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A role for proactive control in rapid instructed task learning

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ABSTRACT

Humans are often remarkably fast at learning novel tasks from instructions. Such rapid instructed task learning (RITL) likely depends upon the formation of new associations between long-term memory representations, which must then be actively maintained to enable successful task implementation. Consequently, we hypothesized that RITL relies more heavily on a proactive mode of cognitive control, in which goal-relevant information is actively maintained in preparation for anticipated high control demands. We tested this hypothesis using a recently developed cognitive paradigm consisting of 60 novel tasks involving RITL and 4 practiced tasks, with identical task rules and stimuli used across both task types. A robust behavioral cost was found in novel relative to practiced task performance, which was present even when the two were randomly inter-mixed, such that task-switching effects were equated. Novelty costs were most prominent under time-limited preparation conditions. In self-paced conditions, increased preparation time was found for novel trials, and was selectively associated with enhanced performance, suggesting greater proactive control for novel tasks. These results suggest a key role for proactive cognitive control in the ability to rapidly learn novel tasks from instructions.

1. Introduction

Imagine a group whose car is stuck in sand. To succeed in freeing their car they need to generate an effective collaborative effort. Some individuals would need to pull up the front of the car, one individual must quickly dig underneath the front wheel, and yet another would place a piece of wood underneath the wheel. None of them has done this before, and a critical feature is their ability to coordinate their effort in a timely and efficient manner. Each person's operation is quite simple, yet requires making novel decisions (such as when to place the piece of wood underneath the wheel). In this scenario, they may instruct one another what to do, but it would be critical to make sure to start the maneuver when all of them have understood the instructions and indicated that they are ready to carry out the instructions. Thus, a key question – the focus of the current study – is whether individuals utilize proactive cognitive processes to prepare to execute newly (relative to previously practiced) instructed tasks.

The ability to engage in rapid instructed task learning (RITL; "rittle"; Cole, 2009; Cole, Bagic, Kass, & Schneider, 2010) is not only an essential skill for human social groups, but also appears to be a uniquely human cognitive achievement (Cole, Laurent, & Stocco, 2013a; Meiran, Cole, & Braver, 2012). Although the processes, dynamics, and proficiency with which novel tasks are learned has long been a mainstay of cognitive psychology (Monsell, 1996; Newell & Simon, 1972; Rabbitt, 1997; Rosenbloom, 2012; Schneider & Shiffrin, 1977), there has been a recent rejuvenation of interest in RITL due to the introduction of new experimental methodologies that enable more sophisticated and detailed investigations of its component processes (Cole et al., 2013a; Liefooghe, Wenke, & De Houwer, 2012; Meiran et al., 2012; Ruge & Wolfensteller, 2010; Wenke, Gaschler, & Nattkemper, 2005).

A key feature and primary focus of the more recent investigations of RITL has been on examining the processes that are initiated immediately after novel task instructions are provided – on the very first trial. This is essential for isolating RITL from other processes that occur later in practice, given that long-term memory traces can facilitate performance on even just the second trial performing a task. The major recent innovation has involved obtaining a stable estimate of first encounter novel task behavior for each subject (Cohen-Kdoshay & Meiran, 2009; Cole, 2009; Hartstra, Kühn, Verguts, & Brass, 2011; Wenke et al., 2005). This involves the use of many novel tasks, such that behavioral and/or neural indices can be measured immediately after the instructions are processed with high statistical power. A second innovation has been to isolate the cognitive processes engaged during RITL, testing if they are distinct from cognitive processes engaged when the task is practiced, or if the same processes are involved but to different degrees (Cole et al., 2013a).

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As the car example above indicates, it is not only important that individuals be able to understand the instructions and be able to immediately carry them out. In some contexts, it is also critical to be able to indicate when one is ready to execute the instructions. The ability to prepare successfully for an upcoming task is a form of proactive cognitive control. According to the Dual Mechanisms of Control (DMC) framework (Braver, 2012; Braver, Gray, & Burgess, 2007), cognitive control can be flexibly utilized in two distinct operating modes that vary in terms of their temporal dynamics and utility in different cognitive situations. In particular, the proactive control mode is one that is prospective or future-oriented, and involves sustained, active maintenance of task goals. It is primarily engaged in an anticipatory fashion, when predictive cues in the environment signal up-coming high control demands, which can be most successfully met based on advanced preparation. Proactive control stands in stark contrast to the reactive control mode, which instead is a present-focused, just-in-time process, involving the transient re-activation or retrieval of task goals (e.g., from long-term) memory based on either the detection of conflict/interference, or via associative (i.e., spreading activation) mechanisms triggered by features of the current situation.

Elsewhere we have argued that RITL contexts likely make particular demands on the engagement of proactive control (Cole, Braver, & Meiran, 2017). The key insight is that, under RITL conditions, the instruction period provides both a clear indication of high upcoming control demands (given that the task is novel), while also signaling in advance the task goals or rules that will be relevant. Moreover, because the task is novel, there are only weak or nonexistent long-term memory representations of the relevant cognitive task procedure. Thus, when environmental features appear indicating that it is time to perform the novel task, these features are unlikely to enable successful retrieval or reactivation of task goals and rules through either episodic/associative pathways or conflict-based triggering. Consequently, in order to ensure successful RITL task performance, proactive control (implemented via sustained active maintenance of task goals from the instruction period) is likely necessary.

A key question is whether individuals have the expected ability to engage proactive cognitive control under RITL conditions, along with the ability to prepare as needed to successfully perform novel tasks. Previous studies have provided a mixed answer to this question. Two early studies by Dixon and colleagues reported positive suggestive evidence. Dixon (1981) focused on stimulus selection effects during performance of a newly instructed choice task. In this study, participants were given a novel pair of letters that were arbitrarily mapped to right/left responses. Importantly, participants had to indicate when they were ready to execute the novel task. Results indicated that preparation time (termed “initiation time”) was a function of the number of possible letter pairs, even when holding constant the number of possible letters. Dixon interpreted this result as indicating individuals prepared longer when they needed to select a novel algorithm (the set of stimulus-response mapping rules relevant for the currently instructed pair) to decide among the letter pairs, rather than just activate a single mapping rule. Dixon and Just (1986) focused on response selection effects in a choice task. In their paradigm, participants were given a new task in which the stimuli “x” and “o” were linked to a novel combination of movements that were specified by several parameters, such as the direction and extent of the movement. The results of that study show that preparation time was mostly determined by the complexity of the movement specification. Along a similar line, Longman, Lavric, and Monsell (2016) have recently shown that self-paced preparation in task switching was advantageous relative to experimenter-paced preparation, again suggesting that participants have some access to their readiness state. These studies thus support the possibility of proactive processes engaged during novel task preparation.

In contrast, a more recent cued task-switching study conducted by Meiran, Hommel, Bibi, and Lev (2002) suggests that individuals may not be effective in strategically preparing for upcoming task demands. Specifically, it was found that shorter preparation times were paradoxically related to better task performance as compared with long preparation. Meiran et al. (2002) interpreted their findings in terms of a lack of meta-cognitive awareness regarding task-set preparation. However, they based this interpretation on several key assumptions, one of which was that task switching must involve loading goals into working memory. This specific assumption was challenged, however, in later studies. Specifically, switching and working memory appear to be related to two separate individual-differences dimensions (Miyake & Friedman, 2012). Furthermore, experimental work employing working-memory load manipulations show minimal if any involvement of working memory in task switching (Kessler & Meiran, 2009; Kiesel, Wendt, & Peters, 2005; van 't Wout, Lavric, & Monsell, 2013). Additionally, in the Meiran et al. (2002) study, participants switched between highly practiced tasks, such that the potential absence of proactive processes may be selective to non-RITL contexts.

In contrast to standard cued task switching (i.e., with practiced tasks), a key requirement of RITL performance appears to be the loading of instructed components into working memory for task-set formation (Cole et al., 2010). In standard cued task-switching experiments, because the tasks are known beforehand and are indicated by unique cues, the task set can be retrieved from long-term memory with relative ease, and at least in some conditions, even automatically (Braverman & Meiran, 2010). In RITL paradigms, in contrast, participants likely need to form the task set in working memory based on instructions. Following from this observation, we hypothesized that individuals likely require additional proactive control processes (that take time and are prone to error) prior to performance of RITL tasks, because RITL tasks involve the formation of a task set in working memory (similar to the Dixon studies), rather than merely being retrieved from long-term memory (as in standard cue task-switching studies, such as Meiran et al., 2002).

To explicitly test the prediction that the need for proactive control increases in RITL situations, we took advantage of a recently developed paradigm for exploring RITL performance within a task-switching context (Cole, Ito, & Braver, 2016; Cole et al., 2010). This permuted rule operations (PRO) paradigm involves performance of tasks constructed from a set of 4 sensory semantic, 4 logical decision, and 4 motor response rules, generating $4 \times 4 \times 4 = 64$ permuted rule sets (Fig. 1). Our core manipulation involved task-rule novelty such that 4 of the 64 possible tasks were extensively practiced before testing, while the remaining 60 tasks were novel combinations of familiar elements. Critically, all 12 rules were included in both the practiced and novel tasks, isolating task-practice effects by controlling for practice across individual rules. Note that the task-practice manipulation included practice both prior to and during (due to multiple practiced-task encounters) the “test” session. Thus, practiced tasks were (unlike novel tasks) encountered multiple times both recently and in a previous session.

As described above, a key prediction was that novel and practiced tasks would be distinguished in terms of how readiness times are related to actual task execution. First, we predicted that preparation for novel tasks would take longer than for familiar tasks, creating “novelty costs”. While novelty costs are not particularly surprising, they provide an important validation of one of our key assumptions: that working-memory involvement is greater in novel than in practiced tasks. To test whether participants prepare for novel tasks in a strategic (proactive) manner, we additionally focused on the relationship between preparation time and task execution success. Specifically, our second prediction was that under conditions involving limited preparation time, the novelty cost would be reflected in poorer task performance when switching to novel tasks. In contrast, when preparation time is unrestricted (i.e., self-paced), we hypothesized that the novelty cost would be substantially reduced and/or even eliminated. The third prediction was that under self-paced conditions longer preparation times would be directly related to improved task performance (reduced

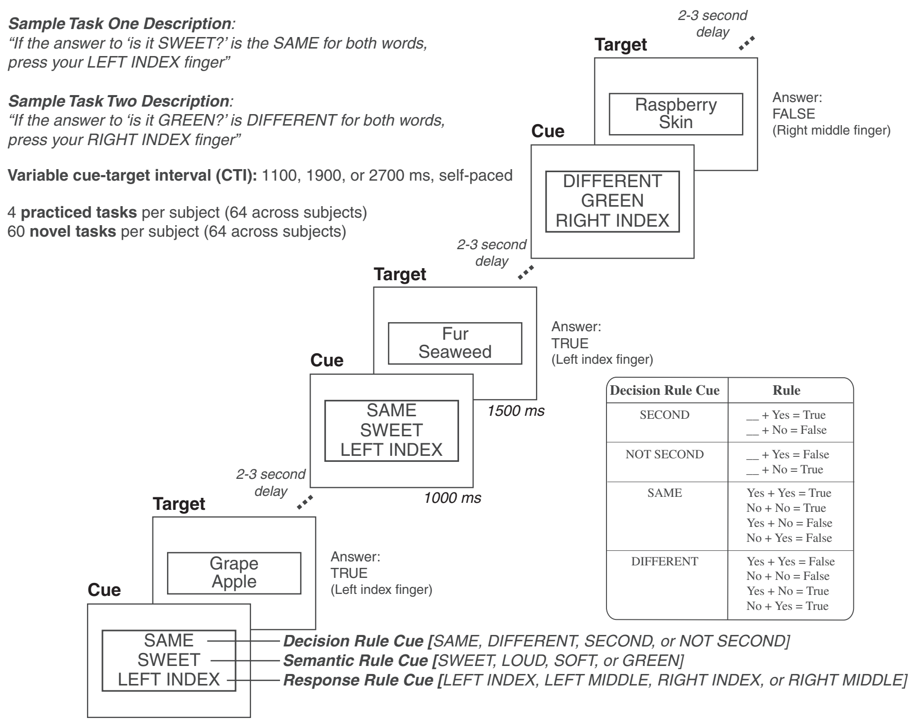

Fig. 1. The PRO cognitive paradigm for investigating RITL. The PRO paradigm was designed to compare novel to practiced tasks, controlling for the particular rules and stimuli used. Twelve rules and associated labels were learned in an initial practice session involving four of the 64 possible tasks (rule combinations). These four practiced tasks were used in the 'practiced' condition during a subsequent test session, along with 60 new tasks (rule combinations) in the 'novel' condition. The response indicated by the response rule indicated which button to press when the task conditions were true, with the other finger on the same hand as the correct response (e.g., left middle finger when the response rule is LEFT INDEX) when the task conditions were false. Cue-target intervals and response deadlines were shorter in this version of the paradigm than previous versions in order to bring participants down from ceiling performance. We expected that this might reveal important differences between novel and practiced task performance. Note that participants reported having sufficient time to read the task cues, and that task cues were always presented for 1000 ms with a fixation screen during CTIs.

novelty cost), again selectively for novel tasks.

We investigate the relationship between preparation and task readiness across three independent experiments. In Experiment 1, task preparation was experimentally manipulated by varying the cue-target interval (CTI) and also including self-paced trials. We reasoned that the required preparation time for task readiness would fluctuate across trials. In conditions for which CTI was experimentally controlled, we predicted that even when the available preparation time was long (>2 s), on some trials full readiness would not be achieved. In contrast, we expected performance to be highest in the self-paced condition, given the additional (and self-determined) preparation time provided. Further, we expected additional preparation time to be taken for novel relative to practiced tasks, and for this to relate to improved performance for novel tasks only. This would provide strong evidence for additional proactive processes present during novel (but not practiced) task preparation. Experiment 2 was designed to replicate the time-limited novelty cost effects observed in Experiment 1 while eliminating a key potential confound. In particular, because novel and practiced tasks were performed in separate blocks in Experiment 1, it was possible that the additional task switches (among 60 possible tasks versus only 4) that occurred during the novel task blocks could explain the observed novelty cost. Thus, novel and practiced tasks were intermixed within task blocks for Experiment 2. Experiment 3 built on the self-paced preparation condition used in Experiment 1, but expanded the number of trials in this condition. The additional statistical power provided a better test of whether self-paced preparation was utilized differently across novel and practiced tasks. The critical test of our hypothesis regarding preparation readiness was that novel tasks would benefit more from self-paced preparation time, reflecting the additional proactive control required for novel task preparation.

2. General materials & methods

2.1. Participants

Participants were recruited from Washington University and surrounding communities. All participants were financially compensated for their participation, and provided informed consent. The experiment was approved by the Washington University Institutional Review Board.

2.2. Experimental paradigm

The PRO paradigm, originally introduced in Cole et al. (2010), was used to investigate RITL performance. Several key modifications relative to the previously published version were implemented. Like the previous version, the paradigm consisted of 12 rules. These 12 rules were grouped into 3 rule dimensions (sensory semantic, logical decision, and motor response), each with 4 possible rules (see Fig. 1). Task trials were structured similarly to standard cued task-switching paradigms, in which each trial was comprised of a cue-target pair, with the cue specifying the relevant task to perform on the subsequent target. The cue consisted of 3 rules, one from each of the rule dimensions, and was presented for 1000 ms. The response indicated by the response rule indicated which button to press when the task conditions were true, with the other finger on the same hand as the correct response (e.g., left middle finger when the response rule is LEFT INDEX) when the task conditions were false. The target consisted of a pair of English words to which the rules were applied to determine the appropriate manual (button press) response. The same stimuli as used by Cole et al. (2010) were used here: 180 concrete semantic nouns, selected based on their clear selectivity into the tested semantic categories. The stimuli were randomly selected for each trial, with the restriction that the same word could not be used for both stimuli in a given trial. Note that stimuli repeats occurred extremely rarely. Forty-five stimuli per semantic category were presented, yet the most meaningful unit for stimulus repetition was word pairs, since each task acted on word pairs (not just individual words). There are 990 unique pairs out of 45 word stimuli, such that there was a 1/990 (0.1%) chance that a given stimulus pair would be repeated for the same task across any two encounters. Thus, it is highly unlikely that any stimulus pair experienced with a given task during the practice session would be experienced with that same task during the test session (or across task encounters within a session). More details regarding stimulus construction and constraints are provided by Cole et al. (2010).

Task rules were learned as part of an initial 2-h "practice" session. In this practice session the rules were grouped into 4 distinct tasks (counterbalanced across participants) that uniquely spanned the complete set of 12 rules. In other words, each of the 12 rules was used exactly one time to form unique rule combinations for the 4 practiced tasks. These four tasks also constituted the "practiced" set that was later performed in the subsequent 2-h "test" session (1–7 days following the practice session). The 12 rules were additionally permuted into 60 novel combinations to comprise the "novel" condition. Novel and practiced rule identities were counterbalanced across participants, such that each condition covered the span of 64 possible tasks across participants. Note that for Experiment 3 the practice and test sessions were on the same day, with the practice and test sessions being shortened to approximately 70 and 60 min, respectively.

As mentioned above, the task procedure involved minor changes relative to the previously published versions of the paradigm: 1) the task cuing instructions included all three task rules presented on the screen simultaneously (as opposed to sequential presentation), 2) both target stimuli were presented on the screen simultaneously (rather than sequentially), 3) the decision/logic rule cue 'JUST ONE' was changed to the more intuitive but logically equivalent 'DIFFERENT', 4) the cue-target interval (CTI) was shortened (from an average of 7000 ms to an average of 1900 ms from cue onset). Finally, unlike previous studies using this paradigm, novel tasks (sets of rules) were allowed to repeat (both immediately and after a lag of intervening task trials). However, immediate repetitions were excluded from analysis for both practiced and novel tasks.

3. Experiment 1

A primary goal of Experiment 1 was to identify novelty costs on task performance, which would provide evidence for the core hypothesis of increased demands on proactive control associated with RITL conditions. We hypothesized that novel task preparation involves a relatively fragile task-set-formation process, in contrast to a more robust task-set-retrieval process during practiced task preparation. The previous study using the PRO paradigm (Cole et al., 2010) found only a small novelty cost (2% accuracy, 23 ms RT). We suspected that the small novelty cost might be due to excess time to prepare (7 s) leading to a ceiling effect. In this experiment, we attempted to increase the robustness of this "novelty cost" by reducing the CTI and by imposing a response window of 1500 ms. We expected that having a response deadline would limit the extension of preparatory processes into the trial period, which would normally reduce our ability to detect preparatory effects in the self-paced condition (and in accuracy effects) independently of RT effects.

In an attempt to maximize differences between novel and practiced task trials: 1) the practice session involved learning of the four practiced tasks in single-task blocks (to reduce practice switching between the tasks); 2) the testing session had the practiced and novel tasks segregated into separate blocks to facilitate a strategic distinction between the conditions; 3) there was a 50% chance of a task repeating on sequential trials (allowing for measuring of switch costs; which was not of primary interest in the present study); and 4) task preparation times (cue-target intervals, CTIs) were manipulated in order to investigate preparation effects on performance. A self-paced condition (in separate blocks from the non-self-paced conditions) was also included to investigate strategic effects of self-paced preparation time across novel and practiced tasks. In self-paced trials, participants were instructed that they could take as long as they wished to prepare for the upcoming task when presented with the task cue. Thus, the cue remained on the screen until participants pressed the space bar (with either their right or left thumb), at which point it was replaced after 100 ms with the target. The same 1500 ms response window was employed on these trials to ensure a high demand on preparation.

We chose to focus primarily on task accuracy rather than reaction time (RT) effects because we expected that insufficient preparation would result in a failure to perform the task correctly (rather than just slow down processing). We discouraged participants from extending preparation into the stimulus period (which would have made our CTI manipulation ineffective) by implementing a response time limit and throwing out trials beyond that limit (1500 ms; the target stimulus duration). Participants were made aware of this time limit via pre-practice instructions and via feedback during the first 30 trials of each practice session task.

3.1. Methods

3.1.1. Participants

There were 33 participants (20 female, aged 18 to 38, median age of 21). This N provides Power > 0.80 to detect Dz > 0.50 in a 2-sided paired *t*-test. Three participants were removed from the analyses due to low overall performance (under 80% accuracy) during the practice session or low overall performance (under 55% accuracy) during the test session.

3.1.2. Procedure

There were 144 trials per task during the practice session. Testing involved 20 blocks with 36 trials per block. Blocks were randomly ordered, with 10 practiced task blocks and 10 novel blocks. There were also five blocks for each CTI (1100 ms, 1900 ms, 2700 ms, or self-paced), randomly assigned to practiced or novel blocks. Each CTI was assigned to a practiced block and, separately, to a novel block at least once per participant. Thus, all CTI and novel/practiced block type combinations were presented to every participant. The same CTI was presented for every trial within a block in order to promote optimal strategic use of the available time to prepare, since this made the available time predictable within a given block (Altmann, 2004). Note that novel tasks could repeat and they repeated 4.8 times on average, with a maximum of 24 repeats for any single task.

3.1.3. Statistical analyses

Statistical analyses were carried out in R (R Development Core Team, 2009). Either repeated-measures ANOVAs or paired *t*-tests were used for comparisons whenever the data were approximately normally distributed. Trials with an RT > 1500 ms (the response cutoff) were discarded from analysis (5.6% of trials). Only accurate trials were used for RT analyses. Self-paced trials were discarded from analysis if the preparation time was either shorter than 250 ms or longer than 8670 ms (two standard deviations above the median); this occurred on 2.7% of the trials. Note that the median was used rather than the mean for identifying outliers since the median is more robust to outliers than the mean.

3.2. Results

Consistent with our expectation, the novel vs. practiced accuracy effect increased more than five-fold from our previous study (Cole et al., 2010) to 11%. Also consistent with our expectation, this "novelty cost" was statistically significant in terms of accuracy (novel: 64%, practiced: 75%, $t(28) = 5.4, p < 0.0001$)[1] (Fig. 2A). Note that, in order to better match the two conditions and focus on pure RITL (i.e., novelty) effects, these analyses included only non-self-paced first encounter trials for the novel tasks, and non-self-paced switch trials for the practiced tasks.

The observation of a novelty cost suggests the presence of a working memory integration process indicative of proactive control during novel task learning.[2] However, another possibility is that novelty costs reflect interference between the novel task procedure and a similar

[1] Novelty costs in RT were also observed (novel: 1024 ms, practiced: 963 ms, $t(28) = 4.3, p = 0.0002$).

[2] We thank an anonymous reviewer for this alternative interpretation of the data.

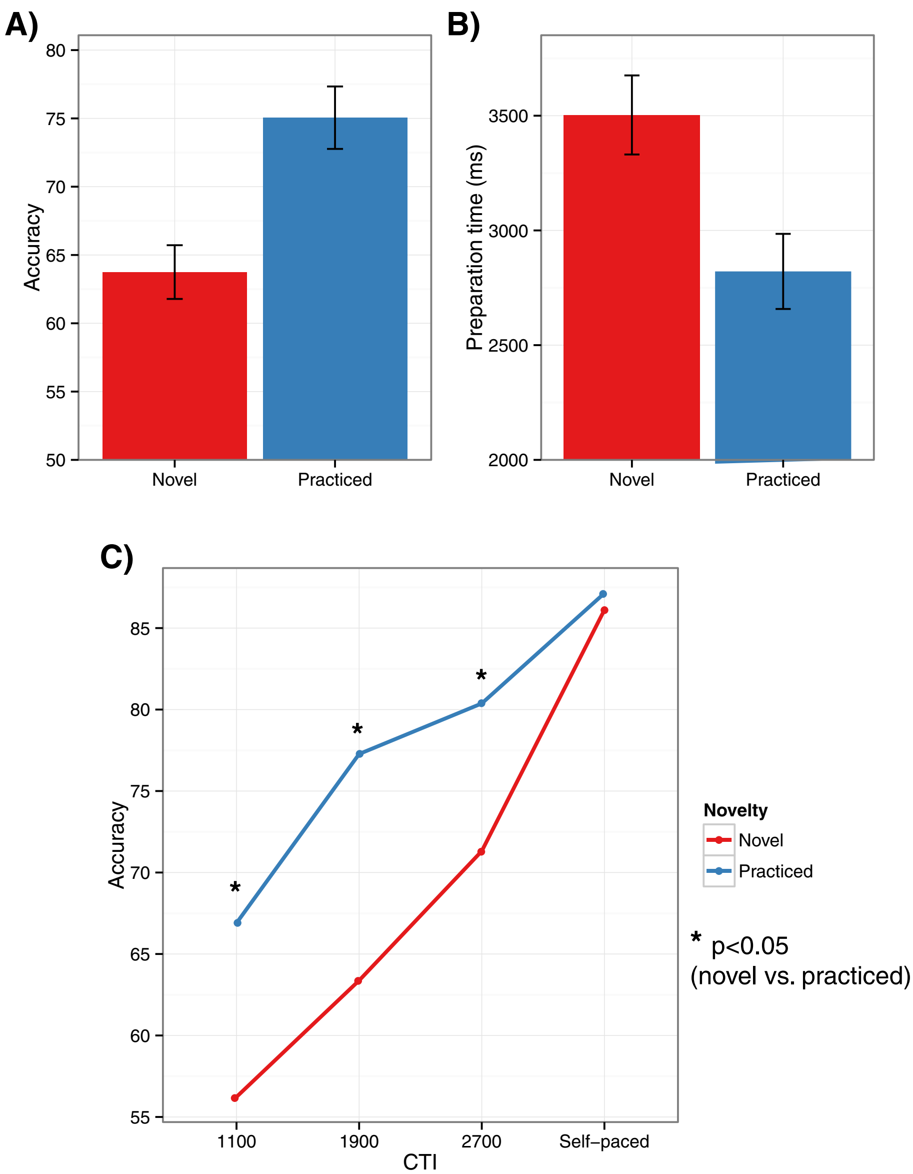

Fig. 2. Novelty cost and preparation time. A) Performance accuracy was consistently higher for practiced tasks than the first encounters of the novel tasks (non-self-paced trials). B) Preparation time was consistently higher for first-encounter novel task trials than for practiced task trials. C) Accuracy was significantly higher for practiced than novel tasks across all cue-target intervals (CTIs) except for self-paced trials. CTIs are indicated in milliseconds from instruction cue onset. Error bars are the across-subject standard errors.

practiced task procedure. For instance, the practiced task SAME-SWEET-LEFTINDEX might interfere more with the novel task SAME-SWEET-RIGHTINDEX (2 overlapping rules) than the novel task SECOND-SWEET-RIGHTMIDDLE (1 overlapping rule). If novelty costs were due to interference we would therefore expect larger novelty costs for the 2-rule-overlap than the 1-rule-overlap condition. Each novel task had either a 2-rule-overlap or a 1-rule-overlap relationship with the practiced tasks. Note that a 0-rule-overlap condition would have been useful for this particular analysis, but would have introduced a practice confound wherein the 0-rule-overlap rules necessarily would have been practiced less than the others. Inconsistent with interference driving novelty costs, accuracy was highly similar for 2-rule-overlap (65%) and 1-rule-overlap (63%) novel tasks ($t(28) = 0.44$, $p = 0.67$). Similar results were obtained for RT: 2-rule-overlap (1018 ms) was similar to 1-rule-overlap (1033 ms) novel tasks ($t(28) = 0.87$, $p = 0.39$). These results suggest differential interference between a given novel task and its most similar practiced task was not responsible for the observed novelty costs.

In an additional analysis, we included self-paced trial blocks, in which participants took as much time as they wanted to prepare for the upcoming trial. This allowed us to test for novelty costs in preparation time, which would suggest that participants proactively utilize the cue-target interval to perform additional processing (e.g., working memory integration) in preparation for novel task performance. First, we found that the accuracy novelty cost essentially disappeared during self-paced trials (novel: 86%, practiced: 87%, $t(28) = 0.6$, $p = 0.6$), suggesting participants strategically eliminated the novelty cost.[3] Consistent with strategic elimination of accuracy-based novelty costs, participants had significantly longer preparation time (accurate trials only) for novel than practiced trials (novel: 3503 ms, practiced: 2821 ms, $t(28) = 5.8$, $p < 0.0001$) (Fig. 2B). This was true even when restricting preparation times to the range included in the CTI manipulation (see below; 1100 ms to 2700 ms). Specifically, novel: 2160 ms, practiced: 1943 ms, $t(26) = 4.7$, $p < 0.0001$. Overall these results suggest participants were successful in strategically applying proactive control to reduce novelty costs on performance.

Among the non-self-paced trials, CTI varied by trial block, such that participants could perform blocks with either 1100 ms, 1900 ms, or 2700 ms CTIs (times from cue onset to target onset). We used this manipulation to test whether increasing the amount of available preparation affected performance. We found a large main effect of CTI on

[3] Note, however, that the RT novelty cost was not eliminated (novel: 955 ms, practiced: 910 ms, $t(29) = 2.6$, $p = 0.02$).

overall accuracy ($F(2,56) = 18$, $p < 0.0001$) and RT ($F(2,56) = 25$, $p < 0.0001$) (Fig. 2C). Yet novelty costs were not impacted by CTI, as indicated by a non-significant novelty (novel/practiced) × CTI (1100, 1900, 2700) interaction ($F(2,56) = 1.2$, $p = 0.3$).[4] This suggests that although providing additional time to prepare was generally beneficial (in terms of improving task performance), it did not confer any preferential benefits to novel tasks.

However, the self-paced effect above suggests that we may have simply not given participants enough time to prepare in order to overcome the accuracy novelty cost. Consistent with this, the accuracy novelty cost was still strong even with the longest non-self-paced CTI of 2700 ms (novel: 72%, practiced: 80%, $t(28) = 2.3$, $p = 0.03$), but when the self-paced condition was added as an additional level of CTI (now including 4 levels: 1100 ms, 1900 ms, 2700 ms, and "self-paced"), a significant novelty × CTI interaction did emerge $F(3,84) = 3.2$, $p = 0.03$. Also consistent with this, when we split the self-paced trials into two separate subsets, one with preparation times in the range of the CTI manipulation (short-preparation time: 1100 ms to 2700 ms) and one with preparation times above that range (i.e., long-preparation time: > 2700 msec), significant differences emerged between them. Specifically, accuracy was significantly higher on the long-preparation time novel trials compared to short-preparation time novel trials (long:91%, short: 80%; $t(25) = 2.5$, $p = 0.025$). This was not the case for the practiced trials (long: 87%, short: 89%; $t(28) = 0.810$, $p = 0.430$). Verifying that the two conditions were affected differentially by preparation time, the novelty (novel, practiced) × preparation time (short, long) interaction was significant $F(1,25) = 5.20$, $p = 0.031$. Together these results suggest that having additional time to prepare beyond 2700 ms was disproportionately helpful for novel relative to practiced tasks, consistent with additional proactive control being necessary for novel instructed task performance.

Also consistent with a disproportionate effect of proactive control on novel relative to practiced tasks, we found that subjects that had larger self-paced preparation times had better novel (but not practiced) task accuracies. Specifically, there was a significant positive correlation between novel task preparation time and novel task accuracy across subjects ($r = 0.39$, $p = 0.036$; Spearman rank rho = 0.36, $p = 0.058$) (Fig. 3A). There was a significant difference (Silver, Hittner, & May, 2004) between the preparation time-accuracy correlation for novel tasks ($r = 0.39$) and practiced tasks ($r = -0.24$): $z = 2.18$, $p = 0.029$. This suggests that while there was a trend toward long preparation time being associated with worse performance during practice trials (e.g., due to general distraction or lack of motivation across both preparation and execution of practiced tasks), this trend reversed for novel tasks such that longer preparation times promoted more accurate performance. The finding that longer preparation time (associated with more proactive control) increased performance accuracy on novel tasks is consistent with the hypothesis that proactive control plays a particularly important role in novel task preparation.

4. Experiment 2

Experiment 1 involved a variety of manipulations that were extraneous to testing for the predicted novelty cost effect. We therefore conducted Experiment 2 with only a single manipulation to replicate but also isolate the novelty cost under more stringent conditions. In particular, Experiment 2 involved only a single CTI (1900 ms), no sequential task repeats (previously included in case we wanted to test for task switching effects), and intermixing of novel and practiced trials within every block. This final change was included in order to rule out the smaller number of task-to-task switch combinations occurring among the 4 practiced tasks (relative to the 60 novel tasks) as a possible confound for novelty costs. Specifically, in Experiment 1 there were $60*60–60 = 3540$ possible task-to-task switch combinations for the novel task blocks, but only $4*4–4 = 12$ possible task-to-task switch combinations for the practiced task blocks. Experiment 2 involved an equal number of potential task-to-task switch combinations across novel and practiced task conditions.

4.1. Methods

4.1.1. Participants

Twenty participants (13 female, aged 18 to 29, median age of 20.5) took part in this experiment. This sample size provided Power > 0.80 to detect Dz > 0.66. Four participants were removed from the analyses due to low overall performance (under 80% accuracy) during the practice session or low overall performance (under 55% accuracy) during the test session.

4.1.2. Procedure

The number of blocks, practice, etc. were all identical to those of Experiment 1 except that this experiment involved a single CTI (1900 ms), and unlike in Experiment 1, novel and practiced trials were intermixed within a block. Novel tasks repeated 4 times on average, with a maximum of 15 repeats for any single task.

4.1.3. Statistical analyses

As in Experiment 1, trials with an RT > 1500 ms (the response cutoff) were discarded from analysis (1.5% of trials). Only accurate trials were used for RT analyses.

4.2. Results

The results replicated the robust novelty cost observed in Experiment 1, even under more stringent conditions (novel: 70%, practiced: 84%, $t(19) = 8.3$, $p < 0.0001$)[5] (Fig. 4). Note that this pattern remained present when all novel trials (not just the first encounters of each task) were included in the analysis: accuracy (novel: 75%, practiced: 84%, $t(19) = 6.2$, $p < 0.0001$). The decrease in effect size when including all novel trials was likely driven by the small amount of practice with subsequent encounters of each novel task. Overall these results confirm the robustness of the novelty cost effect, while also indicating that the complex manipulations and the unnecessary differences between novel and practiced tasks present in Experiment 1 did not drive the observed effects.

5. Experiment 3

The self-paced condition in Experiment 1 provided an important signature of attempts to eliminate novelty costs. However, Experiment 1 included only a small number of self-paced trials (and Experiment 2 included none), limiting our ability to more comprehensively test hypotheses related to the self-paced condition. Experiment 3 therefore included self-paced trials exclusively, increasing statistical power for detecting self-paced effects. Further, Experiment 3 retained the improvements in experimental design from Experiment 2, including the lack of sequential repeats and intermixing of novel and practiced trials.

5.1. Methods

5.1.1. Participants

Fifty-nine participants took part in this experiment. Six participants did not complete both portions of the study because the session ran past

[4] A similar pattern was observed in RT ($F(2,56) = 0.1$, $p = 0.900$).

[5] Similar effects were found in RT: first trial only (novel: 976 ms, practiced: 888 ms, $t(19) = 5.6$, $p < 0.0001$), all trials (novel: 948 ms, practiced: 888 ms, $t(19) = 6.4$, $p < 0.0001$).

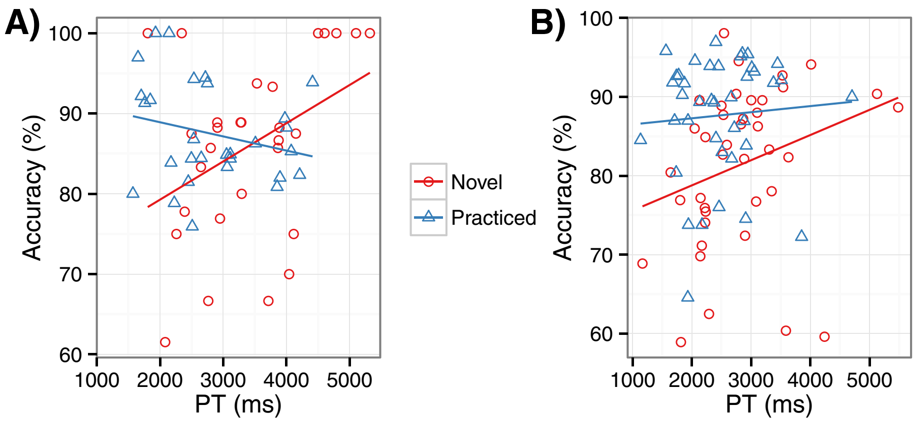

Fig. 3. Individuals with longer preparation times (PTs) for novel tasks were more accurate. A) Experiment 1 PT by performance accuracy plot, with regression line for novel and practiced tasks fit separately. Each point represents a single subject. There was a significant positive relationship between novel PT and novel accuracy ($r = 0.39$, $p = 0.036$; Spearman rank rho = 0.36, $p = 0.058$). B) Experiment 3 PT by performance accuracy plot, with regression line for novel and practiced tasks fit separately. Each point represents a single subject. There was again a significant positive relationship between novel PT and novel accuracy ($r = 0.28$, $p = 0.08$; Spearman rank rho = 0.36, $p = 0.02$).

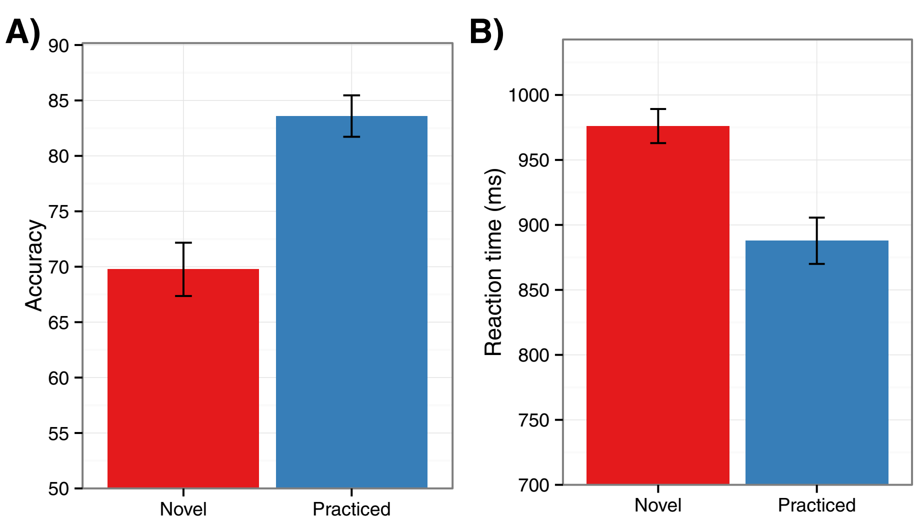

Fig. 4. Experiment 2: Replicating novelty cost effects. A) As in Experiment 1, practiced task trials were consistently more accurate than novel task trials. B) Again replicating Experiment 1, participants responded consistently faster for practiced task trials than novel task trials. Error bars are the across-subject standard errors.

the anticipated duration (given that it was self-paced) and those participants chose to not complete the session. Thirteen participants were removed from the analyses due to low performance during the practice session (failure to reach 80% accuracy in any block) or low performance during the test session (under 55% overall accuracy). Thus, 40 participants (28 female, aged 18 to 23, median age of 19) were included in the study, with this sample size providing Power > 0.80 to detect Dz > 0.41 with an individual differences design.

5.1.2. Procedure

There were 54 trials per task during the practice session. There were 10 task blocks during the test session, with 36 trials per block. Novel tasks repeated 3 times on average, with a maximum of 6 repeats for any single task. Analyses were conducted using only the first encounters for the novel tasks and, separately, when also including non-sequential repeats for the novel tasks, with similar results for both types of analyses (see Results). All RT values over 1500 ms were excluded from analysis (3.54% of trials). Trials that were over 2.5 standard deviations from the individual subject z-normed preparation time and RT values were excluded from analysis (2.97% of trials). For the trial-by-trial analysis the preparation time values, overall individual differences in preparation time were removed by z-scoring each subject's preparation times. Unlike the other experiments, in Experiment 3 the preparatory period of every trial was self-paced.

5.2. Results

As in the previous experiments, a novelty cost was observed (novel: 83.4%, practiced: 87.7%, $t(39) = 6.38$, $p < 0.0001$).[6] Note that unlike Experiment 1, the novelty cost was present even though all trials were self-paced. The preparation time novelty cost (longer preparation for novel tasks) observed in Experiment 1 was also replicated (novel: 2687 ms, practiced: 2514 ms, $t(39) = 4.53$, $p < 0.0001$).

We next tested if this increased preparation time on novel task trials improved task performance (Fig. 3B), focusing on first-encounter novel trials as in Experiment 1. Supporting this conclusion and replicating Experiment 1, there was a marginally significant correlation between novel accuracy and novel preparation time ($r = 0.28$, $p = 0.08$; Spearman rank rho = 0.36, $p = 0.02$). Again consistent with Experiment 1, there was an increase in the preparation time-accuracy correlation for novel tasks ($r = 0.28$) relative to practiced tasks ($r = 0.07$, $p = 0.67$), though this difference was not significant (Silver, Hittner, & May, 2004): z = 1.10, $p = 0.27$. In order to make an inference across both Experiments 1 and 3, we performed a meta-analysis across them using Fisher's combined probability test (Rosenthal, 1978) (as implemented in the "metap" R package). The combined p-value for the novel preparation time-accuracy Pearson correlations (combining $p = 0.036$ for Experiment 1 and $p = 0.08$ for Experiment 3) was $p = 0.02$ (chi-squared = 12, df = 4). Similarly, the combined p-value for the novel preparation time-accuracy Spearman rank correlations (combining $p = 0.058$ for Experiment 1 and $p = 0.02$ for Experiment 3) was $p = 0.009$ (chi-squared = 14, df = 4). Finally, the combined p-value for the novel vs. practiced Pearson correlation difference

[6] In RT as well (novel: 904 ms, practiced: 883 ms, $t(39) = 3.51$, $p = 0.001$).

(combining $p = 0.029$ for Experiment 1 and $p = 0.27$ for Experiment 3) was $p = 0.046$ (chi-squared = 9.7, df = 4). These results suggest there was a significant ($p < 0.05$) positive preparation time-accuracy correlation for novel tasks that was stronger than for practiced tasks across Experiments 1 and 3.

The effects of novelty on preparation were present even when restricting analyses to the first trial performed of each novel task (novel: 81%, practiced: 87%, $t(39) = 3.62$, $p = 0.0008$).[7] It was also found that there was an increase in preparation time (novel: 2853 ms, practiced: 2640 ms, $t(39) = 4.37$, $p < 0.0001$), which is consistent with strategic use of additional proactive control processes (e.g., working memory integration) for completely novel tasks. Similar effects were seen when comparing the first novel encounters to subsequent novel encounters. Across participants, there was a reliable effect of encounter, in that preparation time for first novel task encounters was significantly greater than preparation time for subsequent novel task encounters (first: 2853 ms, post-first: 2598 ms, $t(39) = 3.03$, $p = 0.004$).[8] The difference between novel first and novel post-first encounter accuracy did not reach significance (first: 81%, post first: 84%, $t(39) = 1.62$, $p = 0.11$), suggesting that the accuracy novelty cost remained robust across encounters. These results indicate that it is possible for novelty costs to be reduced even after a small number of encounters with novel tasks, supporting the utility of paradigms such as PRO, which are unique in having many first encounter trials.

We further capitalized on the increased number of self-paced trials relative to Experiment 1, in order to more comprehensively test the relationship between preparation time and performance accuracy at the single-trial level. Specifically, we hypothesized that trial-by-trial fluctuation in preparation time would be positively correlated with trial-by-trial fluctuations in performance accuracy selectively when the task were novel (i.e., first encounter). To examine the relationship between preparation time and accuracy at the single-trial level, we utilized a mixed-effects logistic regression analysis, since it has recently been argued that this analysis approach is the most powerful and appropriate way to control for between-participant variability, while also accounting for nonlinearities present in proportional data (i.e., 0–100% accuracy data) (Dixon, 2008; T. Florian Jaeger, 2008). The analysis was implemented with the mixed linear modeling package lmer in R statistical software (Bates, Mächler, Bolker, & Walker, 2014). The model examined whether single-trial accuracy could be predicted by preparation time, and further whether this interacted with trial type (novel vs. practiced). Because only the first encounter was used for each of the novel tasks, this yielded 60 novel trials per participant. To match the practiced and novel conditions, the first 15 encounters with the four practiced tasks were used (i.e., $4 \times 15 = 60$ total practiced trials). Because the mean and variance of preparation times differed strongly across participants (see Fig. 3B), the data were z-normalized prior to analysis (i.e., referenced to each subject's mean preparation time and standard deviation).[9]

The results of this analysis indicated a significant fixed effect for trial type (novel vs. practiced), indicating the expected novelty cost (estimate: 0.47; standard error: 0.12, Z = 3.88, $p < 0.001$), and also a marginally significant positive effect for normalized preparation time, indicating that increased preparation time was associated with higher accuracy (estimate: 0.117; standard error: 0.06; Z = 1.95; $p = 0.051$). Most critically, the trial type × preparation time interaction was also significant (estimate: 0.20; standard error: 0.09; Z = 2.24; $p = 0.025$), indicating that the preparation time effect was significantly stronger for novel than practiced trials.

To further investigate the source of this interaction, we examined each trial type separately. On novel trials, preparation time was positively associated with accuracy (estimate: 0.12; standard error: 0.06; Z = 2.01; $p = 0.04$), but for practiced trials, there was a negative, though non-significant, preparation time effect (estimate: −0.08; standard error: 0.065; z-value: −1.25; $p = 0.21$). Together, these results suggest that trials with longer-than-average preparation times were associated with reduced novelty cost, whereas trials with shorter-than-average preparation times were associated with increased novelty cost. This pattern is illustrated in Fig. 5, which plots estimated accuracy (reconverted from odds ratio to proportion correct, for descriptive ease) against normalized preparation time on novel and practiced trials. Together, these results replicate and extend the findings from Experiment 1, by demonstrating more systematically the consistent positive relationship between preparation time and accuracy, and moreover that this positive relationship was selective to novel trials.

6. General discussion

Using a recently developed RITL paradigm that includes a well-matched practice control condition (Cole et al., 2010) we observed the presence of robust novelty costs on task performance. These effects were largest for the first encounters with novel tasks, demonstrating the importance of cognitive paradigms, such as the PRO paradigm used here, that include many novel tasks. Results were replicated with various types of preparatory periods (CTI manipulations and self-paced preparation) and in independent groups of participants.

The presence of novelty costs across various CTIs seems to suggest that – unlike switch costs (Monsell, 2003) – novelty costs are not reduced when CTI increases. However, we also found that novelty costs were substantially reduced (to non-significance in Experiment 1) when the preparatory delay was self-paced. This suggests self-pacing may have allowed participants to select the optimal amount of preparation time for task performance. Additionally, self-pacing may have reduced cognitive demands by reducing the need to monitor the passage of time (due to anticipation of the end of the CTI). Notably, however, participants took approximately 3500 ms on average for novel task preparation time, which was longer than our longest CTI (2700 ms). Further, novelty costs were found for self-paced trials with preparation times under 2700 ms, but not when preparation times were above 2700 ms. This suggests that longer CTIs may have resulted in meaningful reductions in novelty costs. It will be important for future research to include longer CTIs to adjudicate between the effects of self-paced vs. experimentally controlled preparation time length on novelty costs. This question was beyond the scope of the present study, given our focus on establishing the presence of novelty costs and the role of proactive control processes in reducing that cost. In other words, we did not define proactive control as being necessarily isolated to self-paced scenarios, leaving open the possibility that similar novelty costs (and associated proactive control processes) may be identified with longer CTIs.

Self-paced results differed somewhat between Experiments 1 and 3. Most notably, novelty costs essentially disappeared during self-paced trials during Experiment 1, while they remained present during Experiment 3. This discrepancy between the experiments could have been driven by a number of factors. Perhaps most prominent was the mixing of novel and practiced task trials within each block during Experiment 3; novel and practiced tasks were in separate blocks in Experiment 1. This may have led to a change in strategy for novel tasks in Experiment 3, in which preparation time was not used as often to improve task performance, given that increased preparation time appeared to not be helpful for practiced tasks. However, this is a factor

[7] However, the RT effect was not significant in this analysis (novel: 922 ms and practiced: 907 ms, $t(39) = 1.55$, $p = 0.13$).

[8] The post-first trial effect on preparation time may have accounted for the reduction in the RT novelty cost (first: 922 ms, post first: 894 ms, $t(39) = 2.24$, $p = 0.03$).

[9] The model equation was the following: glmer(accuracy ~ zPT * taskType + (taskType | participants, family = "binomial"). This model expresses the effects of predictor variables in terms of odds ratios. The model also assumes a maximal random effects structure, following recent suggestions in the literature (Barr, 2013), in which each subject is allowed a random intercept (baseline accuracy), a random slope for the trial type effect, and potential interactions between intercept and slope.

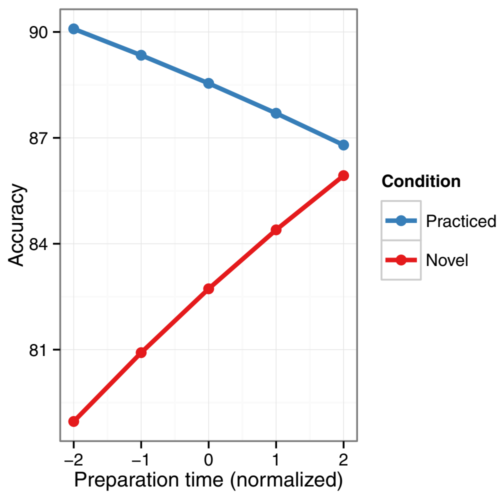

Fig. 5. Additional preparation time facilitates performance for novel tasks only. Illustrating the logistic regression results, greater preparation time is associated with greater novel-task trial accuracy. In contrast, there is a trend toward greater preparation time being associated with lower practiced-task trial accuracy. It may have been the case that longer preparation time was mostly due to trial-to-trial variability in distraction or motivation during practiced task trials (lowering accuracy), while during novel task trials the additional preparation time was likely utilized by proactive control processes to facilitate performance. Note that these are trial-by-trial effects (with overall individual differences removed), unlike the results illustrated in Fig. 3B.

that needs to be explored more directly in future studies. Another difference between Experiments 1 and 3 was the average preparation time for novel tasks: 3503 ms for Experiment 1 and 2687 ms for Experiment 3. We found that preparation times above 2700 ms were associated with significantly better performance on novel trials, suggesting participants in Experiment 3 (with an average preparation time below 2700 ms) may have not given themselves enough time to perform optimally on the novel tasks. Despite these differences, the self-paced results demonstrated two effects that were reliable across the experiments: 1) that participants know to prepare longer on novel task trials compared to practiced task trials (whether in mixed or blocked conditions), and 2) that longer preparation time was associated with higher performance accuracy for novel tasks only.

Overall, the present results suggest that novelty costs reflect the additional preparatory control demands associated with the requirement to form new task sets based on instructional cues. This is distinct from task-set retrieval, which prior work suggests underlies practiced task preparation (Cole et al., 2010; Mayr & Kliegl, 2000). Consistent with a distinction between proactive versus reactive control (Braver, 2012; Braver et al., 2007; Cole et al., 2017), novel task preparation benefitted from additional (proactive) preparation time (Fig. 5), whereas practiced task preparation did not (consistent with being reactive, or at least requiring less proactive resources). This shift from high to low proactive control with practice may parallel the distinction between controlled and automatic processing – in which additional practice reduces the need for control as automatic associations are built (Schneider & Chein, 2003; Schneider & Shiffrin, 1977). In the case of classical cued task-switching, it is likely that only a subset of relevant processes – such as the association between presentation of the task cue and the practiced task representation – become automatic with practice, while other processes still require cognitive control (e.g., initiating task-set retrieval). However, when task switching with well-practiced tasks, the timing of control initiation is more flexible, such that it might be initiated following target presentation (i.e., in a reactive manner), rather than after instructional cues. An important direction for further research will be to examine the potential reduction in proactive control that may occur during cued task-switching as tasks transition from being novel to highly practiced across successive encounters. This may be particularly relevant in the case of cued task-switching, when full development of automaticity is likely not possible, given the high cognitive-control demands present even when switching among highly practiced tasks (but see Schneider & Logan, 2005).

Proactive preparation for the complex novel tasks presented here likely involves multiple cognitive processes. These may include task rule retrieval from long-term memory, activation and maintenance of task rule semantics, working memory integration of task rules into a novel task procedure, and maintenance of the integrated task set. It will be important for future research to isolate and characterize these potential sub-processes within the larger proactive control construct. In particular, the complexity of the task sets used here are consistent with many real-world novel tasks, such as learning how to use a new smartphone app. Like the PRO paradigm, such real-world tasks involve abstract rules tied to concrete motor actions and reuse of abstract rules across task contexts (e.g., rules learned for previously "practiced" smartphone apps). Unlike more concrete novel tasks, the complex tasks learned here likely do not involve preparation of stimulus-response mappings, since so many such mappings are possible for any given task. A natural direction for future research would be to examine the effects of task-rule complexity and abstraction on preparatory processes.

The sensitivity of self-paced preparation time to novelty suggests the novelty cost could be under volitional control. Moreover, one speculative interpretation is that, under RITL conditions, participants have greater meta-cognitive awareness regarding their preparatory readiness. This is in contrast to findings related to the magnitude of switch costs during cued task-switching with highly-practiced tasks, as these were found to be unrelated to self-paced preparation time (Ruge & Braver, 2007). Specifically, previous work found that preparation time is not longer for switch than repeat trials, and that there was no trial-by-trial correspondence between preparation time and switch cost (Meiran et al., 2002). This suggests the possibility that when task-sets are retrieved from long-term memory, rather than formed in working memory, there is reduced volitional control over the preparatory process – which is also consistent with a shift away from proactive control and toward greater automaticity with practice.

Note, however, that although the self-paced novel task effects suggest that participants can tell when they are ready, we do not claim that this implies they necessarily have direct conscious access to their current readiness state. Alternatively, they can rely on some heuristics to estimate the time it would take them to be ready. One conceivable heuristic is the number of elements that need to be combined. This strategy in itself would generate longer preparation times for novel rules (in which three elements need to combine) than for familiar rules that can be retrieved as a unit. It will be important for future research to investigate these possibilities.

Two findings from the current study suggest that proactive control during novel task-set formation may vary across individuals and trials. Specifically, the between-subjects correlation observed in Experiments 1 and 3 indicates that participants varied in how long they were willing to prepare on self-paced trials, and that this variation was systematically related to their novel task performance. Thus, one possible interpretation of this finding is that individuals may differ in their ability to access their state of readiness, with individuals exhibiting greater access being willing to wait longer. Alternatively, it may be the case that other factors govern willingness to prepare, for example, competing pressures against exerting cognitive effort (Shenhav, Botvinick, & Cohen, 2013; Westbrook & Braver, 2015), or performing with greater urgency (i.e., impulsively), or whether preparation is corrupted by transient periods of mind-wandering. Support for these factors come from the fact that preparation times appeared to vary systematically not only across individuals, but also within individuals in terms of trial-by-trial fluctuations. If other factors, such as effort costs, urgency, and mind-wandering also fluctuate on a trial-by-trial basis (as seems likely) this could explain observed trial-by-trial variability in preparation time and its relationship to task performance. Likewise, it could explain the weak negative relationship between preparation time and performance for practiced trials (e.g., if effort costs and mind wandering are dominant factors driving the relationship in non-RITL contexts). Moreover, if participants were not fully able to monitor these competing factors and their resolution, then it might be the case that preparation times, while still under volitional control, might not be a transparent reflection of the individuals' direct access to readiness state. As this discussion makes clear, the current work only scratches the surfaces of this fascinating issue, but does highlight the potential utility of RITL task paradigms and self-paced preparation as a means to investigate issues related to volitional control and task readiness.

Increased automaticity with practice may appear to be inconsistent with recent RITL results indicating that novel tasks are associated with reflexive (i.e., automatic-like) task performance (Cohen-Kdoshay & Meiran, 2009; Meiran, Pereg, Kessler, Cole, & Braver, 2015; Vandierendonck, Demanet, Liefooghe, & Verbruggen, 2012). In particular, it was shown that while waiting to carry out a novel task, interference was observed in responses to task-irrelevant stimuli that shared features with the task, suggesting an automatic influence of the prepared task in triggering action tendencies (Cohen-Kdoshay & Meiran, 2009; Hartstra et al., 2011; Meiran et al., 2015). However, this automatic influence pattern is actually quite compatible with a proactive control account, since proactive control requires that task-relevant information be actively maintained in a highly accessible form where it can bias on-going processing (Cole et al., 2017). If novel tasks are most likely to be represented and maintained in this format, then it would be expected that it should produce top-down attentional and action biases that would have the potential to interfere with ongoing performance. Thus, a counter-intuitive prediction of the proactive account of RITL is that, when participants are waiting to perform an instructed novel task, this waiting period should produce stronger biasing effects and observed interference than when they are instructed to wait before performing a well-practiced task (Cole et al., 2017). Our current results add to this prediction that these novelty-based interference (i.e., intention-based reflexivity) effects will be strongest when participants are allowed a period of self-paced preparation, which would enable task-set formation to be completed, before beginning the waiting period. This is an important direction for future research.

The present study provides evidence that RITL can be quantified using several distinct metrics, and that these metrics differ from a well-controlled practiced task condition. In particular, we quantified novelty costs in terms of both accuracy and preparation time (and RT as well), observing both overall and trial-by-trial effects. Importantly, we found that RITL effects were most prominent for first encounters with tasks, suggesting RITL should be primarily investigated based on first encounters. The PRO paradigm and several other recently developed paradigms make statistical analysis of first encounters possible, by including many novel tasks per subject (Cohen-Kdoshay & Meiran, 2009; Cole et al., 2010; Hartstra et al., 2011; Ruge & Wolfensteller, 2010; Stocco, Lebiere, O'Reilly, & Anderson, 2012). Unlike the PRO paradigm, however, most of these paradigms (including those used to demonstrate intention-based reflexivity effects) involve simple visual-motor tasks. It will be important for future studies to characterize the differences and similarities of RITL involving such simple associative tasks and the more complex and abstract tasks investigated with the PRO paradigm.

We found evidence that RITL is especially dependent on proactive control. The neural mechanisms that enable proactive control processes to support RITL have also become a topic of increased research interest. Recent neuroimaging findings have demonstrated that the rule representations used during practiced tasks are reused during novel tasks (Cole, Etzel, Zacks, Schneider, & Braver, 2011; Cole et al., 2013b; Cole et al., 2016). This suggests RITL is made possible in part based on transfer of previously learned task rules into novel contexts, such that each task does not need to be relearned from scratch but can benefit from previous practice. Importantly, however, little work has been done to determine what is unique about RITL relative to practiced task preparation. One study (using the PRO paradigm) found evidence for a hierarchy within lateral prefrontal cortex (LPFC), in which novel and practiced tasks involved activity flow in opposite directions within the hierarchy (Cole et al., 2010). This was thought to reflect the transfer of lower-level rules represented in posterior LPFC into an integrated task representation in anterior LPFC during RITL. In contrast, this order was reversed during practiced task preparation, possibly because the integrated task representation would be recalled first, followed by "unpacking" of that representation into its constituent rules in posterior cortex. Nevertheless, these issues need to be addressed more systematically, for example by comparing the more complex PRO task with simpler RITL paradigms involving novel stimulus-response associations. Also interesting could be the use of motivational incentives during novel and practiced task preparation, given the possibility that the additional cognitive control demands, and potentially also volitional cognitive effort engagement during RITL, would increase the effect of incentives on performance (relative to practiced task preparation). Such an effect would further solidify the conclusion that RITL involves additional demands on volitional proactive control.

In conclusion, the current study reveals the distinctive control processes associated with RITL, by demonstrating that switching to perform an instructed novel task involves a unique novelty cost on behavioral performance that is most apparent in accuracy, but also in preparation time. This cost profile clearly distinguishes novelty costs from the standard task-switch costs that are found when individuals switch between well-practiced tasks. Although novelty costs were found to be highly robust across three separate studies, our data also clearly show that they reflect increased demands on proactive cognitive control, as they were strongly reduced when: a) individuals were allowed to self-regulate their preparation time; and b) they allotted sufficient time for preparation on a given trial. In providing a new experimental window into RITL, the current data highlight the critical role of proactive cognitive control in the performance of instructed novel tasks, and open the door to further investigations into the neurocognitive mechanisms that enable the core process of task-set formation.

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Conflict of Interest

None to report.

Ethical approval

All procedures performed in studies involving human participants were in accordance with the ethical standards of the institutional and/or national research committee and with the 1964 Helsinki declaration and its later amendments or comparable ethical standards.

Informed consent

Informed consent was obtained from all individual participants included in the study.

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