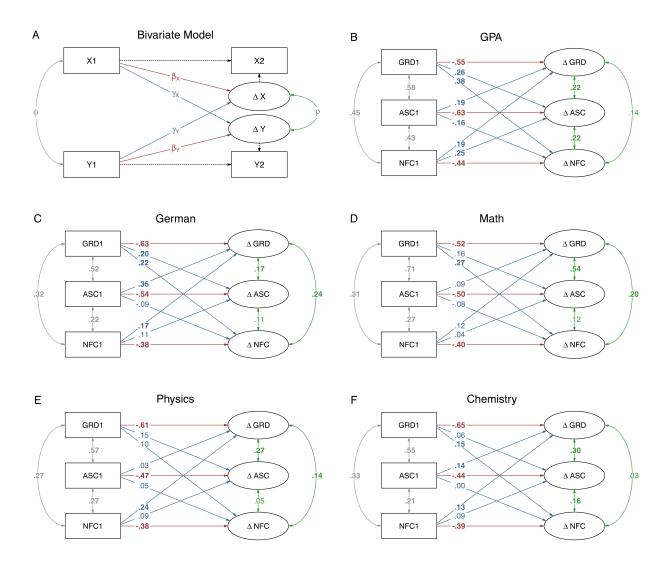


Figure 1. Latent change score models. (A) Example of a bivariate latent change score model (for details see text); legend to lines: dotted = loadings fixed to zero, red = self-feedback β , blue = cross-domain coupling γ , grey = correlation ϕ of predictors at T1, green = correlated change ρ ; (B) Grade Point Average (GPA) and (C) to (F) subject-specific changes in grades at T2 (indicated by prefix Δ) as predicted by their respective T1 levels as well as by Need for Cognition (NFC) and (overall as well as subject specific) Ability Self-Concept (ASC) at T1; coefficients are standardized coefficients.