The Relationship between Metamotivational Knowledge and Performance

by

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Author’s Declaration

I hereby declare that I am the sole author of this thesis. This is a true copy of the thesis, including any required final revisions, as accepted by my examiners.

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Abstract

Self-regulation research increasingly highlights the performance trade-offs of different motivational states. For instance, eager motivation promotes performance on divergent creativity tasks (e.g., brainstorming), and vigilant motivation (e.g., proofreading) promotes performance on convergent analytic tasks. Recent work on metamotivation – people's understanding and regulation of their motivational states – shows that, on average, people demonstrate accurate knowledge of how to create such task-motivation fit for eager and vigilant tasks; at the same time, there is significant variability in this accuracy (Scholer & Miele, 2016). The present research examines whether having accurate metamotivational knowledge predicts performance. Results revealed that more accurate metamotivational knowledge predicted better performance on proofreading and brainstorming tasks, though there was variability in the robustness of this effect across studies. Potential implications of this variability are discussed. By demonstrating the role of metamotivational knowledge in performance, this research offers novel insights for metamotivation research and highlights the advantages of taking a metamotivational approach to studying self-regulation.

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Introduction

There is no way around it: succeeding at our goals can be difficult. Different goals place distinct performance demands on us (Avnet & Higgins, 2003; Freitas & Higgins, 2002; Lee & Aaker, 2004; Woolley & Fishbach, 2015), and they never stop calling. Yet responding effectively pays off: Individuals who navigate their goals effectively experience benefits in a number of diverse areas, including higher life satisfaction, better psychological adjustment, better interpersonal relations, and fewer health issues (Briki, 2018; de Ridder et al., 2012; Mokdad et al., 2004; Tangney et al., 2004). Because self-regulatory success plays such a crucial role in so many significant life outcomes, it is not surprising that there has been great interest in understanding what makes some people perform better on their goals than others.

Not surprisingly, research has revealed a number of answers to when and why some people are more likely than others to perform well on their goals. Some approaches have focused on differences in general capacities or vulnerabilities, such as people's general ability to regulate their thoughts, emotions, and behavior (i.e., trait self-regulation; Carver & Scheier, 1982, 1998; Vohs & Baumeister, 2004), superior executive functions (Hofmann et al., 2012; Miyake & Friedman, 2012), or cue-reactivity (Boswell & Kober, 2016). Other approaches have looked outside the individual to general contextual factors that influence performance, such as the availability of temptations in one's environment (Milyavskaya & Inzlicht, 2017), environments that nudge individuals towards desired defaults (Beshears et al., 2009; Johnson & Goldstein, 2003) or social contexts that provide goal support (Briskin et al., 2019; Fitzsimons & Shah, 2008). Yet other approaches have focused on goal-specific factors that improve performance, such as higher goal commitment (Latham & Yukl, 1975; Locke, 1968; Locke et al., 1988), goal specificity (Locke & Latham, 1990; Mento et al., 1987), or the extent to which goals align with an individual’s interests and values (Sheldon & Elliot, 1999; Sheldon & Houser-Marko, 2001).

Beyond these factors, a nascent area of research is beginning to examine the role of meta-level processes in motivation—metamotivation—as another element that may have implications for when and why individuals succeed or fail in pursuit of their goals (Miele et al., 2020; Scholer & Miele, 2016; Scholer et al., 2018). This approach builds on work about individual's lay beliefs about the way the world works (e.g., Dweck, 2006) to suggest that individuals, based on their beliefs and knowledge about how motivation works, may take an active role in directing their motivation in ways that can support versus undermine the likelihood of goal success. Prior work has examined the nature of people's motivational knowledge, but the current paper is the first examination of whether one specific form of this metamotivational knowledge—people’s metamotivational knowledge of task-motivation fit in the domain of regulatory focus—predicts performance.

Metamotivation

As noted above, metamotivation refers to the processes and knowledge involved in regulating one’s own motivational states (Miele et al., 2020; Scholer & Miele, 2016; Scholer et al., 2018). Building especially on insights from the metacognition (Flavell, 1979) and metamemory literatures (Nelson & Narens, 1990) and a long tradition of the study of motivation regulation in educational psychology (Boekaerts, 1995, 1996; Schunk & Zimmerman, 1994; Schwinger & Otterpohl, 2017; Wolters, 2003, 2011; Wolters et al., 2011), this emerging area of research examines what people know about managing both the quantity and quality of their motivation. Metamotivation consists of two reciprocal processes—metamotivational monitoring, which involves assessing the motivation needed to pursue a goal successfully—and metamotivational control, which involves identifying and implementing strategies to upregulate or sustain desired motivational states (Miele & Scholer, 2018). Critically, the effectiveness of both monitoring, as well as control, is posited to rely on people's knowledge about how motivation works.

Recent work in metamotivation has focused particular attention on what people know about the regulation of qualitative differences in motivation. Long traditions in motivation science have distinguished between qualitative differences in motivation type (Deci & Ryan, 2000; Higgins, 1997; Liberman & Trope, 2008; Trope & Liberman, 2000). Research provides evidence that qualitatively distinct types of motivations can be helpful, harmful, or irrelevant depending on the situation (e.g., Fujita et al., 2019; Sansone, 2009; Scholer & Higgins, 2012). For example, research in regulatory focus theory (Higgins, 1997) has shown that promotion motivation (enthusiastically seeking opportunities for gains, advancement, or growth) best supports innovation when inventing a new product, whereas prevention motivation (carefully protecting against potential losses or other negative outcomes) is particularly effective when it comes time to carefully ensure that the product meets all safety standards. In other words, there are times when either a promotion or prevention motivational state will lead to more optimal performance on a certain type of task, identified as regulatory focus task-motivation fit (Scholer & Miele, 2016).

Metamotivational Knowledge of Regulatory Focus Task-Motivation Fit

Initial forays in metamotivational knowledge have examined what people know about this type of self-regulatory challenge—knowing what type of motivation is optimal for tasks that vary in their motivational affordances. Specifically, Scholer & Miele (2016) assessed what people know about creating task-motivation fit in a regulatory focus context. Regulatory focus theory distinguishes between two primary motivational systems, promotion and prevention, which serve distinct but necessary survival needs (Higgins, 1997). Predominantly promotion-focused individuals represent their goals as hopes and aspirations and are maximally sensitive to the presence of gains and the absence of non-gains. To achieve their goals, promotion-focused individuals prefer eager strategies of goal pursuit (Scholer et al., 2019). In contrast, predominantly prevention-focused individuals represent their goals as duties and responsibilities and are maximally sensitive to the absence of losses and the presence of non-losses. To achieve their goals, prevention-focused individuals prefer vigilant strategies of goal pursuit (Scholer et al., 2019).

Importantly, prior work reveals that performance in some situations is enhanced by promotion motivation, whereas performance in other situations is enhanced by prevention motivation. For example, performance on eager tasks that rely primarily on divergent or associative thinking (e.g., a brainstorming task) benefit most from promotion motivation which supports enthusiastically seeking opportunities for gains and processing information in a creative, flexible manner (Beuk & Basadur, 2016; Bittner et al., 2016; Friedman & Förster, 2001; though see Baas et al., 2011). On the other hand, for vigilant tasks that require convergent thinking and attending to errors (e.g., proofreading a text), performance is enhanced by prevention motivation which supports protecting against potential losses and processing information in a careful manner (Förster et al., 2003; Seibt & Förster, 2004)

Scholer and Miele (2016) assessed metamotivational knowledge by having participants complete a recall preference measure in which they reported their preferences for engaging in different recall activities (neutral, promotion-inducing, or prevention-inducing) as preparatory exercises for different tasks (eager vs. vigilant). Across five studies conducted with North

American samples, Scholer & Miele (2016) found that people on average demonstrated knowledge of task-motivation fit in this domain, such that they rated promotion-inducing recall activities as preferable for eager vs. vigilant tasks and prevention-inducing recall activities as preferable for vigilant vs. eager tasks. At the same time, there was significant variability in the accuracy of this knowledge, and variation in this knowledge is related to consequential behaviors such as choosing what task to engage in based on a given motivational state (Scholer & Miele, 2016) or appropriately motivating others for work tasks with distinct demands (Jansen et al., 2020). However, no work to date has examined whether this knowledge is related to better goal-relevant task performance.

The Present Research

Across two studies, the present research tests whether metamotivational knowledge of regulatory focus task-motivation fit predicts performance in single-shot lab tasks. First, in an initial session, participants completed the knowledge assessment measure created by Scholer & Miele (2016), in which they reported their preferences for engaging in different recall activities as preparatory exercises for eager and vigilant tasks. Then, in a second session, participants were randomly assigned to complete either an eager (brainstorming; Friedman & Förster, 2001) or vigilant (proofreading; Förster et al., 2003) task. I hypothesized that metamotivational knowledge of regulatory focus task-motivation fit would predict better task performance in the second session.

Given that Study 1b represents a near-direct replication of Study 1a, I present combined analyses for these studies. Combining the studies allows for more precise estimates of effect sizes and is consistent with recent recommendations to evaluate evidence across all data available to test hypotheses rather than individual studies (Fabrigar & Wegener, 2016; Goh et al., 2016; McShane & Böckenholt, 2017). The data reported in the manuscript comprise all the data that we have collected to test these hypotheses. As I discuss in depth below, the observed effect differs for Study 1a versus 1b; the detailed analyses for each sample are presented in the various appendices and I discuss potential interpretations in the discussion.

Method

Participants

Undergraduate participants at the University of Waterloo (N = 336; M_{age} = 20.15, SD_{age} = 4.24; 245 women, 89 men, 4 did not report gender) completed a two-part online study in exchange for course credit (Study 1a: N = 169, M_{age} = 20.14, SD_{age} = 4.25, 130 women, 39 men; Study 1b: N = 167, M_{age} = 20.16, SD_{age} = 4.23, 115 women, 50 men, 4 did not report gender). There were no significant main effects or interactions with gender, so this variable is not discussed further. My goal was to recruit as many participants as possible over the course of each semester, especially given the possibility of attrition in this two-part study.[1] With a final combined N of 336, we had 99% power to detect an effect as small as f^2 = 0.09 for the primary analysis of our hypothesis – a linear multiple regression analysis (two-tailed, 8 predictors). This was a larger study, of which the current investigation was one component.[2]

[1] The attrition rates varied significantly between the two samples because of some unintended idiosyncrasies with the way the 2-part study was set-up in the participant pool for Study 1a. For Study 1a, many participants who completed Part 1 were unable to sign-up for Part 2. 311 participants completed Part 1 of the study, but many of those participants had received their maximum allowance of credits and were not permitted to automatically sign up for Part 2. I worked with the participant pool program coordinator to implement a manual override to allow participants to sign-up for Part 2 by sending group and individual emails to the original participants. This effort resulted in 171 participants who completed both sessions for Study 1a (two of those participants did not complete any measures in Part 1, resulting in 169 total participants for Study 1a). In Study 1b, this issue was addressed (see Procedure section) and attrition was notably less; 167 of the 234 participants who completed Part 1 also completed Part 2.

[2] Studies 1a and 1b included additional measures beyond the primary construct of interest (lay beliefs of motivation, adapted from King, 2019; proactive personality, Bateman & Crant, 1993; and construal level task-motivation fit knowledge, Nguyen et al., 2019).

Procedure

In Part 1 participants completed a measure of regulatory focus metamotivational knowledge (Scholer & Miele, 2016). In Part 2, participants were randomly assigned to complete either a brainstorming or proofreading task. There were some variations in the length of time between sessions in the two samples. In Study 1a the time between study sessions ranged from a few minutes to several weeks due to some idiosyncrasies related to the implementation of two-part studies in the participant pool. This issue was resolved in Study 1b, such that participants received a link to complete Part 2 three days after completing Part 1 and were told they had seven days to complete it. Importantly, time between sessions did not affect the results; details are presented in Appendix A. Furthermore, there was no difference in knowledge between those who completed both sessions versus session 1 only (see Appendix B). After completing the task, participants responded to task-related questions, were debriefed, and received their remaining course credit.

Materials

Regulatory Focus Metamotivational Knowledge Assessment. Participants completed an assessment of their metamotivational knowledge of regulatory focus used in prior work (Scholer & Miele, 2016; see Appendix C). Participants were told that they would see descriptions of tasks paired with a recall activity. For each pair, participants rated how much they would prefer to complete that recall activity (e.g., Please write about a time in the past when you felt you made progress toward being successful in life) before doing the task (e.g., Your goal is to imagine a future no one has seen before by seeing possibilities and occasions for advancement) on a scale from 1 (*not at all*) to 7 (*very much*). The regulatory focus knowledge assessment consisted of four tasks (2 eager, 2 vigilant) and 12 recall activities (4 promotion focus, 4 prevention focus, 4 neutral). Thus, participants saw a total of 48 randomly presented task and recall activity pairs.

Task Performance. In the second session of the study, participants were told: “On the next page you will be presented with a computer task designed to measure your performance. You will have 3 minutes to complete the task. Please click next when you are ready.” They were then randomly assigned in a between-participants manipulation to complete one of two of the following tasks:

Eager Task (Brainstorming). Participants completed an unusual uses task (Guilford, 1967; Friedman & Förster, 2001), which asks participants to come up with as many creative ways to use an inanimate object as possible in three minutes. Participants were given the following instructions: "For the brainstorming task, list as many creative ways to use a TIN CAN as possible. The ideas you write down should be neither typical nor virtually impossible. Please list each of your ideas on a separate line in the space below.” Performance was assessed using two metrics: number of ideas and originality ratings (Baas et al., 2011). The number of ideas were measured by the counting the total number of non-redundant ideas generated by each participant. These ideas were then individually coded for originality. Six trained coders (three per study) who were blind to the hypothesis evaluated each use independently and in random order on originality, on a scale from 1 (not at all creative) to 7 (extremely creative). Participant originality scores were created by averaging the ratings for each use they generated. Interrater reliability was good (Cicchetti, 1994), with an intra-class correlation coefficient of .68 for Study 1a and .80 for Study 1b. The two performance metrics were significantly but modestly correlated, $r(161) = .23$, $p = .003$. I created a composite creativity score (the average of the two scores) that I use in the primary analysis predicting overall performance. However, for full transparency—given the modest correlation and given that the results differ depending on the metric—I also present the results in the main text for each metric separately (number of ideas and originality). To preview, the results using the composite creativity score parallel the results observed for the number of ideas metric.

Vigilant Task (Proofreading). The proofreading task involved a 400-word text discussing psychological theories of attraction (see Förster et al., 2003). The text contained a total of 46 errors and participants had three minutes to identify as many as possible. Participants were given the following instructions: "Please proofread the following text AS QUICKLY AND AS ACCURATELY as you can. Click on any word that contains an error (and no other words)." Performance can be assessed based on the number of surface (e.g., misspellings of shorter words, such as "peple" versus "people"; incorrect punctuation) and complex (e.g., misspellings of longer words, such as "affliation" versus "affiliation"; mistakes in subject verb agreement) errors participants identify (Förster et al., 2003). The correlation between these two performance metrics was $r(170) = .43$, $p < .001$. Given the relatively strong correlation and given that the results do not differ as a function of performance metric, I present the results in the main text for the total number of errors recognized per participant and, for full transparency, present the detailed analyses for each individual metric (surface and complex errors) in Appendices D and E.

Task-Related Variables (Skill, Enjoyment, and Familiarity). Participants then answered questions regarding the task (brainstorming or proofreading) they had just completed. Specifically, they responded to three questions designed to assess perceived task skill, enjoyment, and familiarity: How good are you at brainstorming (proofreading)? (1 = *very bad*, 6 = *very good*); How much did you enjoy the brainstorming (proofreading) task? (1 = *not at all*, 6

= *very much*); How often do you engage in brainstorming (proofreading)? (1 = *never*, 6 = *very often).*

Results

Metamotivational Knowledge of Regulatory Focus

To examine participants' metamotivational knowledge about regulatory focus, I submitted their preference ratings to a 2 (task: eagerness vs. vigilance) x 3 (recall activity: promotion vs. prevention vs. neutral) repeated measures ANOVA.[3] Results revealed a main effect of recall type, $F(1.55, 519.10) = 47.75$, $p < .001$, $\eta_p^2 = .13$, revealing that participants preferred promotion activities ($M = 4.34$, $SD = 2.65$) to both prevention activities ($M = 3.71$, $SD = 1.28$) and neutral activities ($M = 3.63$, $SD = 1.45$) at the $p < .001$ level; preference for prevention and neutral activities did not significantly differ (p = .336). There was no main effect of task type, $F(1, 335) = 0.74$, $p = .391$, $\eta_p^2 = .002$. As predicted and replicating past work (Scholer & Miele, 2016), results revealed a significant task x recall activity interaction, $F(1.83, 614.48) = 31.06$, $p < .001$, $\eta_p^2 = .09$ (see Figure 1).

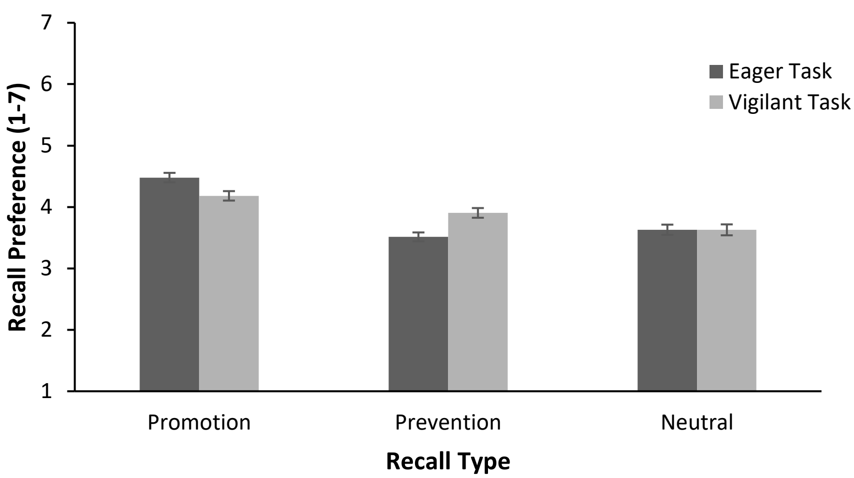

Figure 1. Mean ± *SE* recall preferences as a function of recall type and task type.

[3] Results revealed a violation of sphericity for both the main effect of recall type, Mauchly's $W(2) = .71$, $p < .001$, and the interaction, Mauchly's $W(2) = .91$, $p < .001$; a Greenhouse-Geisser correction yielded fractional *df*.

To decompose this interaction, I first conducted simple slopes as a function of strategy. All simple slopes were consistent with past work (Jansen et al., 2020; Scholer & Miele, 2016). Participants preferred promotion recall activities when anticipating an eager task (M = 4.48, SD = 1.41) relative to a vigilance task (M = 4.18, SD = 1.41), $t(335) = 5.66$, $p < .001$, $d = 0.31$. By contrast, participants preferred prevention recall activities when anticipating a vigilance task (M = 3.90, SD = 1.44) relative to an eager task (M = 3.51, SD = 1.35), $t(335) = 6.50$, $p < .001$, d = 0.35. There was no difference in preference for neutral recall activities when anticipating vigilance tasks (M = 3.62, SD = 1.63) vs. eagerness tasks (M = 3.63, SD = 1.52), $t(335) = 0.03$, p = .979, d = 0.001. These comparisons reflect knowledge of task-motivation fit.

Next, I conducted simple slopes as a function of task. Comparing promotion, prevention, and neutral recall activities for eager tasks, participants preferred promotion activities to both prevention activities, $t(335) = 13.77$, $p < .001$, $d = 0.75$, and neutral activities, $t(335) = 8.32$, $p <$ .001, d = 0.45 ; prevention and neutral ratings did not significantly differ, $t(336) = 1.43$, $p = .153$, d = 0.08. For vigilance tasks, participants once again preferred promotion activities to both prevention activities, $t(335) = 4.49$, $p < .001$, $d = 0.24$, and neutral activities , $t(335) = 5.16$, $p <$ .001, d = 0.28. They also preferred prevention activities to neutral activities, $t(335) = 2.65$, p = .008, d = 0.14.

In sum, replicating past work, participants demonstrated, on average, knowledge of task-motivation fit (as indicated by the significant task x recall activity interaction). In addition, participants also demonstrated an overall preference for promotion activities, also consistent with past work in this domain using these materials (Jansen et al., 2020; Scholer & Miele, 2016).

Predicting Overall Task Performance from Total Metamotivational Knowledge

Next, I conducted a regression analysis to examine whether participants' metamotivational knowledge predicted their performance on eager and vigilant tasks (i.e., brainstorming and proofreading), above and beyond other variables that may be related to task performance (i.e., task skill, enjoyment, and familiarity); see Table 1 for zero-order correlations.

To prepare the data, I standardized performance scores for both tasks – using the composite score for the brainstorming task and total number of errors detected for the proofreading task. I created an overall metamotivational knowledge index (M = 0.69, SD = 1.35) following the procedure used by Scholer & Miele (2016; [promotion recall preferences for eager tasks– prevention recall preference for eager tasks] + [prevention recall preferences for vigilant tasks– promotion recall preferences for vigilant tasks]). As can be observed in this index and consistent with the task x recall type interaction, on average participants had accurate knowledge, but there was also significant variability in this knowledge. Continuous predictors were mean centered in all regression analyses in this set of studies. Task type was effects-coded (brainstorming coded -1), as was study (Study 1a coded -1). See Table 2 for descriptive statistics of Session 2 variables.

I regressed participants' performance scores on study, task type, task skill, task enjoyment, task familiarity, total knowledge, and the interactions between total knowledge and both task type and study. This model was significant, $F(8, 325) = 5.04$, $p < .001$, $R^2 = .11$ (see Table 3). As one might expect, task enjoyment and task skill predicted performance. In addition, as predicted, participants' total metamotivational knowledge was related to task performance. Notably, knowledge emerged as a significant predictor while controlling for skill, enjoyment, performance on both tasks (i.e., there was no task type x knowledge interaction).[4] There was a marginal interaction between knowledge and study, indicating that the effect of knowledge on performance was likely moderated by study (as also indicated by looking at the raw correlations). Knowledge emerged as a significant predictor of task performance in Study 1a (b = 0.19, p = .001), but not in Study 1b (b = 0.03, p = .640; see Appendix F).

Table 1
Zero-Order Correlations

	Total RF Knowledge	Eager Knowledge	Vigilant Knowledge	Task Skill	Task Enjoyment	Task Familiarity
Task Performance (Full Sample)	0.16 .004	0.16 .004	0.01 .807	0.24 < .001	0.24 .001	0.16 .002
Study 1a	0.21 .005	0.23 .003	-0.01 .905	0.18 .019	0.22 .004	0.14 .062
Study 1b	0.10 .194	0.07 .342	0.04 .648	0.29 <.001	0.26 .001	0.17 .029
Proofreading Performance (Full Sample)	.20 .010	.12 .128	.09 .254	.34 <.001	.37 <.001	.12 .122
Study 1a	.23 .038	.19 .091	.03 .766	.24 .026	32 .003	.08 .486
Study 1b	.17 .121	.03 .808	.17 .130	.42 < .001	.41 <.001	.15 .173
Brainstorming Performance (Full Sample)	.13 .094	.20 .011	-.07 .365	.13 .103	.11 .151	.21 .006
Study 1a	.21 .055	.25 .022	-.03 .810	.11 .337	.10 .368	.23 .035
Study 1b	.01 .925	.12 .275	-.12 .291	.14 .217	.10 .357	.22 .055
Brainstorming: # of ideas (Full sample)	.13 .086	.21 .006	-.09 .269	.13 .097	.10 .213	.20 .012
Study 1a	.21 .055	.27 .014	-.05 .656	.11 .315	.09 .411	.21 .056
Study 1b	.01 .914	.13 .237	-.13 .255	.14 .225	.08 .486	.20 .078
Brainstorming: Originality (Full Sample)	-.02 .815	.02 .809	-.05 .543	.08 .338	.11 .160	.19 .017
Study 1a	-.01 .944	.09 .410	-.14 .213	.11 .302	.03 .769	.20 .064
Study 1b	-.01 .950	-.03 .826	.02 .868	.06 .605	.19 .092	.17 .123

Note. Total RF Knowledge represents the knowledge score obtained using the overall metamotivational knowledge index.
Eager and Vigilant Knowledge represent the two separate components that make up this index.

[4]Although there was no task type x knowledge interaction, we also ran separate models for each task and for each performance metric within brainstorming (number of alternatives, originality; see Appendix E).

Table 2
Task performance descriptive statistics.

Task	Performance Metric	Performance *M* (*SD*)	Performance Min-Max	Task Skill *M* (*SD*)	Task Enjoyment *M* (*SD*)	Task Frequency *M* (*SD*)
Brainstorming	Composite	5.48 (2.29)	0-12.5	3.46 (1.05)	3.56 (1.38)	3.26 (1.27)
	Number of Ideas	7.41 (4.29)	0-21			
	Idea Originality	3.06 (0.64)	0-5			
Proofreading	Number of Errors	12.38 (6.33)	0-34	3.61 (1.15)	3.46 (1.59)	3.44 (1.40)

Table 3
Regression analyses predicting task performance from total knowledge, controlling for study and task type, skill, enjoyment, and familiarity.

Predictors	*B*	*SE*	β	*t*	*p*	95% CI
Intercept	-0.25	0.17		-1.99	.047	[-0.50, 0.003]
Total Knowledge	0.11	0.04	.15	2.70	.007	[0.03, 0.18]
Task Type	0.08	0.05	.02	.34	.737	[-0.08, 0.12]
Study	-0.03	0.05	-.03	-.59	.556	[-0.13, .07]
Task Skill	0.11	0.06	.12	1.83	.069	[-0.01, 0.23]
Task Enjoyment	0.09	0.04	.14	2.17	.031	[0.01, 0.17]
Task Familiarity	0.04	0.05	.05	0.81	.421	[-0.05, 0.13]
Knowledge*Task Type	0.06	0.04	.08	1.41	.159	[-0.02, 0.14]
Knowledge*Study	-0.08	0.04	-.11	-1.96	.051	[-0.16, 0.003]

How do Eager and Vigilant Knowledge Relate to Overall Performance?

To examine the extent to which eager versus vigilant knowledge accounted for the performance effects, I calculated separate indices for eager knowledge (promotion recall preferences for eager tasks– prevention recall preference for eager tasks) and vigilant knowledge (prevention recall preferences for vigilant tasks– promotion recall preferences for vigilant tasks) and examined their relation with overall performance, using the composite scores from the previous analysis. This model was significant, $F(11, 332) = 3.96$, $p < .001$, $R^2 = .12$ (see Table 4). Results revealed a main effect of eager knowledge on task performance; there was no interaction between eager knowledge and task type. In contrast, there was no main effect of vigilant knowledge on task performance. Rather, there was a significant task type x vigilant knowledge interaction, such that vigilant knowledge was only a significant predictor of performance on the vigilant task.

Table 4
Regression analyses predicting task performance from eager and vigilant knowledge, controlling for study and task type, skill, enjoyment, and familiarity.

	Predictors	*b*	*SE*	β	*t*	*p*	95% CI
Task Performance	Intercept	-0.26	.13		-2.07	.039	[-0.51, -0.01]
	Eager Knowledge	0.12	.05	.16	2.67	.008	[0.03, 0.22]
	Vigilant Knowledge	0.07	.05	.08	1.39	.166	[-0.03, 0.17]
	Task Type	0.01	.05	.01	0.25	.803	[-0.09, 0.12]
	Study	-0.03	.05	-.03	-0.60	.547	[-0.13, 0.07]
	Task Skill	0.10	.06	.12	1.70	.090	[-0.02, 0.22]
	Task Enjoyment	0.10	.04	.15	2.26	.025	[0.01, 0.18]
	Task Familiarity	0.03	.05	.05	0.73	.464	[-0.06, 0.12]
	Eager*Task Type	0.03	.05	.04	0.62	.539	[-0.06, 0.12]
	Vigilant*Task Type	0.11	.05	.12	2.07	.039	[0.01, 0.21]
	Eager*Study	-0.09	.05	-.12	-1.96	.051	[-0.18, 0.004]
	Vigilant*Study	-0.05	.05	-.06	-1.07	.286	[-0.15, 0.05]
Brainstorming	Intercept	0.34	0.31		1.09	.276	[-0.28, 0.96]
	Eager Knowledge	0.13	0.07	.16	1.86	.065	[-0.01, 0.26]
	Vigilant Knowledge	-0.003	0.08	-.003	-0.04	.968	[-0.16, 0.15]
	Study	-0.20	0.15	-.10	-1.31	.192	[-0.50, 0.10]
	Task Skill	-0.01	0.09	-.01	-0.12	.908	[-0.19, 0.17]
	Task Enjoyment	-0.03	0.07	-.04	-0.37	.710	[-0.16, 0.15]
	Task Familiarity	0.20	0.08	.25	2.61	.010	[0.05, 0.35]
	Eager*Study	-0.07	0.07	-.09	-0.98	.328	[-0.20, 0.07]
	Vigilant*Study	-0.07	0.08	-.07	-0.85	.398	[-0.22, 0.17]
Proofreading	Intercept	-0.46	0.27		-1.72	.087	[-0.98, 0.07]
	Eager Knowledge	0.14	0.06	.18	2.20	.029	[0.01, 0.26]
	Vigilant Knowledge	0.17	0.07	.21	2.62	.010	[0.04, 0.30]
	Study	0.02	0.14	.01	0.12	.908	[-0.27, 0.30]
	Task Skill	0.18	0.08	.21	2.27	.025	[0.02, 0.33]
	Task Enjoyment	0.16	0.05	.26	2.97	.003	[0.05, 0.27]
	Task Familiarity	-0.05	0.06	-.07	-0.89	.374	[-0.16, 0.06]
	Eager*Study	-0.13	0.06	-.17	-2.06	.041	[-0.25, -0.01]
	Vigilant*Study	-0.07	0.07	-.09	-1.07	.287	[-0.20, 0.06]

There was also a marginal interaction between study and eager knowledge that paralleled the pattern found with total knowledge (running the regression analysis separately for each study, eager knowledge emerged as a significant predictor of performance in Study 1a, but not Study 1b; see Appendix E). There was no significant interaction between study and vigilant knowledge.

How do Eager and Vigilant Knowledge Relate to Performance on Each Task Metric?

To explore the impact of knowledge on performance in a more fine-grained fashion, I examined the association of eager knowledge (promotion recall preferences for eager tasks– prevention recall preference for eager tasks) and vigilant knowledge (prevention recall preferences for vigilant tasks– promotion recall preferences for vigilant tasks) separately with each metric of task performance (brainstorming: number of ideas, brainstorming: originality, and proofreading errors). I regressed each performance metric on eager knowledge, vigilant knowledge, study, task skill, task enjoyment, task familiarity, and the interactions between both types of knowledge and study. These analyses allow us to examine if these knowledge components are more closely associated with the relevant task (e.g., if eager knowledge uniquely predicts performance on the eager task) or are more strongly related to performance on particular metrics. Because the results differ for the two metrics on the brainstorming task, I present the analyses for each metric separately in the main text. Appendix E contains the analyses for the brainstorming composite (which parallels the results for the number of ideas metric) and the two types of proofreading errors (each of which parallels the results for the total number of errors).

Brainstorming: Total Number of Ideas. This model was significant, $F(8, 155) = 2.24$, $p = .027$, $R^2 = .10$ (see Table 5). As one might expect, task familiarity predicted the total number of ideas generated. In addition, participants' eager metamotivational knowledge was related to the total number of ideas generated for the brainstorming task, while vigilant knowledge was not. Study did not moderate this effect.

Table 5

Regression analyses predicting brainstorming performance (total number of ideas) from eager and vigilant knowledge, controlling for study and task skill, enjoyment, and familiarity.

Predictors	*B*	*SE*	β	*t*	*p*	95% CI
Intercept	8.23	0.87		9.42	<.001	[6.50, 9.99]
Eager Knowledge	0.59	0.29	.17	1.99	.048	[0.01, 1.17]
Vigilant Knowledge	-0.05	0.35	-.01	-0.14	.890	[-0.74, 0.64]
Study	-0.50	0.33	-.12	-1.52	.132	[-1.16, 0.15]
Task Skill	0.04	0.40	.01	0.10	.918	[-0.75, 0.83]
Task Enjoyment	-0.16	0.29	-.05	-0.55	.586	[-0.74, 0.42]
Task Familiarity	0.79	0.34	.23	2.34	.021	[0.12, 1.46]
Eager*Study	-0.27	0.29	-.08	-0.93	.353	[-0.85, 0.31]
Vigilant*Study	-0.27	0.34	-.07	-0.79	.433	[-0.94, 0.41]

Brainstorming: Originality. This model was not significant, $F(8, 155) = 1.17$, $p = .322$, $R^2 = .06$ (see Table 6). None of the variables emerged as significant predictors of brainstorming originality, though task familiarity was marginally significant.

Table 6

Regression analyses predicting brainstorming performance (originality) from eager and vigilant knowledge, controlling for study and task skill, enjoyment, and familiarity.

Predictors	*B*	*SE*	β	*t*	*p*	95% CI
Intercept	2.96	0.13		22.15	<.001	[2.69, 3.22]
Eager Knowledge	-0.003	0.05	-.01	-0.06	.950	[-0.09, 0.09]
Vigilant Knowledge	-0.03	0.05	-.05	-0.57	.569	[-0.14, 0.08]
Study	0.06	0.05	.09	1.13	.261	[-0.04, 0.16]
Task Skill	-0.04	0.06	-.06	-0.62	.539	[-0.16, 0.08]
Task Enjoyment	0.04	0.05	.08	0.82	.415	[-0.05, 0.13]
Task Familiarity	0.10	0.05	.18	1.85	.066	[-0.01, 1.00]
Eager*Study	-0.04	0.05	-.07	-0.78	.435	[-0.12, 0.05]
Vigilant*Study	0.03	0.05	.05	0.65	.520	[-0.07, 0.14]

Proofreading: Total Errors. This model was significant, $F(8, 160) = 5.48$, $p < .001$, $R^2 = .22$ (see Table 7). As one might expect, task skill and task enjoyment predicted performance. Of note, participants' eager and vigilant metamotivational knowledge were both related to the total number of errors identified in the proofreading task. There was also an interaction between eager knowledge and study, indicating that the effect of eager knowledge on performance was moderated by study. Eager knowledge emerged as a significant predictor of proofreading performance in Study 1a ($b = 1.72$, $p = .005$), but not in Study 1b ($b = 0.05$, $p = .927$; see Appendix E for details of these analyses). There was no significant interaction between vigilant knowledge and study.

Table 7

Regression analyses predicting proofreading performance (total errors) from eager and vigilant knowledge, controlling for study and task skill, enjoyment, and familiarity.

Predictors	*B*	*SE*	β	*t*	*p*	95% CI
Intercept	9.61	1.01		9.48	<.001	[7.61, 11.61]
Eager Knowledge	0.87	0.39	.18	2.23	.027	[0.10, 1.64]
Vigilant Knowledge	1.10	0.42	.21	2.63	.009	[0.27, 1.92]
Study	-0.45	0.45	-.07	-0.99	.324	[-1.34, .45]
Task Skill	1.11	0.49	.20	2.25	.026	[0.14, 2.08]
Task Enjoyment	1.01	0.34	.26	2.98	.003	[0.34, 1.68]
Task Familiarity	-0.31	0.35	-.07	-0.89	.376	[-1.01, 0.39]
Eager*Study	-0.82	0.39	-.17	-2.10	.037	[-1.59, -0.05]
Vigilant*Study	-.464	0.42	-.090	-1.111	.268	[-1.29, 0.36]

General Discussion

The successful pursuit of goals is vital for individual and societal well-being, yet it is challenging. The current work provides an initial examination of whether metamotivational knowledge of regulatory focus task-motivation fit predicts performance. There were several notable findings, each of which will be considered in more detail below. First, metamotivational knowledge was related to task performance in the combined sample, the first demonstration that metamotivational knowledge of regulatory focus task-motivation fit can be associated with performance. Second, eager knowledge was associated with the total number of ideas generated on the brainstorming task, but not the coded originality of the responses, suggesting that eager knowledge was not equally related to these components of creativity. Third, eager knowledge was related to performance on both the brainstorming and proofreading task, whereas vigilant knowledge was related to performance only on the proofreading task. Fourth, the relationship between metamotivational knowledge and performance was consistently observed in Study 1a but not 1b.

Implications

By demonstrating a positive relation between metamotivational knowledge of regulatory focus task-motivation fit and performance, the current work advances our understanding of factors that may contribute to successful goal pursuit. Previous research in the regulatory focus domain has emphasized that being in the right motivational state for a given task – i.e., having task-motivation fit – leads to increased performance (Freitas & Higgins, 2002; Higgins, 2000, 2005; Motyka et al., 2014; Scholer et al., 2014). The metamotivational framework, however, postulates that what may also be important is people's awareness of this task-motivation fit and their ability to create it themselves to promote goal-directed outcomes. Across several studies, researchers have demonstrated that people are on average accurate in their regulatory focus metamotivational beliefs (Scholer & Miele, 2016; Jansen et al., 2020). However, no research to date has provided evidence for the performance benefits of having this knowledge in the regulatory focus domain (Miele et al., 2020). Notably, these findings emerged even while controlling for skill, enjoyment, and frequency of engaging in these types of tasks – i.e., variables we would expect to be related to performance.

Further, the present work has important implications for the study of goal pursuit and self-regulation more broadly. Prior research has explored a number of factors in explaining why some people perform better on their goals than others, including differences in general capabilities (Carver & Scheier, 1998; Mikaye & Friedman, 2012), contextual factors (Milyavskaya & Inzlicht, 2017; Briskin et al., 2019), or goal-specific factors (Locke et al., 1998; Sheldon & Houser-Marko, 2001). The current thesis suggests that metamotivational knowledge could also be an important predictor of goal success. These findings suggest that it may be beneficial to consider how to develop interventions aimed at increasing people's metamotivational knowledge in order to increase self-regulatory effectiveness.

Previous interventions designed to increase performance have often focused on strategies targeted at changing these more general capacities or situational factors – for example, bolstering motivation by writing about the value and usefulness of a task (Hulleman & Harackiewicz, 2009), or reflecting on one's mastery of a skill to increase goal adoption (Bernacki et al., 2014). One limitation of these approaches is that they often, at least implicitly, imply a "one size fits all" approach to motivation, suggesting that one type of approach will generally be beneficial ("the fallacy of uniform efficacy"; Bonanno & Burton, 2013). In contrast, a metamotivational intervention approach could be built around improving people's knowledge of "if…then" contingencies in motivational effectiveness. One strength of this approach is that it recognizes that any given individual will likely face a unique combination of self-regulatory obstacles standing in their way of successful goal performance, and therefore the intervention may better equip them to flexibly navigate these challenges (Miele et al., 2020). Examining how to effectively develop such interventions will be an important direction for future work.

The Dynamic Relation Between Knowledge and Performance

One unexpected finding in the present work is the relation between metamotivational knowledge and performance appearing in Study 1a, but not Study 1b. As detailed in Appendix G, there were no clear differences between the samples in terms of demographics or performance level that can easily explain this unpredicted difference. Rather, I think this may be due to both the nature of the performance assessment—a single-shot, 3-minute task—and the dynamics of how metamotivational knowledge gets translated into action. In other words, I believe this variability in the apparent robustness of the effect is conceptually meaningful for understanding when and why metamotivational knowledge may be directly associated with performance.

Although speculative, many factors likely influence the probability that knowledge will get effectively translated into performance. In any given situation, the likelihood that an individual's metamotivational knowledge is reflected in their performance may be affected by several factors, such as their awareness of their current motivational state (self-knowledge), knowledge and beliefs about other viable strategies (see Nguyen et al., 2019), and their investment in the task. Further, there are a number of different ways that individuals may deploy their knowledge that were not available to participants in this single-shot performance opportunity where the task was assigned. I explore these ideas below.

Opportunities

In many contexts, people have the option to regulate goal performance not only by selecting a motivational strategy for a given task (e.g., "I'll think about what I can gain by doing well on this task!"), but by selecting a task based on a current motivational state ("I'm feeling really eager, so I think I'll start with the creativity task!"). In the assigned tasks in this study, the only way to create task-motivation fit is to change or sustain a desired motivational orientation via the strategies one uses. Not only were participants constrained in this way, but they also may not have had the same strategies available to them that they typically would spontaneously use or may not have been able to quickly generate strategies in this unfamiliar context. Thus, when performance is a brief, single-shot opportunity such as the paradigm in the present study, there is only one chance for these factors to align such that a direct association between knowledge and performance is observed.

Many self-regulatory situations, however, provide multiple opportunities for people to pursue their goals more or less effectively. For instance, students in a college course have many occasions that contribute to their learning and performance. Support for this possibility comes from one of my papers in preparation (in a study that was run by colleagues at The Ohio State University; Ross et al., 2020). Specifically, we examined whether students' metamotivational knowledge predicts their final grade in an undergraduate psychology course (Introduction to Psychology) – a situation which offers numerous opportunities for knowledge to shape outcomes.

Individuals recruited from an introductory psychology course over the course of two semesters completed an assessment of their metamotivational knowledge of regulatory focus along with various measures of traditional correlates of grades, including academic achievement motivation, history of academic success, high school GPA, gender, age, and major at the beginning of the semester. Final grades were obtained at the end of the course. We found support for our hypothesis – student's knowledge of how to create regulatory focus fit predicted their performance in the course. Notably, these results are very robust, such that across both semesters of data collection, we consistently found a strong link between metamotivational knowledge and performance (see Table 7). Indeed, both total metamotivational knowledge and its individual components (i.e., eager and vigilant knowledge) significantly predicted performance above and beyond traditional predictors of academic success.

This study complements and extends the study in the current thesis, not only because it demonstrates that metamotivational knowledge predicts performance in distinct contexts, but also because it provides some initial support for the possibility that having multiple performance opportunities may be an important factor that determines whether knowledge gets translated into performance. In the case of the present multi-shot performance opportunity, students had the chance to take notes more or less effectively, read the text more or less effectively, study for exams more or less effectively, show up to class (or not), discuss the materials with peers and

Table 7
Regression analysis predicting final grades – Study conducted at The Ohio State University

Predictors	*b*	*SE*	β	*t*	*p*	95% CI
Intercept	3.40	0.06		62.07	< .001	[3.29, 3.50]
Total knowledge	0.18	0.04	.24	5.31	< .001	[0.12, 0.25]
High school GPA	0.13	0.04	.17	3.53	< .001	[0.06, 0.21]
Academic achievement motivation	0.03	0.04	.04	0.92	.357	[-0.04, 0.10]
History of academic success	0.25	0.04	.33	7.14	< .001	[0.18, 0.32]
Gender	0.11	0.07	.07	1.49	.138	[-0.03, 0.25]
Age	-0.10	0.04	-.12	-2.55	.011	[-0.17, -0.02]
Major	-0.003	0.11	-.001	-0.03	.978	[-0.22, 0.21]
Study	-0.02	0.07	-.01	-0.31	.760	[-0.16, 0.11]
Total knowledge * Study	-0.04	0.07	-.03	-0.60	.549	[-0.18, 0.09]
Intercept	3.40	0.06		61.80	< .001	[3.29, 3.50]
Eager knowledge	0.16	0.04	.21	4.31	< .001	[0.08, 0.23]
Vigilant knowledge	0.07	0.04	.09	1.97	.050	[0.00002, 0.14]
High school GPA	0.13	0.04	.17	3.47	.001	[0.06, 0.21]
Academic achievement motivation	0.03	0.04	.04	0.90	.368	[-0.04, 0.10]
History of academic success	0.25	0.04	.33	7.17	< .001	[0.18, 0.32]
Gender	0.10	0.07	.06	1.37	.171	[-0.04, 0.24]
Age	-0.10	0.04	-.13	-2.59	.010	[-0.17, -0.02]
Major	-0.004	0.11	-.002	-0.04	.971	[-0.22, 0.21]
Study	-0.02	0.07	-.01	-0.27	.788	[-0.15, 0.12]
Eager knowledge * Study	-0.03	0.07	-.02	-0.39	.698	[-0.17, 0.11]
Vigilant knowledge * Study	-0.02	0.07	-.01	-0.31	.757	[-0.16, 0.12]

instructors more or less effectively. They were able to select tasks based on their current motivational state or attempt to change their current motivational state to meet current task demands. They could experiment with the effectiveness of strategies across learning opportunities. Thus, situations such as this, that afford multiple opportunities for the application of metamotivational knowledge, may allow for a stronger link between knowledge and performance.

Self-Knowledge

There is also likely significant variability in the extent to which participants are aware of their own motivational states and of the particular strategies that would be most be effective for them, and it is possible that having this knowledge influences whether metamotivational knowledge gets translated into performance. Indeed, the metamotivational framework proposes that having self-knowledge – i.e., insights into one's motivational states and tendencies – is likely a crucial component for effective regulation of one's own motivation (see Flavell, 1979; Pintrich, 2002 for related discussions in the realm of metacognition). Concerning the present work, having insight into one's motivational states and tendencies, in addition to identifying the optimal motivational states for a given situation, may be an important factoring in determining whether knowledge enhances performance. For example, even if an individual knows that a brainstorming task is best tackled with a promotion motivation, they may not be able to accurately identify their current motivational state and consequently will not take the necessary steps to shift their motivational state if needed. Furthermore, they may be able to recognize the need to shift their current state but may not know which strategies would work most effectively for them.

Additional research is needed before we can fully understand the role of self-knowledge in performance. For instance, although people show some awareness for task-motivation fit/non-fit (Appelt et al., 2010; Higgins, 2010; Spiegel et al., 2004), there is scant evidence to suggest that people can reliably report whether they are experiencing a promotion vs. prevention focus. Therefore, before we can assess whether individuals can accurately identify these motivational states, we first need a better understanding of what these motivational states subjectively feel like and what cues people use to recognize them. Miele and Scholer (2018) suggest that people may monitor their motivation by attending to their metamotivational feelings – i.e., a unique set of feelings and phenomenological experiences associated with different components of motivation – and thus is it possible that these feelings serve as cues for particular motivational states. This is an interesting area for future research.

Furthermore, not much is currently known about how people's implicit beliefs and theories of motivation affect their use of metamotivational knowledge. For example, do people think that motivation is a malleable state of which they have the power to mold and transform? And, if so, what effect does this have on the likelihood of one's metamotivational knowledge being put into action? Previous research suggests that a person's implicit beliefs can have an impact on their engagement with regulation strategies (King, 2019; Thoman et al., 2019). For example, Thoman et al. (2019) found that people who believed that interest was something that could be upregulated (i.e., believed that interest was malleable) were more likely to use interest regulation strategies during a boring task than those who held a more fixed theory of interest regulation. Hence, if someone does not think that motivation or any of its related components are changeable, they may not make use of their metamotivational knowledge. Future research should explore people's lay beliefs about motivation and how this affects the likelihood of metamotivational knowledge getting translated into performance.

Availability of Motivational Strategies

Situations may differ in the extent to which motivational strategies are available, whether this is due to situational constraints or shortcomings in one's personal repertoire of strategies. For instance, there may be situational constraints in place that impede the translation of knowledge, such as insufficient time, planning, or resources. Indeed, for the tasks in the present study, participants were not given much time to prepare and relatively little information was given regarding how their performance would be assessed. This could have hindered their capacity to engage in strategies that would bolster the superior motivational state for that given situation.

Furthermore, even if the situation does facilitate the translation of knowledge to performance, a person may have a limited repertoire of strategies they know how to use to upregulate a desired motivational state, and the feasibility of these strategies could vary in different situations. Having a limited repertoire of strategies is not something for which the current assessments of metamotivational knowledge accounts, as they measure people's ability to recognize the task-strategy pairings being presented to them but fail to capture variability in how many strategies people actually have at their disposal. In addition, there could be significant differences in how well people can spontaneously generate effective strategies, particularly in contexts similar to those used in the present study that demand immediate action. Being able to recognize or spontaneously generate strategies in the moment may be an important determining factor of whether metamotivational knowledge gets translated to performance.

Motivation to Self-Regulate

It is possible that the relation between knowledge and goal performance depends on having the motivation to self-regulate in the first place. For instance, an individual may tick all of the boxes for these potentially important factors: they have knowledge of how to create task motivation fit; they are able to accurately identify their current motivational state and which strategies would be most optimal in a given context; the situation offers multiple opportunities to make use of such motivational strategies; and they have the belief, whether it be implicit or explicit, that motivation is a malleable state that can be actively shaped and guided. Nonetheless, even with all of these elements falling into place, it is possible that the individual will lack the necessary motivation to regulate their own motivation. Without this motivation, a person will be less likely to put their metamotivational knowledge into practice (Smit et al., 2017; Wolters & Benzon, 2013; Wolters & Rosenthal, 2000), and therefore will not experience any performance benefits.

One reason someone may lack sufficient motivation to self-regulate is that the goal which they are pursuing is not one that is highly valued. For instance, we might expect that when the goal-domain is highly valued, participants might be more likely to deploy their knowledge. Indeed, Macgregor et al. (2017) found that individuals' knowledge in the construal level domain predicted self-control success – particularly for those who were motivated by the self-control conflict. Thus, even though people may understand how to create task-motivation fit, they may lack the necessary motivation to use their metamotivational knowledge for a goal that is not highly valued (Miele & Scholer, 2018; Wolters & Rosenthal, 2000). Future work should further explore goal value to determine its role in the translation of knowledge to performance.

Eager/Vigilant Knowledge and Task Performance

Another noteworthy finding that emerged in the current work was that relation between the knowledge components and task performance was not symmetric. Eager knowledge was related to performance on both tasks, whereas vigilant knowledge was related to performance only on the proofreading task. It may seem particularly surprising that eager knowledge was related to performance on the proofreading task; why would an understanding of the relative advantages of promotion versus prevention motivation for eager tasks be associated with performance on vigilant tasks? There are a number of possibilities, of course, with interesting implications for investigating these relations further. One possibility is that understanding when a given motivation is *not* useful plays an important role in understanding when it *is* useful. Specifically, the knowledge that prevention motivation is less optimal than promotion motivation for eager tasks may contribute to a generalizable understanding of the trade-offs of these motivational states. Indeed, Nguyen et al. (2019) found a similar pattern in the relation between knowledge of construal level task-motivation fit and consequential strategy choices.

It is also very likely that these tasks are not process pure. Thus, although I and others have characterized these as eager and vigilant tasks, and I do believe the dominant motivational affordances correspond to that, it may be that both eagerness and vigilance can contribute to performance, even if one motivational affordance is primary. Indeed, one methodological reality that may have contributed to the proofreading task being less than process pure could be related to the nature of the task appearance as programmed in Qualtrics, in which identified errors are, by default, highlighted in green (rather than crossed out). This presentation may have inadvertently made the finding of errors something that could be perceived both as eliminating a loss (taking away the error) and adding a gain (emphasizing the addition of another successful error identification).

There were also notable differences with respect to the brainstorming task. As captured in Tables 4 and 5, while metamotivational knowledge was related to overall performance on the brainstorming task, this was driven by its relation to the number of ideas generated rather than the coded originality of the responses. Prior work in regulatory focus has shown that promotion motivation is related both to the number of ideas that people are likely to generate (Crowe & Higgins, 1997; Friedman & Förster, 2001) and the originality of those ideas (Beuk & Basadur, 2016; Friedman & Förster, 2001). One might argue that the task instructions used in the current study placed greater emphasis on the number of ideas as the primary performance metric, and so one possibility is that the relationship was stronger for the number of alternatives generated because participants with greater knowledge might have been savvier and more likely to focus on that aspect of performance. It is also possible that greater knowledge of regulatory focus task-motivation fit is more strongly related to the generation of many ideas (i.e., increased output), regardless of their uniqueness. It would be useful to examine how varying task instructions influences performance on different metrics. Future work could benefit from exploring this question using a variety of different regulatory focus tasks, which, as I discussed previously, may pull for different components of metamotivational knowledge.

Normative vs. Idiographic Knowledge

Until now, work in the metamotivational domain has explored knowledge of normative effects – i.e., whether participants understand the qualitatively distinct motivations that would best serve performance based on work drawn from the empirical literature. For instance, we know from previous research that people tend to do better on creativity tasks when they are in a promotion motivational state (Beuk & Basadur, 2016; Crowe & Higgins, 1997; Friedman & Förster, 2001), while people tend to do better on vigilant tasks when they are in a prevention motivational state (Förster et al., 2003; Seibt & Förster, 2004). The existing methods for assessing metamotivational knowledge have measured people's awareness of these types of effects, and the present thesis suggests that this type of knowledge does matter for performance. However, research has yet to explore how knowledge of one's own past experiences – i.e., idiographic knowledge – interacts with normative knowledge, and the role it might play in performance. For example, people may decide which strategies to use in a given situation based on what has worked for them in the past, rather than what the research suggests would typically work best.

People may develop these personal task-motivation associations in a number of ways, such as a particularly salient experience, or through trial-and-error wherein a person repeatedly experiences success (or avoids failure) using a particular strategy for certain types of tasks. Regardless of how it develops, there could be interesting implications in terms of how it affects performance. For instance, it may be especially useful to have this type of knowledge in situations where there is no one qualitative motivational state that can clearly be identified as superior. In that case, it may be best to use a motivational strategy that has worked in the past. On the other hand, for a task that has been repeatedly shown to be best performed with a certain approach, it may be more useful to have knowledge of normative effects. Additionally, it could be particularly useful to have both types of knowledge during those multi-shot performance opportunities discussed previously, as these situations allow for multiple opportunities for both types of knowledge to contribute to success.

One question I think it would be particularly interesting to explore is how these two types of knowledge interact in a situation where one's personal experiences conflict with what we see as normatively more effective. That is, if people have both types of knowledge that offer conflicting information, how would this influence performance? For example, if an individual is presented with a task that has been reliably shown to benefit from being in a vigilant state, but they have previously experienced success on similar tasks using strategies that enhance an eager state, would it be better to rely on one type of knowledge over the other? Although speculative, it is possible that idiographic knowledge may be a stronger predictor of performance particularly in situations in which motivational affordances are more muted or mixed (i.e., a situation that could benefit from vigilance but is not harmed by eagerness). These are exciting questions for future research.

Limitations

One limitation of the present work, which I have alluded to throughout my discussion, is the measure used to assess metamotivational knowledge. As I mentioned, the existing knowledge measure assesses people's ability to recognize task-motivation fit based on normative effects we see in the literature, such that scoring high on the accuracy index indicates that people recognize the normative benefits (or drawbacks) of the task-strategy pairings being presented to them. While assessing knowledge in this way is useful, it is also constrained in that it imposes a relatively narrow definition of what it means to have accurate metamotivational knowledge. That is to say, the current knowledge assessment fails to capture a number of potentially important factors, including whether people are able to spontaneously generate strategies in the moment, and whether their own prior experiences would conflict with these normative performance standards (i.e., whether an individual knows that eagerness generally works better for them). Therefore, the ability to fully understand the role of knowledge in performance may require further development and validation of diagnostic measures of metamotivational knowledge.

Another limitation of the current work is the relatively artificial nature of the lab performance tasks. The benefit of using the brainstorming and proofreading tasks is that prior work has shown that these specific tasks do have eager and vigilant motivational affordances, respectively (Beuk & Basadur, 2016; Friedman & Förster, 2001; Förster et al., 2003), and thus they provide a relatively "clean" test of people's metamotivational knowledge in this domain. However, a significant downside of this paradigm is that the tasks are presumably low-stakes to most participants (there were no clear incentives for performing well). Furthermore, the study was conducted online, which reduced my capacity to control the environments in which participants were engaging with these tasks. Thus, the ability to generalize from these tasks to richer, more complex real-world contexts is constrained. While the data I described earlier in the General Discussion looking at effects of knowledge on course grades addresses some of these concerns, this is a limitation that needs to be further explored. Specifically, the robustness of the effect in the multi-shot performance opportunity compared to the single-shot task suggests that there may be value in exploring the complex relation between knowledge and performance in a longitudinal context. Doing so would provide insight into the dynamic relationship between metamotivational knowledge and performance, including how the various factors discussed in the present thesis might interact with knowledge to predict performance. In particular, I think the present work would benefit from a daily diary study to see how knowledge and other potentially relevant factors predict outcomes in daily life, especially as people deal with goal conflicts and other self-regulatory challenges.

Conclusion

The present research provides initial evidence that having metamotivational knowledge of regulatory focus task-motivation fit predicts performance. Specifically, more accurate metamotivational knowledge was related to increased performance on brief, single-shot brainstorming and proofreading tasks. However, there was significant variability in the robustness of this relationship, signaling the need for further examination of the dynamics of how metamotivational knowledge gets translated into action. Future research can extend this work by examining potential moderators that could explain under which conditions does knowledge lead to enhanced performance. Furthermore, it will be important to extend this line of work to investigate the relation between knowledge and real-world outcomes. We find initial evidence for this in the study conducted at The Ohio State University in the context of academic goals; future work should explore this relationship in other goal domains. Finally, given that those who are able to effectively manage and pursue their goals experience benefits in a number of domains – including higher life satisfaction, better psychological adjustment, better achievement in work and academic domains, and fewer health problems (see Tangney et al., 2004) – I would be interested in exploring whether we find a similar pattern on such outcomes among those with accurate metamotivational knowledge. These are all exciting questions for future research.

In conclusion, by examining the role of metamotivational knowledge in goal-relevant task-performance, this research offers new insights for goal-pursuit and self-regulatory success. The more we understand about individuals' beliefs and knowledge of motivation, the more we can think about how to target interventions effectively and think about where and when people tend to go right and go wrong in pursuing their goals.

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Appendix A

Is Time between Sessions related to Key Variables?

Because of idiosyncrasies related to the implementation of the two-part study in Study 1a, the time between Part 1 and Part 2 ranged from a few minutes to several weeks. This was controlled for in Study 1b, with all participants receiving a link to complete Session 2 three days after completing Session 1, with instructions to finish within seven days of receiving the e-mail. Due to the range of time between sessions both within and between studies, we examined whether time between sessions affected the results. Results for the full sample as well as each study separately showed that time was not significantly correlated with performance (see Table A1) and did not interact with task type or knowledge to predict performance (see Table A2).

Table A1
Zero-order correlations: Time between sessions and performance

	Full Sample	**Study 1a**	**Study 1b**
Overall Performance	.05 .388	.08 .295	-.08 .316
Brainstorming Performance (Composite)	.05 .567	.07 .540	-.22 .053
Brainstorming Performance (Number of Ideas)	.06 .477	.07 .504	-.20 .071
Brainstorming Performance (Originality)	-.07 .402	-.04 .747	-.15 .175
Proofreading Performance	.07 .384	.09 .402	-.03 .791

Table A2
Regression analyses for Studies 1a and 1b: Metamotivational knowledge predicting task performance while controlling for task type and time between sessions.

Study	Predictors	*b*	*SE*	β	*t*	*p*	95% CI
1a	Intercept	-0.04	0.09		-0.40	.691	[-0.21, 0.14]
	Task Type	-0.01	0.09	-.01	-0.14	.886	[-0.19, 0.17]
	Time	0.0002	0.0002	.09	1.21	.227	[-0.0001, 0.001]
	Total Knowledge	0.16	0.06	.23	2.60	.010	[0.04, 0.28]
	Knowledge*Time	-0.000003	0.0001	-.02	-0.24	.809	[-0.0002, 0.0002]
	Task Type*Time	-0.000003	0.0002	-.002	-0.02	.984	[-0.0003, 0.0003]

1b	Intercept	0.17	0.15		1.15	.254	[-0.12, 0.45]
	Task Type	-0.13	0.14	-.12	-0.90	.371	[-0.40, 0.15]
	Time	-0.002	0.001	-.20	-1.85	.066	[-0.003, 0.0001]
	Total Knowledge	0.09	0.10	.12	0.90	.369	[-0.11, 0.30]
	Knowledge*Time	-0.0001	0.001	-.03	-0.24	.815	[-0.001, 0.001]
	Task Type*Time	0.001	0.001	.26	1.67	.096	[-0.0002, 0.0003]

Appendix B

Full Sample Metamotivational Knowledge of Regulatory Focus Task-Motivation Fit

The first analysis presented in the main text examines metamotivational knowledge of regulatory focus task-motivation fit, conducted on participants who completed both Parts 1 and 2. We also conducted these analyses for the full sample who completed Part 1 (N = 558)—reported below; the pattern of results is the same.

Full Sample. To examine participants' metamotivational knowledge about regulatory focus, we submitted their preference ratings to a 2 (task: eagerness vs. vigilance) x 3 (recall activity: promotion vs. prevention vs. neutral) repeated measures ANOVA. Results revealed a main effect of recall type, $F(1.55, 829.52) = 64.80$, $p < .001$, $\eta_p^2 = .11$, revealing that participants preferred promotion activities (M = 4.33, SD = 1.30) to both prevention activities (M = 3.78, SD = 1.43) and neutral activities (M = 3.71, SD = 1.43) at the $p < .001$ level; preference for prevention and neutral activities did not significantly differ (p = .286). There was no main effect of task type, $F(1, 536) = 1.34$, $p = .247$, $\eta_p^2 = .002$. As predicted, results revealed a significant task x recall activity interaction, $F(1.81, 969.06) = 44.97$, $p < .001$, $\eta_p^2 = .08$ (see Figure B1).

Participants preferred promotion recall activities when anticipating an eager task (M = 4.46, SD = 1.39) relative to a vigilance task (M = 4.19, SD = 1.39), $t(536) = 6.56$, $p < .001$, d = 0.28. In contrast, participants preferred prevention recall activities when anticipating a vigilance task (M = 3.95, SD = 1.43) relative to an eager task (M = 3.58, SD = 1.41), $t(536) = 7.79$, $p < .001$, d = 0.34. There was no difference in preference for neutral recall activities when anticipating vigilance tasks (M = 3.70, SD = 1.61) vs. eagerness tasks (M = 3.70, SD = 1.54), $t(536) = 0.16$, $p = .871$, d = 0.01.

Next, we conducted simple slopes as a function of task. Comparing promotion, prevention, and neutral recall activities for eager tasks, participants preferred promotion activities ($M = 4.46$, $SD = 1.38$) to both prevention activities ($M = 3.59$, $SD = 1.41$), $t(538) = 16.27$, $p < .001$, $d = 0.70$, and neutral activities ($M = 3.71$, $SD = 1.53$), $t(538) = 9.68$, $p < .001$, $d = 0.42$; prevention and neutral ratings did not significantly differ, $t(539) = 1.84$, $p = .066$, $d = 0.08$. For vigilance tasks, participants once again preferred promotion activities ($M = 4.19$, $SD = 1.39$) to both prevention activities ($M = 3.96$, $SD = 1.43$), $t(339) = 4.98$, $p < .001$, $d = 0.21$, and neutral activities ($M = 3.70$, $SD = 1.61$), $t(339) = 6.02$, $p < .001$, $d = 0.26$. They also preferred prevention activities to neutral activities, $t(339) = 3.27$, $p = .001$, $d = 0.14$.

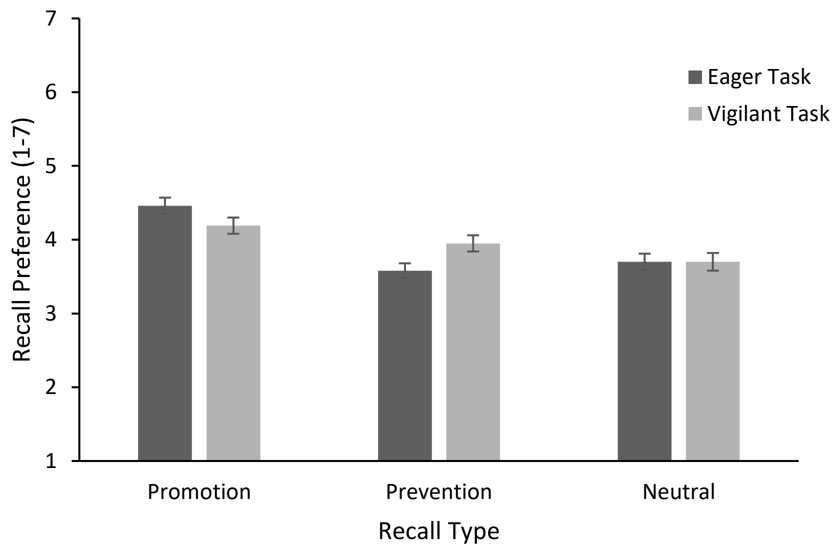

Figure B1. Mean ± *SE* recall preferences as a function of recall type and task type.

Appendix C

Metamotivational Knowledge Assessment

Eagerness Task Descriptions:

1. Your goal is to be as creative as possible by seizing opportunities to take the ordinary and innovate.
2. Your goal is to imagine a future no one has seen before by seeing possibilities and occasions for advancement.

Vigilance Task Descriptions:

1. Your goal is to be as accurate as possible by making sure to avoid lurking errors and pitfalls.
2. Your goal is to be precise and make sure that you don't make a wrong turn in figuring out

Promotion Recall Activities:

1. Please write about a time in the past when you felt you made progress toward being successful in life.
2. Please write about a time in the past when compared to most people you were able to get what you wanted out of life.
3. Please write about a time in the past when trying to achieve something important to you, you performed as well as you ideally would have liked to.
4. Please write about your hopes and aspirations as a child. What accomplishments did you ideally want to meet when you were a child?

Prevention Recall Activities:

1. Please write about a time in the past when being careful enough avoided getting you into trouble.
2. Please write about a time in the past when you stopped yourself from acting in a way that your parents would have considered objectionable.
3. Please write about a time in the past when you were careful not to get on your parents' nerves.
4. Please write about your duties and obligations as a child. What responsibilities did you think you ought to meet when you were a child?

Neutral Recall Activities:

1. Please describe what your kitchen looked like when you were a child.
2. Please describe the physical layout of the most recent restaurant you visited.
3. Please describe the various floor surfaces in your home.
4. Please describe the inside of the last bus on which you traveled.

Appendix D

How does Total Metamotivational Knowledge Relate to Performance?

The main text presents the analyses for the relation between total knowledge and task performance, which was standardized using the composite score for the brainstorming task and total number of errors for the proofreading task. Here we present several additional analyses for full transparency. As can be seen in Tables D1, D2, and D3, there was no main effect of total knowledge on any of the three brainstorming performance metrics (i.e., composite score, number of ideas, and originality), nor was there an interaction between knowledge and study. Total knowledge was a significant predictor of the total number of proofreading errors detected (see Table D5, and these results do not differ as a function of proofreading performance metric (i.e., surface vs. complex errors; see Tables D6 and D7). There was a marginal interaction between total knowledge and both the total number of proofreading errors and number of surface-level errors. Results revealed a pattern similar to that of the analyses in the main text, such that there was a main effect of knowledge in Study 1a but not 1b.

Table D1
Regression analyses predicting brainstorming performance (composite score) from total knowledge, controlling for study and task skill, enjoyment, and familiarity

Predictors	*B*	*SE*	β	*t*	*p*	95% CI
Intercept	5.61	0.45		12.37	<.001	[4.71, 6.50]
Total Knowledge	0.18	0.14	.11	1.30	.195	[-0.09, 0.45]
Study	-0.24	0.17	-.11	-1.38	.170	[-0.58, 0.10]
Task Skill	0.01	0.21	.002	0.03	.980	[-0.41, 0.42]
Task Enjoyment	-0.07	0.15	-.04	-0.46	.646	[-0.37, 0.23]
Task Familiarity	0.47	0.18	.26	2.68	.008	[0.12, 0.82]
Knowledge*Study	-0.17	0.13	-.10	-1.27	.205	[-0.44, 0.09]

Table D2
Regression analyses predicting brainstorming performance (number of ideas) from total knowledge, controlling for study and task skill, enjoyment, and familiarity

Predictors	*B*	*SE*	β	*t*	*p*	95% CI
Intercept	8.27	0.87		9.52	<.001	[6.56, 10.0]

Total Knowledge	0.35	0.26	.11	1.35	.179	[-0.16, 0.87]
Study	-0.52	0.33	-.12	-1.57	.118	[-1.18, 0.13]
Task Skill	0.10	0.40	.03	0.25	.801	[-0.69, 0.89]
Task Enjoyment	-0.19	0.29	-.06	-0.64	.523	[-0.76, 0.39]
Task Familiarity	0.83	0.34	.24	2.44	.016	[0.16, 1.49]
Knowledge*Study	-0.32	0.26	-.10	-1.23	.220	[-0.82, 0.19]

Table D3

Regression analyses predicting brainstorming performance (originality) from total knowledge, controlling for study and task skill, enjoyment, and familiarity

Predictors	*B*	*SE*	β	*t*	*p*	95% CI
Intercept	2.98	0.13		22.57	<.001	[2.72, 3.24]
Total Knowledge	-0.01	0.04	-.02	-0.17	.864	[-0.09, 0.07]
Study	0.06	0.05	.09	1.15	.251	[-0.04, 0.16]
Task Skill	-0.03	0.06	-.05	-0.51	.613	[-0.15, 0.09]
Task Enjoyment	0.03	0.04	.06	0.64	.522	[-0.06, 0.12]
Task Familiarity	0.09	0.05	.18	1.85	.066	[-0.01, 1.00]
Knowledge*Study	-0.01	0.04	-.02	-0.28	.784	[-0.09, 0.07]

Table D4

Regression analyses predicting proofreading performance from total knowledge, controlling for study and task skill, enjoyment, and familiarity

	Predictors	*B*	*SE*	β	*t*	*p*	95% CI
Full Sample	Intercept	9.69	1.01		9.64	<.001	[7.71, 11.68]
	Total Knowledge	0.98	0.34	.21	2.86	.005	[0.30, 1.66]
	Study	-0.41	0.44	-.07	-0.93	.357	[-1.28, 0.47]
	Task Skill	1.10	0.49	.20	2.26	.025	[0.14, 2.06]
	Task Enjoyment	1.01	0.34	.26	2.96	.003	[0.34, 1.67]
	Task Familiarity	-0.29	0.35	-.06	-0.81	.417	[-0.98, 0.41]
	Knowledge*Study	-0.65	0.34	-.14	-1.90	.059	[-1.33, 0.03]
Study 1a	Intercept	9.77	1.43		6.81	<.001	[6.91, 12.62]
	Total Knowledge	0.71	0.68	.13	1.04	.301	[-0.65, 2.06]
	Task Skill	1.16	0.48	.29	2.41	.018	[0.20, 2.13]
	Task Enjoyment	-0.37	0.53	-.08	-0.70	.489	[-1.42, 0.69]
	Task Familiarity	1.65	0.55	.31	3.03	.003	[-0.57, 2.73]
Study 1b	Intercept	9.88	1.46		6.78	<.001	[6.98, 12.78]
	Total Knowledge	1.59	0.72	.29	2.23	.029	[0.17, 3.02]
	Task Skill	0.79	0.49	.21	1.63	.107	[-0.18, 1.76]
	Task Enjoyment	-0.20	0.48	-.05	-0.43	.670	[-1.15, 0.75]

	Task Familiarity	0.33	0.44	.08	0.75	.459	[-0.55, 1.20]

Table D5

Total knowledge predicting surface-level proofreading errors from total knowledge, controlling for study and task skill, enjoyment, and familiarity

	Predictors	*B*	*SE*	β	*t*	*p*	95% CI
Full Sample	Intercept	6.74	0.68		9.94	<.001	[5.40, 8.07]
	Total Knowledge	0.52	0.23	.17	2.23	.027	[0.06, 0.98]
	Study	-0.06	0.30	-.02	-0.21	.836	[-0.65, 0.53]
	Task Skill	0.68	0.33	.19	2.07	.040	[0.03, 1.33]
	Task Enjoyment	0.55	0.23	.22	2.43	.016	[0.10, 1.01]
	Task Familiarity	-0.39	0.24	-.13	-1.64	.104	[-0.86, 0.08]
	Knowledge*Study	-0.43	0.23	-.14	-1.84	.068	[-0.88, 0.03]
Study 1a	Intercept	6.40	0.88		7.28	<.001	[6.91, 12.62]
	Total Knowledge	0.24	0.42	.07	0.58	.564	[-0.65, 2.06]
	Task Skill	0.75	0.30	.31	2.52	.014	[0.20, 2.13]
	Task Enjoyment	-0.55	0.32	-.20	-1.69	.095	[-1.42, 0.69]
	Task Familiarity	0.96	0.33	.29	2.87	.005	[-0.57, 2.73]
Study 1b	Intercept	7.37	1.05		7.03	<.001	[6.98, 12.78]
	Total Knowledge	1.24	0.52	.32	2.40	.018	[0.17, 3.02]
	Task Skill	0.31	0.35	.12	0.88	.383	[-0.18, 1.76]
	Task Enjoyment	-0.23	0.34	-.08	-0.68	.497	[-1.15, 0.75]
	Task Familiarity	0.09	0.32	.03	0.28	.781	[-0.55, 1.20]

Table D6

Total knowledge predicting contextual-level proofreading errors from total knowledge, controlling for study and task skill, enjoyment, and familiarity

Predictors	*B*	*SE*	β	*t*	*p*	95% CI
Intercept	2.96	0.56		5.32	<.001	[1.86, 4.05]
Total Knowledge	0.47	0.19	.18	2.45	.015	[0.09, 0.84]
Study	-0.35	0.25	-.10	-1.42	.158	[-0.83, 0.14]
Task Skill	0.42	0.27	.14	1.57	.119	[-0.11, 0.95]
Task Enjoyment	0.45	0.19	.21	2.40	.017	[0.08, 0.82]
Task Familiarity	0.10	0.19	.04	.52	.604	[-0.28, 0.49]
Knowledge*Study	-0.23	0.19	-.09	-1.20	.232	[-0.60, 0.15]

Appendix E

How do Eager and Vigilant Metamotivational Knowledge Relate to Performance?

As reported in the main text (see Table 4), we regressed participants' overall performance on study, task skill, task enjoyment, task familiarity, eager and vigilant knowledge, and the interactions between both types of knowledge and study. There was a marginal interaction between study and eager knowledge that paralleled the pattern found with total knowledge. Running the regression analysis separately for each study, eager knowledge emerged as a significant predictor of performance in Study 1a, but not Study 1b (see Table E1).

Table E1

Regression analyses predicting task performance from eager and vigilant knowledge, controlling for study and task type, skill, enjoyment, and familiarity

Predictors		*b*	*SE*	β	*T*	*p*	95% CI
Study 1a	Intercept	-0.29	0.19		-1.58	.117	[-0.66, 0.07]
	Eager Knowledge	0.23	0.06	.31	3.70	<.001	[0.11, 0.35]
	Vigilant Knowledge	0.11	0.08	.13	1.48	.140	[-0.04, 0.26]
	Task Type	0.02	0.08	.02	00.29	.775	[-0.13, 0.17]
	Task Skill	0.05	0.09	.05	0.53	.597	[-0.12, 0.21]
	Task Enjoyment	0.10	0.06	.15	1.65	.101	[-0.02, 0.22]
	Task Familiarity	0.05	0.07	.07	0.73	.466	[-0.09, 0.19]
	Eager*Task Type	0.04	0.06	.06	.71	.478	[-0.08, 0.17]
	Vigilant*Task Type	0.11	0.08	.12	1.49	.138	[-0.04, 0.26]
Study 1b	Intercept	-0.16	0.18		-0.87	.385	[-0.52, 0.20]
	Eager Knowledge	0.04	0.07	.05	0.57	.567	[-0.10, 0.18]
	Vigilant Knowledge	0.02	0.07	.03	0.29	.772	[-0.12, 0.17]
	Task Type	-0.02	0.08	-.02	-0.25	.800	[-0.17, 0.13]
	Task Skill	0.18	0.09	.20	2.03	.044	[0.01, 0.35]
	Task Enjoyment	0.07	0.06	.11	1.14	.256	[-0.05, 0.19]
	Task Familiarity	0.02	0.07	.02	0.29	.776	[0.11, 0.15]
	Eager*Task Type	-0.01	0.07	-.01	-0.07	.946	[-0.14, 0.13]
	Vigilant*Task Type	0.10	0.07	.11	1.33	.187	[-0.05, 0.24]

Brainstorming: Composite

In this analysis, we examined the association of eager and vigilant knowledge separately with the composite score for the brainstorming task. Results revealed a marginal main effect of eager knowledge on task performance; there was no main effect of vigilant knowledge on task performance. These results were consistent across Studies 1a and 1b (see Table E2).

Table E2
Regression analyses predicting brainstorming performance (composite score) from eager and vigilant knowledge, controlling for study and task skill, enjoyment, and familiarity

Predictors	*B*	*SE*	β	*t*	*p*	95% CI
Intercept	5.58	0.46		12.21	<.001	[4.68, 6.48]
Eager Knowledge	0.29	0.15	.16	1.86	.065	[-0.02, 0.59]
Vigilant Knowledge	-0.01	0.18	-.003	-0.04	.968	[-0.37, 0.35]
Study	-0.23	0.17	-.10	-1.31	.192	[-0.57, 0.12]
Task Skill	-0.02	0.21	-.01	-0.12	.908	[-0.44, 0.39]
Task Enjoyment	-0.06	0.15	-.04	-0.37	.710	[-0.36, 0.25]
Task Familiarity	0.46	0.18	.25	2.61	.010	[0.11, 0.80]
Eager*Study	-0.15	0.15	-.09	-0.98	.328	[-0.45, 0.15]
Vigilant*Study	-0.15	0.18	-.07	-0.85	.398	[-0.50, 0.20]

Proofreading: Total Errors – Study Level Analysis

As reported in the main text, we regressed participants' proofreading performance on study, task skill, task enjoyment, task familiarity, eager and vigilant knowledge, and the interactions between both types of knowledge and study. As indicated in Table 7 in the main text, there was a significant interaction between eager knowledge and study, indicating that the effect of eager knowledge on proofreading performance was likely moderated by study. Conducting the regression analyses separately for each study, eager knowledge emerged as a significant predictor of proofreading performance in Study 1a ($b = 1.72$, $p = .005$), but not in Study 1b ($b = 0.05$, $p = .927$; see Table E3). Additionally, although there was no significant interaction between vigilant knowledge and study, we see the same pattern emerge such that vigilant knowledge emerged as a significant predictor in Study 1a ($b = 1.54$, $p = .022$), but not in Study 1b ($b = 0.63$, $p = .242$)

Table E3
Eager and Vigilant knowledge predicting total proofreading errors

	Predictors	*B*	*SE*	β	*t*	*p*	95% CI
Study 1a	Intercept	9.72	1.45		6.71	<.001	[6.84, 12.61]
	Eager Knowledge	1.72	.60	.35	2.88	.005	[0.53, 2.91]
	Vigilant Knowledge	1.54	.66	.28	2.33	.022	[0.23, 2.85]
	Task Skill	.68	.69	.12	.98	.329	[-0.70, 2.05]
	Task Enjoyment	1.17	.49	.29	2.40	.019	[0.20, 2.14]
	Task Familiarity	-.36	.53	-.08	-.67	.504	[-1.42, 0.70]
Study 1b	Intercept	9.76	1.46		6.682	<.001	[6.85, 12.70]
	Eager Knowledge	.05	.52	.010	.092	.927	[-0.99, 1.08]
	Vigilant Knowledge	.63	.53	.128	1.178	.242	[-0.43, 1.68]
	Task Skill	1.62	.72	.295	2.266	.026	[0.20, 3.05]
	Task Enjoyment	.80	.49	.210	1.643	.104	[-0.17, 1.77]
	Task Familiarity	-.26	.48	-.059	-.543	.589	[-1.22, 0.70]

Proofreading: Surface Errors

In this analysis, we examined the association of eager and vigilant knowledge separately with the detection of surface-level proofreading errors. Results revealed a significant main effect of vigilant knowledge on proofreading performance; there was no main effect of eager knowledge. There was a significant interaction between study and eager knowledge that paralleled the pattern found with total knowledge (running the regression analysis separately for each study, eager knowledge emerged as a significant predictor of performance in Study 1a, but not Study 1b; see Table E4).

Table E4
Eager and Vigilant knowledge predicting surface-level proofreading errors

	Predictors	*B*	*SE*	β	*t*	*p*	95% CI
Full Sample	Intercept	6.66	0.68		9.81	<.001	[5.32, 8.00]
	Eager Knowledge	0.36	0.26	.12	1.38	.169	[-0.16, 0.88]
	Vigilant Knowledge	0.68	0.28	.21	2.45	.015	[0.13, 1.24]
	Study	-0.12	0.30	-.03	-0.39	.700	[-0.71, 0.48]
	Task Skill	0.70	0.33	.20	2.11	.036	[0.05, 1.34]
	Task Enjoyment	0.56	0.23	.22	2.46	.015	[0.11, 1.01]
	Task Familiarity	-0.42	0.24	-.15	-1.78	.077	[-0.89, 0.05]
	Eager*Study	-0.59	0.26	-.19	-2.26	.025	[-1.11, -0.08]
	Vigilant*Study	-0.25	0.28	-.07	-0.88	.380	[-0.80, 0.31]
Study 1a	Intercept	6.38	.89		7.18	<.001	[4.61, 8.15]
	Eager Knowledge	.99	.37	.33	2.70	.009	[0.26, 1.72]

	Vigilant Knowledge	.91	.41	.28	2.25	.027	[0.11, 1.72]
	Task Skill	.23	.42	.07	.54	.590	[-0.61, 1.07]
	Task Enjoyment	.75	.30	.31	2.51	.014	[0.15, 1.34]
	Task Familiarity	-.54	.33	-.20	-1.66	.100	[-1.20, 0.11]
Study 1b	Intercept	7.24	1.04		6.95	<.001	[5.17, 9.32]
	Eager Knowledge	-.23	.37	-.07	-.61	.541	[-0.96, 0.51]
	Vigilant Knowledge	.43	.38	.13	1.13	.264	[-0.33, 1.18]
	Task Skill	1.27	.51	.33	2.49	.015	[0.25, 2.29]
	Task Enjoyment	.32	.35	.12	.91	.367	[-0.38, 1.01]
	Task Familiarity	-.30	.34	-.10	-.87	.386	[-0.98, 0.38]

Proofreading: Contextual Errors

In this analysis, we examined the association of eager and vigilant knowledge separately with the detection of contextual-level proofreading errors. Results revealed a significant main effect of eager knowledge and a marginal main effect of vigilant knowledge on task performance. These results were consistent across Studies 1a and 1b (see Table E5).

TableE5

Eager and Vigilant knowledge predicting contextual-level proofreading errors

Predictors	*B*	*SE*	β	*t*	*p*	R^2
Intercept	2.95	0.56		5.25	<.001	[1.84, 4.06]
Eager Knowledge	0.51	0.22	.20	2.34	.020	[0.08, 0.94]
Vigilant Knowledge	0.41	0.23	.15	1.78	.077	[-0.05, 0.87]
Study	-0.33	0.25	-.10	-1.32	.190	[-0.82, 0.17]
Task Skill	0.41	0.27	.14	1.51	.134	[-0.13, 0.95]
Task Enjoyment	0.45	0.19	.21	2.39	.018	[0.08, 0.82]
Task Familiarity	0.11	0.12	.05	0.55	.583	[-0.28, 0.50]
Eager*Study	-0.23	0.22	-.09	-1.06	.292	[-0.66, 0.20]
Vigilant*Study	-0.22	0.23	-.08	-0.94	.349	[-0.68, 0.24]

Appendix F

Total Metamotivational Knowledge Predicting Overall Performance – Study Level Analysis

As reported in the main text, we regressed participants' performance scores on study, task type, task skill, task enjoyment, task familiarity, total knowledge, and the interactions between total knowledge and both task type and study. As indicated in Table 3 in the main text, there was a marginal interaction between knowledge and study, indicating that the effect of knowledge on performance was likely moderated by study. Conducting the regression analyses separately for each study, knowledge emerged as a significant predictor of task performance in Study 1a (b = 0.19, p = .001), but not in Study 1b (b = 0.03, p = .599; see Table F1).

Table F1

Regression analyses for Studies 1a and 1b: Metamotivational knowledge predicting task performance while controlling for task type, skill, enjoyment, and familiarity

	Predictors	*b*	*SE*	β	*t*	*p*	95% CI
Study 1a	Intercept	-0.26	0.18		-1.40	.164	[-0.62, 0.11]
	Total Knowledge	0.19	0.06	.27	3.41	.001	[0.08, 0.30]
	Task Type	0.03	0.08	.03	0.35	.724	[-0.13, 0.17]
	Task Skill	0.06	0.08	.07	0.74	.458	[-0.10, 0.23]
	Task Enjoyment	0.09	0.06	.13	1.47	.144	[-0.03, 0.21]
	Task Familiarity	0.05	0.07	.07	0.76	.450	[-0.08, 0.19]
	Knowledge*Task Type	0.06	0.06	.09	1.10	.274	[-0.05, 0.17]
Study 1b	Intercept	-.16	.18		-0.90	.370	[-0.52, 0.20]
	Total Knowledge	.03	.06	.04	0.53	.599	[-0.01, 0.15]
	Task Type	-.01	.08	-.01	-0.09	.927	[-0.16, 0.14]
	Task Skill	.18	.09	.20	2.02	.045	[0.004, 0.35]
	Task Enjoyment	.07	.06	.11	1.18	.239	[-0.05, 0.19]
	Task Familiarity	.03	.06	.04	0.43	.670	[0.10, 0.16]
	Knowledge*Task Type	.04	.06	.06	0.70	.485	[-0.08, 0.16]

Appendix G

Sample Comparisons

Results revealed a consistent pattern such that the relation between metamotivational knowledge and performance was observed in Study 1a, but not Study 1b. There were no clear differences between the samples in terms of demographics or performance level that can easily explain this unpredicted difference (see Table G1)

Table G1
Study-level descriptive statistics

	Mean (SD)			
	Study 1a	Study 1b	*t*	*p*
Age	20.14 (4.25)	20.16 (4.23)	0.04	.966
Proofreading Performance	12.85 (6.44)	11.94 (6.22)	0.93	.351
Brainstorming Performance (Composite)	5.68 (2.10)	5.19 (2.37)	1.40	.163
Brainstorming Performance (Number of Ideas)	8.48 (4.20)	7.26 (4.51)	1.80	.074
Brainstorming Performance (Originality)	3.00 (0.53)	3.21 (0.73)	1.15	.252
Metamotivational Knowledge	0.79 (1.39)	0.59 (1.29)	1.40	.164