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Predicting Academic Performance with an Assessment of Students' Knowledge of the Benefits of High-Level and Low-Level Construal

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Abstract

Metamotivation research suggests that people understand the benefits of engaging in high-level versus low-level construal (i.e., orienting toward the abstract, essential versus concrete, idiosyncratic features of events) in goal-directed behavior. The current research examines the psychometric properties of one assessment of this knowledge and tests whether it predicts consequential outcomes (academic performance). Exploratory and confirmatory factor analyses revealed a two-factor structure, whereby knowledge of the benefits of high-level construal (i.e., high-level knowledge) and low-level construal (i.e., low-level knowledge) were distinct constructs. Participants on average evidenced beliefs about the normative benefits of high-level and low-level knowledge that accord with published research. Critically, individual differences in high-level and low-level knowledge independently predicted grades, controlling for traditional correlates of grades. These findings suggest metamotivational knowledge may be a key antecedent to goal success and lead to novel diagnostic assessments and interventions.

Keywords

metamotivation, construal level, academic performance, self-regulation, psychometrics

Goal pursuit presents distinct challenges that may be best addressed by different strategies (Gollwitzer, 1990; Higgins, 2000; Mann et al., 2013). College students, for example, may face demands for self-control (prioritizing studying over socializing) and behavioral precision (proofreading papers). Whereas thinking about the big picture may be effective for promoting self-control, it may backfire when trying to respond to local contingencies. Whereas immersing oneself in the details may be useful for promoting responsiveness and precision, it may undermine one's ability to transcend beyond immediate temptations. Given that different strategies present distinct trade-offs (Scholer & Higgins, 2012), researchers propose that successful self-regulation requires flexibility in deploying the most appropriate strategies to address particular demands (Bonanno & Burton, 2013; Kashdan & Rottenberg, 2010). Knowing *when* to use *which* strategy may be a critical aspect of successful goal pursuit. Inspired by work on metamotivation—the regulation of motivational states to achieve desired ends (Fujita et al., 2019; Miele et al., 2020; Scholer et al., 2018)—the current work examines whether people's understanding of trade-offs related to different motivational states is associated with consequential outcomes. We investigate whether an assessment of metamotivational knowledge of the normative benefits of high-level versus low-level construal— that is, orienting toward the abstract, essential versus concrete, idiosyncratic features of tasks—predicts academic performance.

Construal-Level Theory

Construal-level theory (Liberman & Trope, 2008; Trope et al., 2021; Trope & Liberman, 2010 for a meta-analysis, see Soderberg et al., 2015) suggests that people's construals—that is, their subjective interpretations and experiences of events as filtered through their cognitive, affective, motivational, and behavioral tendencies—can vary in level of abstraction. Traveling can be construed abstractly as "expanding my horizons" or concretely as

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"taking *this* flight to *that* destination." High-level construal is a representational process that captures the global, essential features of events that are unlikely to change across possible manifestations. Low-level construal is a representational process that captures the local, idiosyncratic features that are unique to a particular context. High-level and low-level construal present distinct regulatory tradeoffs and promote performance in different contexts (Freund & Hennecke, 2015; Fujita & Carnevale, 2012).

High-level construal, for example, enhances self-control—prioritizing global concerns in the presence of local temptations (Fujita, 2008, 2011). Research shows that high-level construal leads people to choose larger-delayed over smaller-sooner rewards (Fujita et al., 2006). By contrast, low-level construal enhances behavioral precision—sensitivity and responsiveness to local contingencies (Maglio & Trope, 2012; Zimmerman & Kitsantas, 1996). For example, low-level construal promotes performance on a cognitive control task that requires modulating behavior in response to contextual cues (Schmeichel et al., 2011). Thus, high-level and low-level construal promote different forms of self-regulation.

Researchers have developed numerous ways to manipulate construal level. Whereas thinking about the ends achieved by an action (i.e., "why") evokes high-level construal, thinking about the means by which to enact an action (i.e., "how") evokes low-level construal (Freitas et al., 2004; Fujita et al., 2006). In addition, engaging in global visual processing induces high-level construal, whereas engaging in local visual processing induces low-level construal (Smith et al., 2008; Wakslak & Trope, 2009). Researchers can thus experimentally manipulate construal level to match what is called for by a task to promote performance.

Metamotivational Knowledge About Construal Level

This matching of the right motivational state to the task (i.e., task-motivation fit; Scholer & Miele, 2016) is central to metamotivation: how people monitor and modulate their motivational states to attain goals (Fujita et al., 2019; Miele et al., 2020; Miele & Scholer, 2018; Scholer et al., 2018). Traditionally, research induced task-motivation fit experimentally; metamotivation research instead examines the mechanisms by which people create this fit on their own. To do this, people must have metamotivational knowledge: understanding what kinds of motivation are useful for the task at-hand as well as the strategies with which to instantiate those motivational states. To proofread effectively, for example, one must recognize that immersing oneself in the details rather than seeing the big picture is more beneficial for performance and find strategies to achieve this immersion—such as thinking about the concrete steps of proofreading (the "how"). Lacking such knowledge may lead one to be motivationally unprepared for the task, potentially hindering performance.

Metamotivational knowledge is theorized to be relatively tacit (Wagner & Sternberg, 1985): people may not be able to articulate what they know or have insight into how much they know. Borrowing methods from tacit knowledge research, metamotivation research assesses knowledge by presenting people with different scenarios and asking them to indicate which strategies are most useful for performance. In this way, these assessments measure situation-specific beliefs (Mischel & Shoda, 1995) that may guide how people navigate various self-regulatory situations. Using these assessments, research reveals that people recognize how to create task-motivation fit in the context of construal-level theory (MacGregor et al., 2017; Nguyen et al., 2019, 2020). MacGregor et al. (2017) showed that people recognize that high-level (versus low-level) construal promotes self-control. When presented with the challenge of resisting temptation, participants reported that it would be more beneficial to engage in high-level construal (think about "why") than low-level construal (think about "how"). We refer to this metamotivational knowledge of the benefits of high-level construal as "high-level knowledge." This knowledge also predicts important outcomes: among students motivated by academic achievement, those who knew to engage in high-level construal when faced with academic self-control conflicts achieved higher end-of-semester grades.

This early work focused exclusively on high-level knowledge. An understanding of the benefits of low-level construal ("low-level knowledge") should also be important for goal outcomes. In addition, MacGregor et al. (2017) assessed knowledge in the same domain as their outcome of interest: using students' knowledge about how to address academic self-control conflicts to predict grades. This leaves unclear whether metamotivational knowledge is specialized to a given context (i.e., domain-specific), or something that generalizes across contexts (i.e., domain-general). Nguyen et al. (2019) provided initial tests of these questions. First, they demonstrated that people, on average, also recognize that low-level construal promotes behavioral precision. Participants reported that thinking about "how" versus "why" would be more useful for enhancing attention to contextual cues (e.g., proofreading). Second, Nguyen et al. (2019) provided evidence that this knowledge may be domain-general: people's high-level and low-level knowledge was apparent across multiple domains (e.g., relationships, finances, exercise), and predicted how they chose to prepare for tasks in novel contexts. Nguyen et al. (2019), moreover, assessed knowledge using different operationalizations of construal level—global and local visual processing, thinking about why and how, and generating superordinate categories and subordinate exemplars—suggesting that this knowledge can be assessed using different operationalizations.

The Present Research

The present research addresses several unresolved questions. First, research has not documented a core tenet of the metamotivational approach: the performance benefits of having conditional knowledge regarding what strategies best fit different conditions (Bonanno & Burton, 2013; Kashdan & Rottenberg, 2010; Mann et al., 2013). Recognizing the trade-offs of high-level and low-level construal should promote flexible regulation that facilitates success. Second, research has not examined whether assessments of metamotivational knowledge are distinct from other constructs (intelligence and motivation), and whether these assessments predict outcomes after controlling for these constructs. Finally, the psychometric properties of the domain-general knowledge assessments have not been rigorously evaluated. The quality of future metamotivation research critically depends on having psychometrically-sound assessments of knowledge for indexing individual differences. The present research improved and evaluated the psychometrics of one domain-general knowledge assessment, specifically operationalizing construal level as global and local visual processing. We examine whether this assessment predicts academic performance.

Method

Participants

Sample A consisted of 718 MTurk workers (M_{age} = 42.93, SD_{age} = 12.75; 397 women, 315 men, five non-binary people, one did not report; 79.2% White, 6.3% Asian American, 5.8% African American, 4.7% mixed racial/ethnic identity, 3.3% Hispanic/Latinx, 0.3% Native American, and 0.3% did not report) who received payment for participating and consented to be part of a longitudinal panel that shares their de-identified data. Participants completed follow-up sessions that occurred 7 months (N = 528; M_{age} = 43.76, SD_{age} = 12.95; 285 women, 239 men, three non-binary people, one did not report), 9 months (N = 513; M_{age} = 43.70, SD_{age} = 12.79; 284 women, 225 men, four non-binary people), and 1 year later (N = 458; M_{age} = 43.65, SD_{age} = 12.70; 256 women, 199 men, three non-binary people). Sample B consisted of 592 undergraduate students (M_{age} = 19.25, SD_{age} = 2.19; 279 women, 306 men, seven did not report; 64.4% White, 18.6% Asian American, 6.3% mixed racial/ethnic identity, 4.9% African American, 3.0% Hispanic/Latinx, 1.2% Middle Eastern, and 1.7% did not report) who received course credit in Introduction to Psychology (PSYCH 1100) for participating. We recruited participants in two multi-week periods (Fall 2018: weeks 12–14 and Fall 2019: weeks 11–15) and combined these subsamples to maximize power (semester did not impact results—see Supplemental Online Materials; SOM).

Both samples completed surveys that assessed several constructs beyond the scope of the present investigation. We report analyses with measures of metamotivational knowledge regarding regulatory focus (which correlated with our primary knowledge measures) in the SOM. The dataset, codebook, and materials for Sample A (longitudinal panel) are available at https://osf.io/jse96/?view_only=32ccbaa47aca463c8b4c844c46d71d70. The syntax for Sample A and the materials for Sample B (student sample) are available at https://osf.io/8hdsb/?view_only=a475ce4c772141e282b4a15e43ba4ab6. Given that students' academic records are FERPA-protected, the dataset, codebook, and syntax for Sample B are only available upon request and with institutional review board (IRB) approval.

Metamotivational Knowledge Assessment

We evaluated and improved the assessment developed by Nguyen et al. (2019). Here, we describe the development of the previous assessment and the changes that we made. Nguyen et al. (2019) first conducted a literature review on the effects of construal level on self-regulation. From this, they generated scenarios about tasks that benefit from high-level construal (high-level tasks) and low-level construal (low-level tasks). Participants indicated to what degree each of two preparatory exercises might benefit performance on these tasks. These exercises were activities that research suggests induce high-level and low-level construal. Recognizing which exercise would be most beneficial for a given task suggests that participants understood how to create task-motivation fit.

In one assessment, these exercises involved global and local visual processing (Kimchi & Palmer, 1982)—a validated operationalization of high-level and low-level construal, respectively (Smith et al., 2008; Wakslak & Trope, 2009). Participants were presented with compound shapes: global shapes made of local shapes (e.g., large square made of small triangles). They were told that the exercises required matching stimuli on their overall form (Global Mindset) or constituent parts (Local Mindset). Participants completed practice trials to ensure familiarity with both exercises. They then read high-level and low-level task scenarios and rated the usefulness of the exercises for performance. Nguyen et al. (2019) assessed knowledge by calculating difference scores (e.g., high-level knowledge = usefulness of global mindset for high-level tasks—usefulness of local mindset for high-level tasks).

We revised the assessment in three ways. First, we added scenarios to improve reliability and made revisions for concision and readability (see SOM).[1] Second, we omitted the practice trials to minimize the potential for demand effects. Third, rather than measuring the usefulness of both mindsets independently to create difference scores, we used a single bipolar measure that assessed participants' preferences between the two exercises for performance preparation (1 = *strongly prefer local mindset*, 6 = *strongly prefer global mindset*).[2] We indexed knowledge by averaging preferences within task type. To assess test–retest reliability, we administered the same assessment to Sample A one year later.

Additional Measures (Sample A)

To test for discriminant validity, we conducted follow-up sessions with Sample A. Seven months after the initial session, we administered the following measures: self-control (Tangney et al., 2004), self-regulatory self-concept (Fishbach et al., 2003), strategic mindset (Chen et al., 2020), grit (Duckworth & Quinn, 2009), spontaneous self-distancing (Ayduk & Kross, 2010), and flexible regulation of emotional expression (Burton & Bonanno, 2016). Nine months after the initial session, we administered a short version of the Big Five personality scale (Donnellan et al., 2006).

Correlates of Academic Performance (Sample B)

To examine whether knowledge predicts grades beyond correlates of academic performance, we measured participants' academic motivation (e.g., How motivated are you to do well in PSYCH 1100? 1 = *not at all*, 7 = *extremely*), academic self-concept (e.g., How successful are you at studying effectively? 1 = *not at all*, 7 = *extremely*; Fishbach et al., 2003), and past academic success (self-reported unweighted high school grade point average [GPA]).

Demographics and Final Measures

Participants reported how distracted they were and how seriously they took the study (1 = *not at all*, 2 = *slightly*, 3 = *somewhat*, 4 = *very*, and 5 = *extremely*). Participants also reported their gender, age, and major (Sample B only). Finally, we debriefed and compensated participants. We obtained students' grades from the registrar.

Results

Exclusion Criteria, Sensitivity Analyses, and Missing Data

Consistent with lab research practices for online studies, we applied *a priori* exclusion criteria based on attention (being very/extremely distracted or taking the study not at all/a little seriously; Sample A: n = 0 and Sample B: n = 122) and English fluency (Sample A: n = 0 and Sample B: n = 84). Given concerns about MTurk data quality (Moss & Litman, 2018), Sample A used additional exclusion criteria: duplicate IP addresses (n = 0), failing an English proficiency check (n = 5), failing an attention check (n = 0), and failing age consistency checks (n = 0). Additional exclusions were necessary in Sample B for participants with incomplete data: those who did not consent to share grades (n = 32), those whose academic records we could not retrieve (n = 5), those who did not report a high school GPA (n = 38). Finally, one participant in Sample B responded to all but one scenario in the assessment; we averaged their available responses rather than excluding them from analyses. Sample A had a final N = 713 and Sample B had a final N = 369.[3] After attention-based exclusions, Sample A (7 months later) had a final N = 521, Sample A (9 months later) had a final N = 506, and Sample A (1 year later) had a final N = 449. For our primary analysis predicting grades in Sample B—a linear multiple regression analysis (two-tailed, nine predictors), a sensitivity analysis revealed that our final N = 369 provided 80% power to detect an effect of f^2 = .021.

Exploratory and Confirmatory Factor Analyses

To conduct exploratory and confirmatory factor analyses (EFA and CFA, respectively) in Sample A, we created two split halves that did not differ in demographics. With the first half, we used the psych package in *R* (Revelle, 2017) to conduct an EFA with principal axis factoring, oblique rotation (direct oblimin), and a polychoric correlation matrix. Inspection of the eigenvalues and factor loadings suggested a two-factor solution consistent with theoretical expectations: low-level knowledge (eigenvalue = 4.29) and high-level knowledge (eigenvalue = 2.91). Next, we conducted two CFAs (second half of Samples A and B). Across samples, a two-factor model resulted in good fit (comparative fit index [CFI] > .90, root mean square error of approximation [RMSEA] < .08, standardized root mean square residual [SRMR] < .08; Hooper et al., 2008; Kline, 2015), Sample A: χ^2 (103) = 309.25, p < .001, CFI = .959, RMSEA = .075, SRMR = .071 and Sample B: χ^2 (103) = 256.33, p < .001, CFI = .94, RMSEA = .06, SRMR = .06 (see Figure 1). Invariance analyses revealed metric and scalar invariance by gender and race, and partial metric and partial scalar invariance by age[4] (see Table 1). For internal consistency results, see the SOM.

Discriminant Validity and Test-Retest Reliability (Sample A Only)

High-level and low-level knowledge were not strongly correlated with measures of self-regulation or personality, suggesting high discriminant validity (see Table 2). Given the nature of the knowledge measures, we anticipated less consistency over time than would be expected in measures of more static traits. The test–retest results over one year for high-level knowledge, $r(449) = .28$, $p < .001$, and for low-level knowledge, $r(449) = .42$, $p < .001$, were consistent with these expectations. Collectively, these analyses provide psychometric support for the knowledge assessment, demonstrate that high-level and low-level knowledge are distinct from other constructs, and suggest that this knowledge is relatively stable over time.

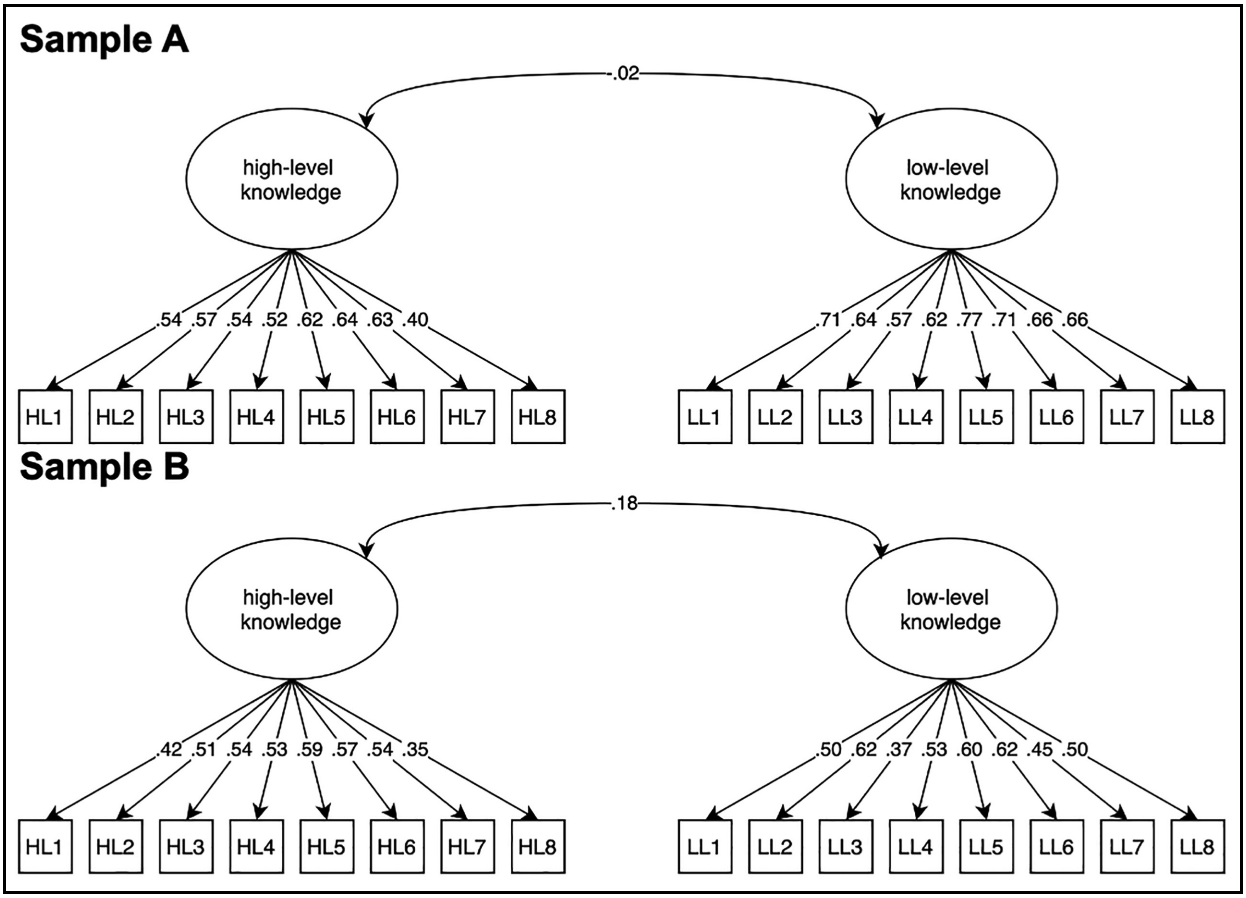

Figure 1. Two-Factor Model of Metamotivational Knowledge of the Benefits of Construal Level (HL = High-Level Scenario; LL = Low-Level Scenario).

Table 1. Confirmatory Factor Analyses Across Gender, Race, and Age (Sample A Only).

Model	Description	χ^2	*df*	CFI	RMSEA	SRMR	Model comparisons
1	Female participants (n = 196)	178.69	103	0.960	0.061	0.072	
2	Male and non-binary participants (n = 161)	268.46	103	0.957	0.100	0.093	
3	Configural invariance	447.15	206	0.958	0.081	0.082	
4	Metric invariance	475.43	220	0.955	0.081	0.084	Model 3 versus 4: χ^2 (14) = 22.34, p = .072
5	Scalar invariance	516.13	282	0.959	0.068	0.083	Model 4 versus 5: χ^2 (62) = 64.08, p = .403
6	White participants (n = 283)	258.34	103	0.969	0.073	0.071	
7	All other participants (n = 74)	286.16	103	0.794	0.156	0.142	
8	Configural invariance	544.49	206	0.942	0.096	0.086	
9	Metric invariance	583.21	220	0.938	0.096	0.088	Model 8 versus 9: χ^2 (14) = 18.35, p = .191
10	Scalar invariance	593.33	282	0.947	0.079	0.086	Model 9 versus 10: χ^2 (62) = 46.84, p = .924
11	Participants $<$ 41 years old (n = 179)	202.52	103	0.970	0.074	0.077	
12	Participants $>$ 40 years old (n = 178)	237.43	103	0.935	0.086	0.089	
13	Configural invariance	439.96	206	0.957	0.080	0.083	
14	Partial metric invariance	462.23	220	0.955	0.080	0.085	Model 13 versus 14: χ^2 (14) = 17.62, p = .091
15	Partial scalar invariance	512.67	282	0.957	0.069	0.084	Model 14 versus 15: χ^2 (62) = 75.15, p = .105

Note. CFI = comparative fit index; RMSEA = root mean square error of approximation; SRMR = standardized root mean square residual.

Table 2. Zero-Order Correlations (Sample A Only)

Scale	Example item (scale points)	N	High-level knowledge	Low-level knowledge
Self-control (Tangney et al., 2004)	"I often act without thinking through all the alternatives." (reverse-scored; 1 = does not describe me, 5 = describes me extremely well)	521	$r = .07$, $p = .090$	$r = -.12$, $p = .005$
Self-regulatory self-concept (Fishbach et al., 2003)	"To what extent are you successful at achieving your goals?" (1 = not at all successful, 7= extremely successful)	521	$r = .04$, $p = .336$	$r = -.12$, $p = .007$
Strategic mind-set (Chen et al., 2020)	"Whenever you feel frustrated with something, how often do you ask yourself: How can I do this better?" (1 = never, 5 = most of the time)	521	$r = .11$, $p = .020$	$r = -.09$, $p = .039$
Grit—perseverance (Duckworth & Quinn, 2009)	"I finish whatever I begin." (1 = does not describe me, 5 = describes me extremely well)	521	$r = .04$, $p = .369$	$r = -.08$, $p = .072$
Grit—consistency (Duckworth & Quinn, 2009)	"I often set a goal but later choose to pursue a different one." (reverse-scored; 1 = does not describe me, 5 = describes me extremely well)	521	$r = .04$, $p = .348$	$r = -.03$, $p = .470$
Spontaneous self-distancing (Ayduk & Kross, 2010)	Recall rejection experience, report distance (1 = mainly immersed participant, 7 = mainly distanced observer)	521	$r = -.11$, $p = .011$	$r = -.06$, $p = .165$
Positive emotion expression (Burton & Bonanno, 2016)	"A coworker gets a promotion and wants to talk about it." (1 = unable [to be even more expressive], 7 = very able [to be even more expressive])	521	$r = .05$, $p = .215$	$r = -.02$, $p = .652$
Negative emotion expression (Burton & Bonanno, 2016)	"You're attending the funeral of someone you don't know." (1 = unable [to be even more expressive], 7 = very able [to be even more expressive])	521	$r = .02$, $p = .738$	$r = -.11$, $p = .016$
Positive emotion suppression (Burton & Bonanno, 2016)	"During a meeting with a supervisor, his/her phone unexpectedly begins to play an embarrassing ringtone." (1 = unable [to conceal], 7 = very able [to conceal])	521	$r = -.02$, $p = .676$	$r = .03$, $p = .522$
Negative emotion suppression (Burton & Bonanno, 2016)	"You are on a first date at a restaurant having dinner, and a stranger spills their drink on you." (1 = unable [to conceal], 7 = very able [to conceal])	521	$r = -.01$, $p = .855$	$r = -.07$, $p = .206$
Big Five—extraversion (Donnellan et al., 2006)	"I am the life of the party." (1 = very inaccurate, 5 = very accurate)	506	$r = -.05$, $p = .308$	$r = -.10$, $p = .024$
Big Five—agreeableness (Donnellan et al., 2006)	"I sympathize with others' feelings." (1 = very inaccurate, 5 = very accurate)	506	$r = .07$, $p = .143$	$r = .01$, $p = .883$
Big Five—conscientiousness (Donnellan et al., 2006)	"I like order." (1 = very inaccurate, 5 = very accurate)	506	$r = .02$, $p = .652$	$r = -.07$, $p = .107$
Big Five—neuroticism (Donnellan et al., 2006)	"I have frequent mood swings." (1 = very inaccurate, 5 = very accurate)	506	$r = .03$, $p = .451$	$r = .03$, $p = .529$
Big Five—openness (Donnellan et al., 2006)	"I am not interested in abstract ideas." (reverse-scored; 1 = very inaccurate, 5 = very accurate)	506	$r = .10$, $p = .029$	$r = .01$, $p = .835$

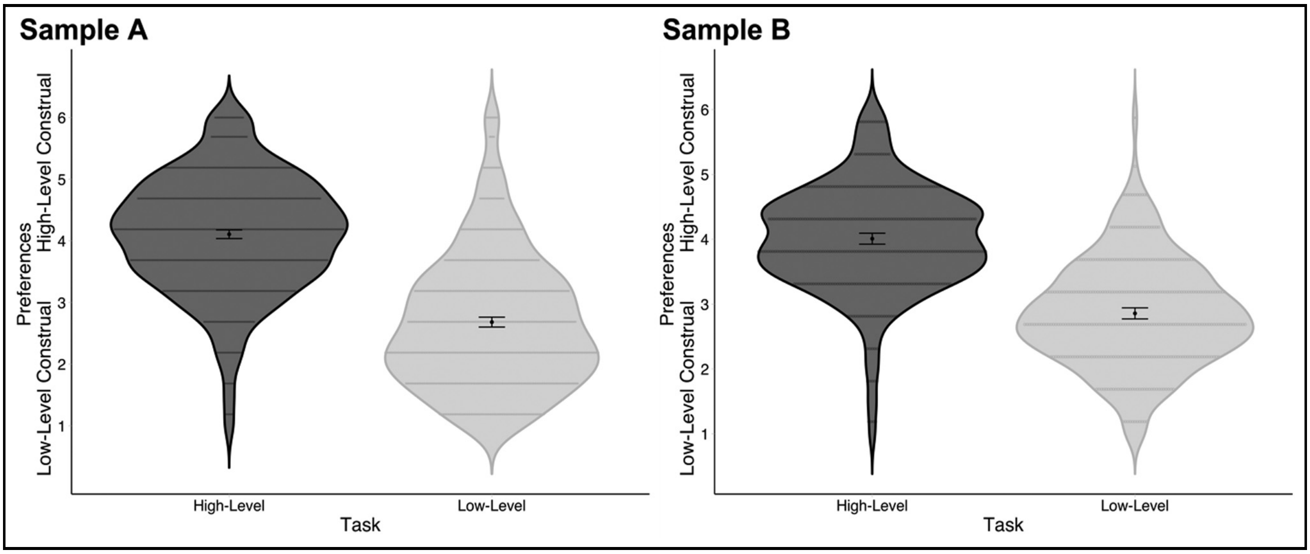

Figure 2. Preferences for High-Level versus Low-Level Construal in Preparation for High-Level versus Low-Level Tasks. Error Bars Represent ±2 SE From the Mean.

Knowledge of the Benefits of High-Level and Low-Level Construal

To examine whether participants on average understand the benefits of high-level and low-level construal, we examined participants' preferences (1 = *strongly prefer local mindset*, 6 = *strongly prefer global mindset*) as a function of task. Indeed, participants preferred to engage in high-level construal for high-level tasks (Sample A: $M = 4.10$, $SD = .94$ and Sample B: $M = 4.01$, $SD = .81$) more than for low-level tasks (Sample A: $M = 2.68$, $SD = 1.07$ and Sample B: $M = 2.86$, $SD = .82$); *Sample A:* $t(712) = 26.69$, $p < .001$, $d = 1.00$, 95% CI [1.32, 1.53] and *Sample B:* $t(368) = 18.20$, $p < .001$, $d = .95$, 95% CI [1.03, 1.28]; see Figure 2). Across samples, preferences were significantly different from the midpoint of the scale (3.5) in the expected direction for all tasks, all *p*s $< .05$ (see SOM). People thus appear, on average, to understand when to engage in high-level versus low-level construal to promote performance. Figure 2, however, reveals variability in this knowledge.

Predicting Performance (Sample B Only)

We examined whether individual differences in the knowledge assessment predicted students' final grade in PSYCH 1100, controlling for traditional correlates of academic performance.[5] We converted letter grades (A = 4.0, A− = 3.7, B+ = 3.4, etc.) to a 4-point scale ($M = 3.40$, $SD = .77$). We averaged preferences for high-level tasks to index high-level knowledge ($M = 4.01$, $SD = .81$). To index low-level knowledge, we reverse-coded and averaged preferences for low-level tasks, such that higher numbers indicated stronger preferences for the local mind-set exercise ($M = 4.14$, $SD = .82$). Notably, high-level and low-level knowledge were significantly correlated with grades, but not with academic motivation, academic self-concept, or previous success[6]—suggesting that knowledge is distinct from these constructs (see Table 3). Moreover, although high-level and low-level knowledge appeared to be positively yet weakly correlated in Sample B, they were not correlated in Sample A, suggesting that these two types of knowledge may be distinct.

We conducted a hierarchical regression analysis to examine whether knowledge predicts grades. We standardized continuous predictors to facilitate interpretations of the results. Prior to model fitting, assumption checking diagnostics were run. Most assumptions were reasonably well satisfied except for one influential observation (DFFITS = 1.43). This observation did not alter our substantive conclusions, represented a reasonable set of responses, and was thus retained in the subsequent analyses. In Step 1, we regressed grades on high school GPA, academic motivation, academic self-concept, gender (−0.5 = male, 0.5 = female or unidentified), age, and major (−0.5 = other major, 0.5 = psychology major). In Step 2, we added high-level knowledge to replicate MacGregor et al. (2017). In Step 3, we added low-level knowledge to test whether it explained additional variance in grades. In Step 4, we included the interaction between high-level and low-level knowledge.

Step 1 revealed that high school GPA, academic self-concept, and age significantly predicted grades (see Table 4). In Step 2, students' high-level knowledge significantly predicted grades, $R^2 = .263$, R^2 change $= .011$, $F(1, 361) = 5.225$, $p = .023$. This result conceptually replicates and

Table 3. Zero-Order Correlations (Sample B Only).

Variables	1	2	3	4	5	6	7	8
1. Final grade in PSYCH 1100	—							
2. High-level knowledge	.11*	—						
3. Low-level knowledge	.15**	.11*	—					
4. High school GPA	.33**	.01	.08	—				
5. Academic motivation	.15**	.06	.08	.10*	—			
6. Academic self-concept	.41**	.01	.03	.19**	.17**	—		
7. Gender (higher = female)	.13*	.10	−.004	.16**	.17**	−.004	—	
8. Age	−.23**	.03	.02	−.35**	−.16**	−.07	−.21**	—
9. Major (higher = psych major)	−.004	−.02	−.03	.01	.15**	−.04	.11*	−.04

Note. GPA = grade point average.
**p < .01. *p < .05.

Table 4. Hierarchical Regression Analysis Predicting Final Grades.

Step	Predictors	*b*	*SE*	ö	*t*	*P*	95% CI
1	Intercept	3.39	0.06		60.17	<.001	[3.28, 3.50]
	High school GPA	0.17	0.04	0.21	4.33	<.001	[0.09, 0.24]
	Academic motivation	0.03	0.04	0.04	0.93	.351	[−0.04, 0.11]
	Academic self-concept	0.27	0.04	0.35	7.48	<.001	[0.20, 0.34]
	Gender	0.10	0.07	0.07	1.39	.164	[−0.04, 0.25]
	Age	−0.08	0.04	−0.11	−2.12	.034	[−0.16, −0.01]
	Major	−0.03	0.11	−0.01	−0.23	.821	[−0.25, 0.20]
2	Intercept	3.39	0.06		60.56	<.001	[3.28, 3.50]
	High school GPA	0.17	0.04	0.21	4.34	<.001	[0.09, 0.24]
	Academic motivation	0.03	0.04	0.04	0.81	.419	[−0.04, 0.10]
	Academic self-concept	0.27	0.04	0.35	7.51	<.001	[0.20, 0.34]
	Gender	0.08	0.07	0.06	1.16	.248	[−0.06, 0.23]
	Age	−0.09	0.04	−0.11	−2.27	.024	[−0.16, −0.01]
	Major	−0.02	0.11	−0.01	−0.14	.889	[−0.24, 0.21]
	High-level knowledge	0.08	0.04	0.10	2.29	.023	[0.01, 0.15]
3	Intercept	3.40	0.06		61.08	<.001	[3.29, 3.51]
	High school GPA	0.16	0.04	0.20	4.11	<.001	[0.08, 0.23]
	Academic motivation	0.02	0.04	0.03	0.62	.536	[−0.05, 0.09]
	Academic self-concept	0.27	0.04	0.35	7.57	<.001	[0.20, 0.34]
	Gender	0.09	0.07	0.06	1.23	.218	[−0.05, 0.23]
	Age	−0.09	0.04	−0.12	−2.43	.016	[−0.17, −0.02]
	Major	0.00	0.11	0.00	−0.04	.970	[−0.22, 0.22]
	High-level knowledge	0.07	0.04	0.09	2.02	.045	[0.002, 0.14]
	Low-level knowledge	0.09	0.04	0.12	2.57	.011	[0.02, 0.16]
4	Intercept	3.40	0.06		61.01	<.001	[3.29, 3.51]
	High school GPA	0.15	0.04	0.20	4.03	<.001	[0.08, 0.23]
	Academic motivation	0.02	0.04	0.03	0.66	.511	[−0.05, 0.10]
	Academic self-concept	0.27	0.04	0.35	7.55	<.001	[0.20, 0.34]
	Gender	0.09	0.07	0.06	1.22	.223	[−0.05, 0.23]
	Age	−0.09	0.04	−0.12	−2.43	.015	[−0.17, −0.02]
	Major	0.00	0.11	0.00	−0.01	.996	[−0.22, 0.22]
	High-level knowledge	0.07	0.04	0.09	1.75	.081	[−0.01, 0.14]
	Low-level knowledge	0.09	0.04	0.12	2.55	.011	[0.02, 0.16]
	High-level × low-level knowledge	0.01	0.03	0.02	0.43	.666	[−0.04, 0.06]

Note. GPA = grade point average.

extends MacGregor et al. (2017) by demonstrating that a domain-general assessment of high-level knowledge predicts academic performance, even when accounting for traditional correlates of grades.[7] Notably, Step 3 revealed that students' low-level knowledge predicted grades beyond their high-level knowledge and other correlates of grades, R^2 = .276, R^2 change = .013, F (1, 360) = 6.589, p = .011. In Step 4, the interaction between high-level and low-level knowledge was not significant, $R^2 = .277$, R^2 change $= .0004$, $F(1, 359) = .186$, $p = .666$. Both types of knowledge predicted grades in an additive, not multiplicative, manner. Those with greater metamotivational knowledge (1 *SD* above the mean on both high-level and low-level knowledge) performed relatively well, whereas those with less knowledge (1 *SD* below the mean) performed relatively poorly. There was no significant difference in grades between those who were high on one knowledge index but not the other. Collectively, these findings suggest that these measures of high-level and low-level knowledge predicted academic performance.

General Discussion

This research examined whether a domain-general assessment of high-level and low-level knowledge predicted impactful outcomes and whether these two types of knowledge were distinct from related constructs. To advance these aims, we also rigorously evaluated the psychometrics of one knowledge assessment. This work offers several novel contributions.

First, results revealed that measures of both high-level and low-level knowledge independently predicted academic performance, even when controlling for typical predictors of grades. This work is the first to document that domain-general assessments of both high-level and low-level knowledge may predict consequential outcomes. These findings are consistent with the notion that knowledge of the trade-offs of distinct motivational states may support flexible regulation (Scholer & Higgins, 2012). Rather than positing which strategy is best overall, this work extends a long research tradition that suggests that goal pursuit involves distinct challenges which may be best addressed by different strategies.

Second, high-level and low-level knowledge were not strongly correlated with self-reported measures (academic self-concept, trait self-control, and personality), suggesting some level of discriminant validity. As mentioned, knowledge is assessed differently than traditional self-reported constructs and may be relatively tacit; the lack of strong correlations may thus be unsurprising. Importantly, this work suggests that knowledge cannot be reduced to a proxy for these constructs. This research is the first to show that a domain-general assessment of metamotivational knowledge of the benefits of construal level is distinct from other regulatory constructs—highlighting new paths for improving self-regulation.

Finally, psychometric analyses revealed that the knowledge assessment captures two distinct factors: high-level and low-level knowledge. Results also generally revealed measurement invariance, such that, the factor structure was consistent across demographics. This work is the first to assess rigorously the psychometric properties of a metamotivational knowledge assessment. Given that research depends on reliable measures (Flake et al., 2017), the current work provides important methodological advances for metamotivation research and, more broadly, self-regulation research.

Limitations and Future Directions

One limitation is that we focused only on one metamotivational knowledge assessment that operationalized construal level as global/local visual processing. Whether the effects in the current work extend beyond global/local visual processing to other operationalizations of construal level (e.g., why/how, category/exemplar) is an empirical question worthy of future research. In addition, the current work used bipolar preferences (anchored at high-level and low-level construal) to measure knowledge rather than separate usefulness scales (as in Nguyen et al., 2019). It may, however, be beneficial to know whether participants endorse a strategy in absolute rather than relative terms. Future research should examine the implications of using two usefulness scales versus one preferences scale.

In addition, participants in the current work were recruited from WEIRD populations (Western, Educated, Industrialized, Rich, Democratic; Henrich et al., 2010). Past research suggests that Easterners and Westerners on average have metamotivational knowledge of construal level (Nguyen et al., 2020). Nevertheless, future work should examine whether the psychometric properties of this knowledge assessment, and its ability to predict performance, generalizes to other cultures.

The effect size of the relationship between domain-general knowledge and grades was smaller than that of the relationship between grades and academic variables (high school GPA, academic self-concept). This may be somewhat unsurprising, however, given that the degree of methodological correspondence between two constructs can impact the strength of their relationship (Ajzen & Fishbein, 1977). The relationship between knowledge and academic performance (past and present) may have been stronger if the assessment included scenarios about specific academic tasks that students in this sample are expected to complete. Future work might examine whether the assessment specificity moderates the strength of the relationship between knowledge and performance. In addition, seemingly small effects can still have meaningful impact "in the long run albeit not very consequentially in the single episode" (Abelson, 1985; Funder & Ozer, 2019). The role of metamotivational knowledge in promoting self-regulatory success may be more apparent in the long run than in a single indicator. Future research may expand on this work by assessing several indicators of performance over time.

Future research should also examine potential mechanisms for the relationship between metamotivational knowledge and performance. Miele and Scholer (2018) suggest that knowledge may shape the effectiveness of two processes: metamotivational monitoring (i.e., assessing the quantity and quality of one's motivation to pursue a goal) and metamotivational control (i.e., selecting and engaging in strategies that bolster or change one's motivation). Building on the current findings, future work might examine students' strategy use in response to specific high-level versus low-level assignments in a course as a potential mechanism.

Previous research (Nguyen et al., 2019; Scholer & Miele, 2016) has speculated that children may develop metamotivational knowledge through observational learning, trial-and-error feedback, or from parents or teachers. Interestingly, the current findings indicate that high-level and low-level knowledge may be relatively independent, suggesting that the development of one may not lead to the development of the other. Future research should investigate how people acquire this knowledge and whether one or the other is more likely to develop in different contexts. For example, perhaps people are more likely to develop low-level knowledge in environments or cultures that reward attention to detail or sensitivity to context.

The current work may inform interventions for improving people's self-regulation. Interventions might focus on fostering normatively accurate metamotivational beliefs by teaching people about the trade-offs of different strategies and when to use which strategy to optimize performance. Another important target for intervention is the implementation of knowledge. Although knowledge is a necessary condition for performance, people may not necessarily apply their knowledge at critical junctures (see Nguyen et al., 2019, for a more in-depth discussion). Poor executive functioning may prevent people from being able to switch into the construal level that they know would be advantageous for a given task (Miyake & Friedman, 2012). Alternatively, they may not have sufficient time or resources to implement a strategy with which to induce the desired construal level. Adolescence appears to be a developmental period in which knowledge and knowledge implementation may diverge (Rodman et al., 2020); future work might examine whether adolescents appreciate the trade-offs associated with different motivational states and when such beliefs translate into successful self-regulation. These future directions could inform the timing and focus of future interventions.

Benefits of the Metamotivational Approach

This work provides important theoretical and methodological contributions. By rigorously assessing the psychometrics of a metamotivational knowledge assessment, this research provides a validated measure that facilitates future research. Importantly, this research demonstrates that conditional knowledge regarding what strategies best fit different conditions may be critical for performance and is distinct from other self-regulation constructs. This work thus highlights how the metamotivational approach illuminates novel and under-explored sources of self-regulatory success.

Authors' Note

Data sharing is essential for transparency, replicability, and future meta-analysis. The dataset, codebook, and materials for Sample A (longitudinal panel) are available at https://osf.io/jse96/?view_only=32ccbaa47aca463c8b4c844c46d71d70. The syntax for Sample A and the materials for Sample B (student sample) are available at https://osf.io/8hdsb/?view_only=a475ce4c772141e282b4a15e43ba4ab6. Given that Sample B data contains students' academic records and are FERPA-protected, the dataset, codebook, and syntax for Sample B are available upon request and by IRB approval.

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Supplemental Material

The supplemental material is available in the online version of the article.

Notes

1. Sample A completed an assessment with 18 scenarios (nine high-level and nine low-level). Sample B completed an assessment with 16 scenarios (eight high-level and eight low-level). For comparability, we report analyses in the main text using the 16 items common across Samples A and B. Analyses with all 18 items produce similar results (see SOM).
2. In Sample B (Fall 2018), participants indicated choices and preferences for each scenario. Given concerns about survey

duration and the overlap between choices and preferences, we omitted choice ratings from the Fall 2019 survey. Choice ratings produced similar results as those reported in text (see SOM).

3. Given the unexpected retention of only 62% of Sample B, we reported analyses in the SOM using lenient exclusion criteria ($N = 520$; 88% of the sample). Results were consistent with those in the main text and stronger given the increased statistical power.
4. Tabled results for Models 14 and 15 are for partial metric and scalar invariance. Three items (LL3: stroop, LL8: stop signal, and HL5: healthy food) did not demonstrate metric invariance and one additional item (HL3: negative feedback) did not demonstrate scalar invariance (see SOM).
5. A linear mixed model with students nested within different course sections failed to converge, likely to due to a low intra-class correlation—only 2.7% of the variance in grades was due to section differences. Modeling section as a fixed effect produced results consistent with those in the main text, suggesting that the findings are robust.
6. We did not have strong predictions for the relationship between knowledge and high school GPA. Future research might examine whether knowledge is more impactful under certain conditions. Compared to high school, for example, college may afford greater autonomy while presenting more difficult challenges, allowing knowledge to play a greater role in shaping performance (Blackwell et al., 2007; Dweck, 2002; Grant & Dweck, 2003). In addition, knowledge may be less stable during certain developmental periods (e.g., from high school to college). The relationship between knowledge and past performance may be stronger when knowledge is stable.
7. MacGregor et al. (2017) found that high-level knowledge interacted with academic motivation to predict grades. We did not find evidence for this interaction. For transparency, we report and discuss this analysis in the SOM.

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