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The Shaping of Cognitive Control Based on the Adaptive Weighting of Expectations and Experience

Jihyun Suh and Julie M. Bugg
Department of Psychological and Brain Sciences, Washington University in St. Louis

Existing approaches in the literature on cognitive control in conflict tasks almost exclusively target the outcome of control (by comparing mean congruency effects) and not the processes that shape control. These approaches are limited in addressing a current theoretical issue—what contribution does learning make to adjustments in cognitive control? In the present study, we evaluated an alternative approach by reanalyzing existing data sets using generalized linear mixed models that enabled us to examine trial-level changes in control within abbreviated lists that varied in theoretically significant ways (e.g., probability of conflict; presence vs. absence of a precue). For the first time, this allowed us to characterize (a) the trial-by-trial signature of experience-based processes that support control as a list unfolds under various conditions and (b) how explicit precues conveying the expected probability of conflict within a list influence control learning. This approach uncovered novel theoretical insights: First, slopes representing control learning varied depending on whether a cue was available or not suggesting that explicit expectations about conflict affected whether and the rate at which control learning occurred; and second, this pattern was modulated by task demands and incentives. Additionally, analyses revealed a cue-induced heightening of control in high conflict likelihood lists that mean level analyses had failed to capture. The present study showed how control is shaped by the adaptive weighting of experience and expectations on a trial-by-trial basis and demonstrated the utility of a novel method for revealing the contributions of learning to control, and modulation of learning via precues.

Keywords: attention, cognitive control, conflict monitoring, learning, Stroop

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Attentional conflicts arise when goal-irrelevant information competes with goal-relevant information to gain attentional priority. For example, an eye-catching billboard could cause attentional conflicts, which may have some drivers mistakenly pass a desired exit ramp. To minimize attentional conflicts from unwanted information (e.g., billboards), cognitive control is required to prioritize goal-oriented attentional allocation (e.g., searching for the exit number). Control is adaptive in that it rapidly adjusts attention to changing contexts and shifting goals when environmental changes are detected or internal goals are updated.

The adaptive nature of cognitive control is exemplified by a well-established pattern in the literature known as the list-wide proportion congruence effect (LWPCE), which has been observed in a variety of conflict tasks such as color-word Stroop (e.g., Kane & Engle, 2003; Lindsay & Jacoby, 1994; Logan & Zbrodoff, 1979; Lowe & Mitterer, 1982; West & Baylis, 1998). The LWPCE is the reduction in the magnitude of the Stroop effect in mostly incongruent (MI) compared with mostly congruent (MC) lists. Although there has been debate about the precise mechanisms underlying the LWPCE (see Schmidt & Besner, 2008; for a contingency learning account; see Schmidt, 2013; for a temporal learning account; but see Cohen-Shikora et al., 2019; Spinelli & Lupker, 2020), there is clear evidence supporting an attentional control account which posits that the degree to which the word and color are processed is globally adjusted based on the overall likelihood of encountering conflict (for evidence from confound-minimized designs, see Bugg, 2014; Bugg & Chanani, 2011; Bugg & Gonthier, 2020; Gonthier et al., 2016; Hutchison, 2011; Spinelli et al., 2019; for evidence in abbreviated lists, see Cohen-Shikora et al., 2018; Colvett et al., 2020; for review, see Braem et al., 2019; Bugg, 2012). In MI lists, the word dimension is processed to a lesser degree relative to MC lists (Melara & Algom, 2003).

A key unanswered question is what processes bring about different attentional control settings in each list. Often it has been assumed that, as participants complete more trials (e.g., MC or MI) in a list, they develop an explicit idea about a given conflict probability which leads to a strategic (e.g., Lowe & Mitterer, 1982) and/or anticipatory adjustment in attentional control, aligning well with a proactive account of control (Braver et al., 2007). However, Blais

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Jihyun Suh https://orcid.org/0000-0001-6528-1489
Julie M. Bugg https://orcid.org/0000-0002-0969-186X
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Correspondence concerning this article should be addressed to Jihyun Suh, Department of Psychological and Brain Sciences, Washington University in St. Louis, Campus Box 1125, St. Louis, MO 63130, United States. Email: jihyun.suh@wustl.edu

et al. (2012) challenged this notion by showing that emergent awareness of conflict proportions is not a main contributor to the LWPCE. In their study, participants completed multiple lists of the color-word Stroop task over several days where LWPC varied from 5% to 95% between lists. At the end of each list, participants were asked to estimate the proportion congruence of the list that they just completed. One important finding was that participants were generally poor at providing accurate estimates, suggesting that awareness of the conflict probability did not tend to emerge with experience. Most interestingly for present purposes, the estimates of proportion congruence did not correlate with the size of the LWPCE. In other words, participants who were more aware of the proportions did not exhibit larger LWPCEs on average as the proactive account would suppose. This finding directly challenged a "strategic" interpretation of the LWPCE (i.e., that participants intentionally assign differential weights to the color and word dimensions across lists) and indicated instead that the modulations of the Stroop effect across lists might be based on an implicit learning mechanism guided by experience. Hereafter we will refer to such a mechanism as *experience-driven control*. That is, the experience of encountering relatively more or less incongruent trials within a list, and thereby learning about the probability of encountering each trial type, leads to different attentional settings.[1]

The findings of Blais et al. (2012) did not, however, refute the possibility that individuals could strategically adjust attention based on explicit knowledge of the PC of a list, as manipulated for example via precues. Indeed, some studies have demonstrated that explicitly provided information about upcoming conflict alone can induce attentional control adjustments and thereby produce LWPCE patterns (Bugg et al., 2015; Entel et al., 2014; for a related but mixed set of findings using trial-by-trial precues, see Bugg & Smallwood, 2016; Hutchison et al., 2016; Jiménez et al., 2020; Wühr & Kunde, 2008). For example, Entel et al. (2014) showed that the Stroop effect was greater when participants were instructed that most of the upcoming trials in a list would be congruent but smaller when participants were informed that most of the upcoming trials would be incongruent although the actual proportion congruency was 50% regardless of the instruction. In such cases modulations of the Stroop effect across lists are based on explicit knowledge about an upcoming event (e.g., a list with a low vs. high conflict probability), which we will refer to as *expectation-driven control*.

Role of Learning in Cognitive Control

The foundation of experience-driven control, including the heightening of control (i.e., focusing more on the color and less on the word dimension in a Stroop task) and the relaxation of control (i.e., focusing more on the word dimension) in response to frequent or infrequent experiences with conflict, respectively, is learning (see, for example, Botvinick et al., 2001; see Verguts & Notebaert, 2008; for a Hebbian learning account of control; see Jiménez & Méndez, 2013; Schlaghecken & Martini, 2012; for evidence that the absence of conflict can also serve as a signal for learning and thereby control adjustments). In particular, attention is adjusted based on one's cumulative conflict experiences within a context as goals become bound with features of the task via associative learning networks (Abrahamse et al., 2016; see also Egner, 2014), a process referred to recently as context-control learning (Chiu & Egner, 2019).[2] In contrast, expectation-driven control, particularly as investigated via explicit precues, need not involve learning about conflict through experience because the information that is used to guide adjustments in attention is explicitly provided in advance of task performance.

Of course, descriptions like this treat these two sources as independent origins of control, but it is conceivable that experience and expectations coexist and interact to affect attention. For example, one might anticipate that in the presence of a valid precue (but not in its absence), all necessary information about upcoming conflict is sufficiently conveyed and therefore control is not further adjusted based on experiences with conflict during the task (i.e., control learning does not occur; see, e.g., Hutchison et al., 2016; for evidence that the LWPCE and the item-specific proportion congruence effect are not observed when trial-by-trial precues are available). Investigating how these sources of control operate, interact, and are adaptively weighted is important because it informs the broader question of how the control system achieves flexible adjustments to attention.

Most analytical approaches that are used in experiments examining cognitive control in conflict tasks may, however, be limited in addressing this question because these approaches almost exclusively target the outcome of control (by comparing mean congruency effects) and not the processes that shape control. Mean-level analyses do not allow examination of the learning underlying control nor how it interacts with explicit knowledge about upcoming conflict because both experience- and expectation-driven control result in the same behavioral outcomes at the mean level (e.g., larger Stroop effect in MC list). Herein, we develop a new analytical approach that enables us to directly examine the contribution that learning makes to adjustments in cognitive control, and how such learning varies depending on explicit knowledge about upcoming conflict. Specifically, we examine the *trial-by-trial changes* in the degree and direction of control (i.e., control learning) in lists that differ in theoretically meaningful ways (e.g., proportion congruence and the presence vs. absence of a precue).

An exception to the tendency to conduct mean-level analyses comparing conditions such as MC and MI lists is an analytical approach developed by Aben et al. (2017). Aben et al. developed a statistical model to estimate the independent influence of each of multiple prior trials on the current trial, thereby extending the congruency sequence effect beyond a single prior trial in the flanker task (see Dey & Bugg, 2020, for extensions of this model to color-word and picture-word Stroop tasks). They found that control on the current trial is influenced by conflict occurring up to 12 trials back with more distant trials having a greater influence in MI compared with MC lists. The present approach is distinct in that the model of Aben et al. focused on the conflict adaptation weights (beta coefficients) for each preceding trial (i.e., how conflict on each preceding trial *independently* influenced the current trial),

[1] Although such learning may be implicit in LWPC paradigms as indicated by the findings of Blais et al. (2012), it is possible that experience-driven control could in some cases be accompanied by awareness of the information that supports the learning and instantiation of different attentional settings.

[2] Hereafter we refer to this process as "control learning" for short to capture all information that may be learned in the context of MC and MI lists and which contributes to changes in performance across a list.

whereas the current model focuses on how the magnitude of the Stroop effect changes across successive trials within a list. In other words, their model captured how far back the control system looks when "determining" the control state of the current trial by iteratively treating each trial[3] within the 160-trial blocks as the current trial and estimating average conflict adaptation weights for the 12 preceding trials (i.e., the model was backward looking). In contrast, our statistical model examined how *cumulative* experience (i.e., performance on Trial 3 includes the influence of the two preceding trials; on Trial 8 it includes the influence of the seven preceding trials) shapes control trial-by-trial as a list unfolds using abbreviated lists of 10 to 20 trials by deriving slopes representing the average Stroop effect on each trial within a list (i.e., the model was forward looking). To our knowledge, no prior work has investigated such trial-by-trial adjustments in the LWPC paradigm (e.g., changes in Stroop effect as each list unfolds). Additionally, we modeled this control learning in the presence and absence of a precue, thereby allowing us to characterize the influence of explicit knowledge about the upcoming probability of conflict on control learning.

The present analytical approach therefore had two major goals. The initial goal was to capture the learning processes underlying the LWPCE. We predicted that the Stroop effect would gradually increase or decrease from its baseline as participants experienced increasing numbers of congruent or incongruent trials in MC and MI lists, respectively. Such gradual changes in the Stroop effect would be considered evidence of the learning that supports experience-driven control. The second and main goal was to examine whether the evidence for experience-driven control is still observed when knowledge about the upcoming conflict is available in the form of a valid precue (i.e., to address the question of whether control learning occurs and/or is necessary in this case). If attentional adjustments are completely driven by expectation-driven control, then no evidence of learning should be found, as indicated by the absence of trial-by-trial adjustments in the Stroop effect across the list (i.e., a zero slope). However, if attentional adjustments are driven by both expectation- and experience-driven control, we could expect to see a cue-induced shift in control (i.e., as evidenced by the magnitude of the Stroop effect being larger [MC] or smaller [MI] in cued vs. uncued lists) as well as trial-by-trial adjustments (i.e., a nonzero slope) indicative of learning. From a theoretical perspective, this analytical approach can provide valuable insight into how people differentially weight experience- and expectation-driven control when both sources are available. The adaptive weighting of these two sources depending on a variety of factors may be a hallmark of a flexible control system.

Overview of Data

To examine the adaptive weighting of expectations and experience, the approach we adopted in the present study was to use linear mixed-effects modeling (LMM) to reanalyze the five data sets reported by Bugg et al. (2015). Bugg et al. (2015) developed a *precued lists paradigm*, which comprised multiple abbreviated lists of MC or MI trials with half of each list type preceded by an explicit precue. When participants were cued, it was always a valid predictor of upcoming conflict such that MI lists were preceded by an "80% conflicting" precue and MC lists were preceded by an "80% matching" precue (with the exception of Experiment 5, which we will return to later). For uncued lists, question marks ("?????") were presented indicating that the upcoming list would be either MC or MI (50% were MC and 50% were MI). The key comparison was the contrast between cued and uncued lists within a given condition (e.g., MC or MI). In the case of MC lists, a larger Stroop effect in cued compared with uncued lists demonstrates a role for expectation-driven control, because experience is 80% congruent in both list types and expectations should drive the relaxation of attention. In the case of MI lists, a smaller Stroop effect in cued compared with uncued lists demonstrates a role for expectation-driven control, because experience is 80% incongruent in both list types and expectations should drive the heightening of attention. Observing no difference between cued and uncued in either case (MC or MI) implies that the precues did not affect control above and beyond the adjustments in control afforded merely by experience with the list (i.e., encountering and responding to congruent and incongruent trials).

In a series of five experiments, Bugg et al. analyzed mean level performance data (for the entire list or just the first trial) using ANOVAs (Table 1 presents the summary), with the first-trial analyses providing a window into any effects of the precues prior to experience accruing during the list (i.e., a pure effect of expectation-driven control). Bugg et al. found that the magnitude of the Stroop effect was greater in a cued compared with uncued list for the MC condition indicating a cue-induced relaxation of attentional control (i.e., MC shift). However, in MI lists, the Stroop effect was equivalent regardless of the cue condition suggesting the absence of the cue-induced heightening of attentional control (i.e., absence of an MI shift). In other words, the cue provided no additional reduction in the Stroop effect beyond experience with the MI list alone. The absence of the MI shift was striking given that the precue is presumably more useful when the upcoming task demand is high. Alongside the consistently observed cue-induced MC shift, the absence implied that explicit information about upcoming conflict can be used to relax but apparently not heighten control.

Given the mean performance patterns observed by Bugg et al. (2015), one might be inclined to conclude that expectations were weighted heavily *throughout* the MC lists such that little control learning was necessary based on experience within the lists. In MI lists, in contrast, one might conclude that the weighting of expectations may have initially been high (at least in Experiments 3 and 4 given the first-trial patterns in the mean-level analyses indicating an initial cue-induced heightening of control [i.e., MI shift]) but the weighting apparently was updated (lowered) as control learning occurred within the list, leading to a shift toward heavier weighting of experience (given no MI shift was observed when mean list level performance was assessed). Although such conclusions are not unreasonable, the key point for present purposes is that the analytical approach of Bugg et al. was limited to mean differences (i.e., coarse) and thus could not directly evaluate these possibilities (or contrast them with alternatives; see section below titled Model Predictions and Hypothetical Outcomes), which require a finer-grained approach.

In contrast to analyzing mean Stroop performance via ANOVA, LMM allows us to examine trial-level changes in control across

[3] Starting with Trial 14 because the first trial was excluded and for each "current trial" the 12 previous trials were modeled.

Table 1
Summary of Key Findings in Bugg et al. (2015)

Experiment	List type	Mean (1–10 trials)		First trial	
		MC shift	MI shift	MC shift	MI shift
Experiments 1 and 2		Yes	No	Yes	No
Experiment 3	Unspeeded	Yes	No	Yes	No
	Speeded	Yes	No	Yes	Yes
Experiment 4	Low incentives	Yes	No	No	No
	High incentives	Yes	No	Yes	Yes
		First half (1–10 trials)		Second half (11–20 trials)	
		MC shift	MI shift	MC shift	MI shift
Experiment 5	PC-50 Invalid cue	Yes	No	No	No

Note. MC = mostly congruent; MI = mostly incongruent; PC-50 = 50% congruent / 50% incongruent. For Experiments 1–4, MC shift indicates a larger Stroop effect in the cued MC list compared with the uncued MC list and MI shift indicates a smaller Stroop effect in the cued MI list compared with the uncued MI list. In Experiment 5, PC was 50% regardless of the cue type. For Experiment 5, MC shift indicates difference in Stroop effect between MC and PC-50 cue. MI shift indicates difference in Stroop effect between MI and PC-50 cue. Unlike Experiments 1–4, which examined the cuing effect for the first trial as a pure index for expectation-driven control, Experiment 5 analyzed the first and second half of the trials to examine the expectation- and experience-driven control, respectively.

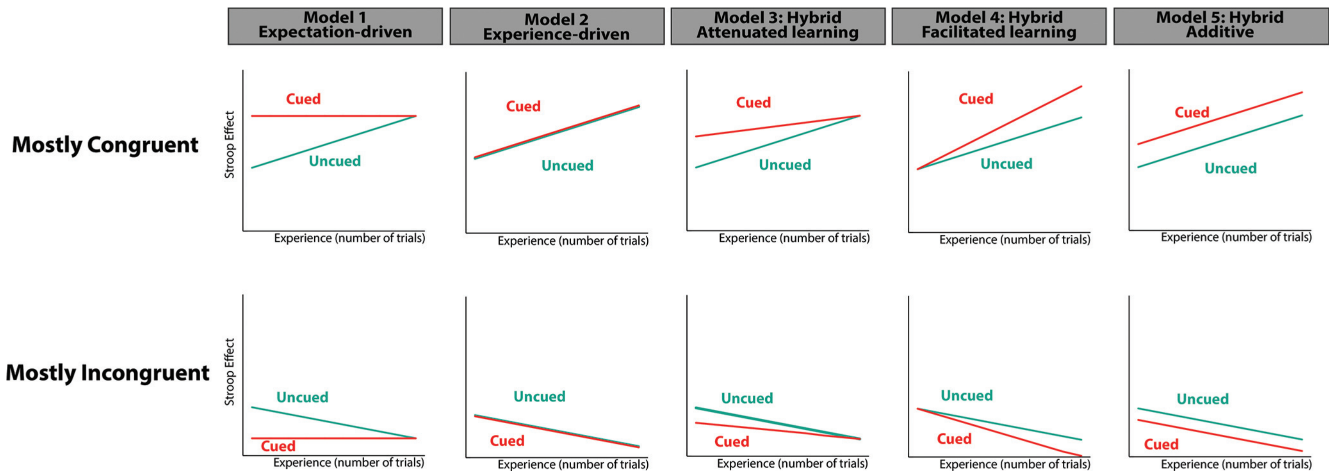
trials, including in data sets with missing data,[4] thereby enabling us to characterize the trial-by-trial signatures of expectation- and experience-driven control as these processes unfold within a list. More specifically, LMM produces estimates of the Stroop effect on each trial, and comparison across trials allows one to ascertain the direction (as indicated by the relative decrease in [heightening of attention] vs. increase in [relaxation of attention] the Stroop effect) and degree of control (as indicated by the relative magnitude of the Stroop effect). The experiments of Bugg et al. were ideal for these purposes for two reasons. First, unlike traditional variants of the list-wide proportion congruence manipulation that comprise ∼100 trials per list with a single item (congruent or incongruent) serving in each trial position, the abbreviated lists paradigm employed by Bugg et al. comprised 10-trial lists (except Experiment 5 which had 20 trials), and there were multiple lists representing low or high conflict likelihood contexts (MC or MI, respectively) such that there were multiple observations per trial position for a given list type. Thus, Stroop effects could be modeled on a trial-by-trial basis within lists whose length was ideally suited for modeling purposes (i.e., if lists are too long, the models often fail to converge due to insufficient numbers of observations). Second, Bugg et al. included valid precues informing participants about the composition of the list in half of the lists in their paradigm (except Experiment 5), thereby enabling them to dissociate expectation-driven control from experience-driven control (see Bugg & Diede, 2018, for replications with between-subjects manipulations of cuing; see also Liu & Yeung, 2020, for reproductions of key findings reported by Bugg et al., 2015, albeit in a task-switching paradigm). This enabled us to model the data from each condition (cued vs. uncued crossed by MC vs. MI), such that for each list type (e.g., MI), we were able to characterize the learning that occurred based on experience within the list (or the learning that did not occur) depending on what the participants' expectations were at the start of the list, as evidenced by the trial-by-trial changes in the Stroop effect.

Model Predictions and Hypothetical Outcomes

In Figure 1, we propose five hypothetical outcomes (referred to here and hereafter as "models") characterizing the time-course of influence for expectations and experience as trials accumulated within a given list type (i.e., the Stroop effect as a function of trial position) in the precued lists paradigm used in Bugg et al. (2015). In all models, we predicted that the Stroop effect for the uncued condition would show a significant slope indicating experience-driven control learning (upward sloping for MC lists and downward sloping for MI lists). In contrast, we expected to see variation in the slopes and the overall magnitudes of the Stroop effect in the cued condition depending on the model. Figure 1 describes the slopes representing trial-by-trial changes in the Stroop effect predicted from the five hypothetical models. Model 1 and Model 2 illustrate hypothetical outcomes postulating that expectation- or experience-driven control, respectively, is the sole source of control adjustments. In specific, Model 1 predicts that participants may completely rely on (i.e., weight highly) the expectation signaled by the precue. If so, then this model anticipates no experience-driven control (i.e., no control learning), which would be evidenced by a flat slope across trials for the cued condition (see Model 1 of Figure 1). In contrast, Model 2 predicts that the precue plays no role in attentional control (see Model 2 of Figure 1) suggesting a pure weighting of experience. Therefore, the cued slope would be identical to the uncued slope as illustrated in Figure 1. Unlike Model 1 and Model 2, it is possible to predict that expectation and experience would interactively guide attentional control. Here, we refer to the interactive models as hybrid models and the model predicted Stroop effect is illustrated in Models 3–5 in Figure 1. The three hybrid models illustrate different patterns of potential interactions between the precue and control learning. Model 3 predicts that advanced knowledge of upcoming conflict (the precue) should shift the initial Stroop effect (i.e., on Trial 1 for which there is no prior experience) in the corresponding direction (e.g., larger when precue is 80% matching), but participants may still learn based on experience within the list. Thus, the slope for the cued condition would not be

[4] Because the Bugg et al. (2015) study was not originally designed to test the trial-by-trial changes in expectation- and experience-driven control, trial position was not orthogonally manipulated which resulted in missing data for some conditions (e.g., not all participants had a congruent trial in Position 4, for example, in MC lists).

Figure 1
Illustration of Predicted Stroop Effect Over Time in Mostly Congruent (Upper Panel) and Mostly Incongruent Lists (Lower Panel) In Precued Lists Paradigm



Note. Red lines indicate predicted Stroop effect for cued condition. Green lines indicate predicted Stroop effect for uncued condition. See the online article for the color version of this figure.

flat; however, it may be shallower than the uncued slope (we refer to this model as "attenuated learning"). Model 3 thus anticipates a similar pattern of results as Model 1, but a major difference from Model 1 is that in Model 3 we predict nonzero slopes for both cued and uncued conditions. Model 4 predicts that the precue might primarily enhance experience-driven control learning by making participants more sensitive to key environmental changes such as proportion congruency. Therefore, the cued and uncued conditions would not differ initially (no expectation-driven shift in control at front end of list) but the cued slope would be steeper than the uncued slope (we refer to this model as "facilitated learning"). Finally, Model 5 predicts that the precue simply shifts the initial starting point (degree to which word relative to color is processed as evidenced by the magnitude of the Stroop effect) but does not necessarily change the rate of control learning, as indicated by the slope of the cued condition being parallel to the slope of the uncued condition (see Model 5 of Figure 1).

It is worth noting that it is possible that the model that best describes the data in the MC condition may be different from the model that best describes the data in the MI condition. For example, basing predictions on the results of Bugg et al. (2015), one might expect to find that Model 1 best describes performance in the MC list (i.e., consistent effect of expectations across the cued condition) and either Model 2 (i.e., experience-driven effects only even in the cued condition) or Model 3 (i.e., a short-lasting effect of expectations in the cued condition for speeded or high incentive lists, consistent with the first-trial analyses, with experience ultimately prevailing in the cued condition) best describes performance in the MI list.

Examining which of the models described in Figure 1 best describes the data under different conditions will provide novel insights into the underlying learning that supports experience-driven control in uncued lists, a question that is important in its own right, and how explicit expectations influence this learning process in cued lists on a continuous time scale.

General Method and Analytical Approach

The primary goal of the present study was to examine the trial-by-trial signature of experience-driven control and how explicit knowledge about upcoming conflict affects the nature of control learning that is rooted in one's experiences during the task. For the analyses, we used the raw data from Experiments 1–5 of Bugg et al. (2015), all of which utilized the precued lists paradigm.[5] In this paradigm, participants were shown a MI ("80% CONFLICTING"), MC ("80% MATCHING"), or uninformative (uncued, "??????") precue at the beginning of each list. When the MI or MC precue was presented, participants were explicitly told that using the precue may benefit performance and were encouraged to use the precue (except Experiment 5). Each participant completed 32–64 lists of 10 Stroop trials (20 trials in Experiment 5) with equal numbers of lists assigned to each of the comparison conditions.[6] The experiments minimized item repetitions (e.g., BLUE in red occurring twice) within a list by selecting congruent and incongruent stimuli for MC and MI lists without replacement. The other published data using the abbreviated, precued lists Stroop paradigm were from a between-subjects design where half the

[5] As such, we inherit the limitations of the designs used in Bugg et al. (2015); for example, the potential for ceiling effects to limit the extent to which any additional increases in control can be observed based on precues in MI lists.

[6] The total number of lists varied across experiments. Participants completed 32 lists in both Experiments 1 and 2 (excluding PC-50 lists, another type of list that appeared in Experiment 2), 64 lists in both Experiments 3 & 4, and 28 lists in Experiment 5. Half of the lists were cued, and the other half were uncued. Among the cued (or uncued) lists, half of the lists were MC, and the other half were MI. For Experiments 3 & 4, half of the lists were speeded or high incentive, and the other half were unspeeded or low incentive, respectively. For MC lists, 8 trials were congruent while 2 trials were incongruent. For MI lists, 8 trials were incongruent, and 2 trials were congruent. In Experiment 5, a list comprised 20 trials, which always involved 10 congruent and 10 incongruent trials. The congruent and incongruent trials were randomly distributed within the list.

participants received cued lists and the other half received uncued lists (Bugg & Diede, 2018). Although the overall mean-level patterns were replicated in this study, using data from Bugg and Diede was not ideal for present purposes because between-subjects designs yield a weaker test, and we were particularly interested in how the same individuals adaptively weighted expectations and experience across lists.

The same data trimming criteria were applied as in the original study (i.e., trials with incorrect, faster than 200-ms, or slower than 3,000-ms responses were excluded; see Bugg et al., 2015, for more details). Because of the skewedness of the (RT) distribution,[7] we used a generalized linear mixed-effect model (GLMM) with a gamma distribution and identity link function (Lo & Andrews, 2015) using lme4 package (Bates et al., 2015) in R. We used GLMM instead of a linear mixed-effect model because of the potential concerns related to RT transformation, which has been known to distort additive effects that reside in raw data structure (Balota et al., 2013). For each data set, MC and MI lists were analyzed separately to simplify the model structure.[8] This was also justified because our main goal was to contrast cued and uncued lists within a particular list type (where experience was matched) to determine which model from Figure 1 best characterized the contributions of expectations and experience within each LWPC condition. We planned two GLMM models. The first GLMM included fixed effect factors of cue type (cued vs. uncued), trial type (congruent vs. incongruent), and trial position (1–10) with random effect factors of response (e.g., color of the color word) and participant (id). Although maximum random slope model is advisable (Barr et al, 2013), we had to choose the random intercept model due to the failure in model convergence.[9] The fixed effect factors except trial position were dummy coded: MC, congruent, and uncued trials were coded as 0, MI, incongruent, and cued trials were coded as 1. Data from each list type (MC and MI) were fitted to a linear model: rt ~ Trial Type + Cue + Trial Position+ Trial Type:Cue + Trial Type:Trial Position + Trial Type:Cue: Trial Position+ (1|Subject) + (1|Response). Because Cue:Trial Position was not theoretically relevant and exclusion of this term did not change the model fit,[10] we did not include this interaction term. Additionally, for each list type (MC and MI), a second GLMM model of rt ~ Trial Type + Trial Position + Trial Type: Trial Position + (1|Subject) + (1|Response) was separately fitted to the cued and uncued lists to reveal the steepness of the individual slope in each cue condition.

With regard to the GLMM output, for the present and subsequent analyses we focused on the Trial Type × Trial Position interaction as an index for experience-driven control (i.e., changes in the Stroop effect across trials indicative of control learning), the Trial Type × Cue interaction[11] as an index for expectation-driven control (i.e., change in the Stroop effect depending on the precue), and the Trial Type × Cue × Trial Position interaction as a signature of *cue-influenced control learning* (i.e., changes in the Stroop effect across trials depending on the precue), for each PC level. In addition, we used the Trial Type × Trial Position interaction from the additional GLMM analysis (the second model described above) that was performed on the two subsets of data (segregated based on cue type) as an index of experience-driven control in isolated cued and uncued lists. Finally, to better understand the three-way interaction, which is of great interest given our theoretical goals, we plotted model-predicted Stroop effects as a function of trial position and precue type. The evaluation of the best model that explains the data was based on the correspondence with the model-predicted outcomes (e.g., specific interactions; significance of slopes) described above.

Analysis 1: Testing Dynamics of Experience- and Expectation-Driven Control

The purpose of Analysis 1 was to reveal how the signature of control learning changes as experience accumulates depending on the availability of explicit knowledge about upcoming conflict. We combined the data sets from Experiments 1 (N = 22) and 2 (N = 20) of Bugg et al. (2015) to predict the Stroop effect as a function of the cue type (MC or MI) and accumulated number of trials (trial position). The same pattern was observed across these experiments (cue-induced MC shift but no cue-induced MI shift, including in the first-trial analyses), and thus we combined them to increase power.

Results

The fixed effect estimates from the GLMM results are in Table 2. Overall, incongruent trials were significantly slower than congruent trials for both MC (β = 100.98, t = 20.65, p < .001) and MI lists (β = 83.29, t = 18.82, p < .001), reflecting a typical Stroop effect. There was a significant main effect of the cue for the MC lists (β = −16.04, t = −6.15, p < .001) indicating that responses were faster in cued compared with uncued lists. However, the main effect of the cue was not significant for the MI lists (β = 3.27, t = .71, p = .477). A significant main effect of trial position was reported in the MC lists (β = −4.45, t = −8.54, p < .001), suggesting that responses were facilitated as participants completed more trials (i.e., faster at 10th trial than 1st trial). The same pattern was observed for the MI lists, β = −1.96, t = −2.06, p = .040.

To test the signature of experience-driven control, we analyzed the Trial Type × Trial Position interaction. For MC lists, the Trial Type × Trial Position interaction was significant (β = 10.10, t = 8.26, p < .001), such that the Stroop effect incrementally increased as participants experienced more MC trials. The Trial Type × Trial Position interaction was also significant for MI lists with a negative estimated coefficient (β = −2.95, t = −3.00, p = .003), indicating that the Stroop effect decreased as participants experienced more MI trials. Both patterns are consistent with the idea that control

[7] See online supplemental materials for distribution of RT and Gamma distribution fitted to the data.

[8] Full model outcomes are available in online supplemental materials.

[9] GLMM models failed to converge with inclusion of any of the random slope factors.

[10] We used likelihood ratio test to compare the two nested models: one with the Cue × Trial Position interaction and the other one without the term.

[11] Note that, in this model, the Trial Type × Cue interaction indicates the difference in the Stroop effect between cued and uncued lists when trial position is zero (i.e., zero experience). This is purely a theoretical estimate of expectation-driven control since it is technically impossible to measure performance at Trial 0 using an experimental procedure.

Table 2
Generalized Linear Mixed Model Output for Experiments 1 and 2 of Bugg et al. (2015)

	Mostly congruent (MC) list				Mostly incongruent (MI) list			
Predictor	Estimates	95% CI	t	p	Estimates	95% CI	t	p
(Intercept)	646.01	[635.26, 656.75]	117.79	<.001	672.93	[661.43, 684.44]	114.62	<.001
Trial Type	100.98	[91.39, 110.56]	20.65	<.001	83.29	[74.62, 91.96]	18.82	<.001
Cue	−16.04	[−21.16, −10.93]	−6.15	<.001	3.27	[−5.74, 12.29]	0.71	.477
Trial Position	−4.45	[−5.47, −3.43]	−8.54	<.001	−1.96	[−3.84, −0.09]	−2.06	.040
Trial Type × Trial Position	10.10	[7.71, 12.50]	8.26	<.001	−2.95	[−4.88, −1.02]	−3.00	.003
Trial Type × Cue	98.80	[89.18, 108.43]	20.13	<.001	−8.99	[−20.47, 2.50]	−1.53	.125
Trial Type × Cue × Trial Position	−9.11	[−12.20, −6.02]	−5.77	<.001	1.53	[−0.43, 3.49]	1.53	.126

Note. CI = 95% confidence interval.

learning occurred as participants experienced more trials and attention was adjusted based on this learning in the anticipated direction.

To examine the signature of expectation-driven control, we examined the Trial Type × Cue interaction. For MC lists, the Trial Type × Cue interaction was highly significant with a positive beta coefficient, $\beta = 98.80$, $t = 20.13$, $p < .001$, suggesting that the Stroop effect was greater in the cued than the uncued lists. For MI lists, however, the Trial Type × Cue interaction was not significant, $\beta = -8.99$, $t = -1.53$, $p = .125$, indicating that the Stroop effect was not modulated by the precue.

Lastly, the Trial Type × Cue × Trial Position interaction was examined to reveal cue-influenced control learning. For MC lists, the three-way interaction was significant, $\beta = -9.11$, $t = -5.77$, $p < .001$, implying that the learning slope for uncued trials was steeper than that of cued trials. However, for MI lists, the three-way interaction was not significant, $\beta = 1.53$, $t = 1.53$, $p = .126$, indicating that the precue did not influence the control learning underlying experience-driven control.

To illustrate the influences of expectations and experience within each list type, the Stroop effect as a function of proportion congruency, cue type, and trial position was calculated from the model predicted RT and plotted in Figure 2.

To further examine whether control learning occurred during cued lists, we conducted the second set of GLMM analyses[12] separately for the cued and uncued conditions in MC and MI lists. For the MC lists (Figure 2a), the uncued Stroop effect showed a gradual increase as participants experienced more trials within the list. The additional analysis confirmed this trend by showing that the uncued slope was steeper than zero, $\beta = 10.67$, $t = 6.48$, $p < .001$. Because no explicit cue was provided about upcoming conflict, the significant slope highlights the fact that a gradual relaxation of control occurred as participants experienced frequent congruent trials, consistent with the notion that participants implicitly learn about conflict probability (Blais et al., 2012). In contrast, the slope analysis showed that the cued MC slope was not different from zero, $\beta = .26$, $t = .16$, $p = .870$. In other words, the cued Stroop effect was relatively stable regardless of the trial position suggesting that participants adopted a relaxed control setting immediately after being presented with a MC precue and did not relax it further based on experience, indicating a pure influence of expectation-driven control (i.e., no influence of control learning). Interestingly, the Stroop effects for uncued and cued lists eventually converged at the last trial (10th). The convergence may indicate a ceiling effect (i.e., the Stroop effect has reached its functional maximum) or suggest that participants calibrated their control settings in uncued lists based on the learned conflict probability and these settings ultimately converged with those that they would have implemented had they received a precue (i.e., they did not over- or undershoot in terms of the degree of control).

For the MI lists (Figure 2b), the Stroop effect decreased as participants completed more trials but the cued and uncued slopes did not differ (nonsignificant three-way interaction). The lack of a three-way interaction suggests that experience-driven control learning was not modulated by the presence of prior knowledge about the amount of upcoming conflict. However, the slope analysis showed that the uncued slope was different from zero, $\beta = -3.69$, $t = -2.80$, $p = .005$, whereas the cued slope was not, $\beta = -.24$, $t = -.18$, $p = .860$. This may suggest that the general trend (i.e., uncued slope is steeper than cued slope) exists in MI lists albeit the effect is weaker than that of MC lists (hence, the three-way interaction was not significant).

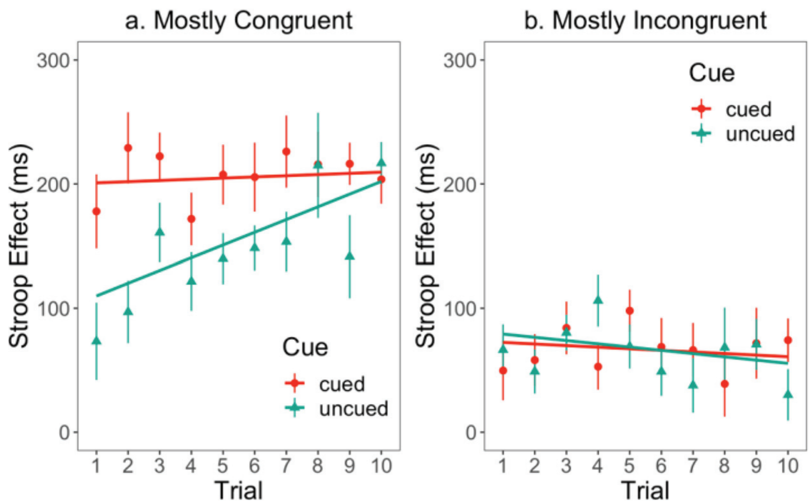
Discussion

Applying a novel analytical approach, we reexamined the effect of the precue manipulation on the experience-driven control learning process by modeling data from Experiment 1 and 2 of Bugg et al. (2015). By using GLMM, we were able to test unique signatures of experience-driven control, expectation-driven control, and the conjoint influence of these two sources (i.e., cue-influenced control learning). First, we found a significant Trial Type × Trial Position interaction in MC and MI lists, which highlights the control learning underlying experience-driven control. The model predicted a gradual increment or decrement in the Stroop effect as experience accumulated in MC or MI lists, respectively. Second, we observed a Trial Type × Cue interaction that was significant for MC but not MI lists, which is highlighting the fact that expectation-driven control played a role in relaxing attentional control but not in heightening it. Finally, and most interestingly, the three-way interaction of Trial Type × Cue × Trial Position was significant for MC lists but not for MI lists. The three-way interactions are plotted in Figure 2 to highlight the slope difference in cued and uncued lists. In MC lists (Figure 2a), the flat cued slope indicates that the Stroop effect was not influenced by the accumulation of experience (trial position), which clearly shows a sharp contrast to the uncued slope that showed an increase in the Stroop effect with accumulated experience (i.e., control learning). In MI lists

[12] The full summary of the additional GLMM analysis is available in the online supplemental materials.

Figure 2

Model-Predicted Stroop Effect (Solid Lines) as a Function of Cue and Trial Position of (a) Mostly Congruent (MC) and (b) Mostly Incongruent (MI) Lists in Experiments 1 and 2 of Bugg et al. (2015)



Note. Each data point indicates the mean Stroop effect calculated from raw data. The color and shape of each point marker indicate the cue type (red/circle: cued, green/triangle: uncued). Error bars depict ±1 standard error. See the online article for the color version of this figure.

(Figure 2b), the learning slopes for cued and uncued lists were equivalent unlike the sharp difference observed in MC lists. We assume that the lack of a difference in slopes could be attributable to the overall shift in the Stroop effect in the presence of the cue being much smaller in MI lists (9 ms) compared with MC lists (99 ms), which could result in a failure to detect cue-influenced control learning.

Taken together, our findings best support Model 1 and Model 2 for MC and MI lists, respectively (see Figure 1). In specific, both modeling results of MC lists and hypothesized outcomes from Model 1 suggest that, with a valid precue, participants rely on expectation-driven control without necessarily learning about conflict probability through experience. Our modeling results for MI lists and hypothesized outcomes from Model 2 suggest that participants did not adopt expectation-driven control in MI lists. That is, performance in the list was influenced exclusively by control learning, which was evidenced in MI lists.

In the next analysis, we performed the GLMM analysis on the data from Experiment 3 to characterize experience-and expectation-driven control under conditions in which Bugg et al. (2015) demonstrated that the precue was at least initially used (on the first trial) in MI lists, in addition to its continued use in the MC lists.

Analysis 2: Testing the Role of Task-Demands

In Experiment 3, Bugg et al. (2015) presented the Stroop stimuli for a brief time to encourage participants to prepare for stimuli in advance by utilizing the precue information. In this speeded condition, they found that participants showed evidence of a cue-induced MI shift showing a smaller Stroop effect in the cued compared with uncued condition, but this difference was limited to the first trial. Bugg et al. interpreted this to mean that participants initially attempted to use the precue, but the effect of the precue quickly disappeared. This could occur either because it is too demanding to sustain heightened control across multiple trials or because experience took over as participants encountered more trials. Here, we reanalyzed the Experiment 3 data ($N = 22$) of Bugg et al. to further investigate how the increased task demands affected experience-driven control learning when the cue was present as well as when it was absent, as well as the possibility that the heightening of control in response to the cue may have extended beyond the first trial.

Results

We modeled the data separately for speeded and unspeeded lists, as well as for the different PC levels (MC and MI) as in the preceding analysis. This was done because our main interest was to examine the different trial-by-trial learning signatures between cued and uncued lists and to simplify the model structure for the sake of avoiding failed model convergence.

Unspeeded MC

The fixed effects estimates from the GLMM output are in Table 3. The GLMM analysis for the unspeeded MC condition revealed that the main effects of trial type ($\beta = 147.68$, $t = 17.78$, $p < .001$) and cue ($\beta = -14.03$, $t = -3.56$ $p < .001$) were significant suggesting that overall responses were slower in incongruent than congruent trials and cued trials were faster than uncued trials. The main effect of trial position ($\beta = -3.24$, $t = -4.40$ $p < .001$) was also significant showing that overall RT decreased as participants completed more trials. The Trial Type × Trial Position interaction (indicative of control learning), $\beta = .83$, $t = .46$, $p = .642$, and Trial

Table 3
Generalized Linear Mixed Model Output of Unspeeded Condition in Experiment 3 of Bugg et al. (2015)

	Mostly congruent (MC) list				Mostly incongruent (MI) list			
Predictor	Estimates	95% CI	*t*	*p*	Estimates	95% CI	*t*	*p*
(Intercept)	664.98	[631.36, 698.60]	38.76	<.001	707.84	[691.52, 724.19]	85.01	<.001
Trial Type	147.68	[131.41, 163.96]	17.78	<.001	91.45	[79.28, 103.62]	14.73	<.001
Cue	−14.03	[−21.74, −6.33]	−3.56	<.001	−5.19	[−15.50, 5.12]	−0.99	.323
Trial Position	−3.24	[−4.69, −1.80]	−4.40	<.001	−1.94	[−4.33, 0.46]	−1.59	.112
Trial Type × Trial Position	0.83	[−2.68, 4.35]	0.46	.642	−2.10	[−4.70, 0.49]	−1.59	.112
Trial Type × Cue	−12.21	[−28.89, 4.48]	−1.43	.151	−19.81	[−34.57, −5.05]	−2.63	.009
Trial Type × Cue × Trial Position	10.13	[−5.46, 14.81]	4.25	<.001	2.27	[−0.44, 4.98]	1.64	.100

Note. CI = 95% confidence interval.

Type × Cue interaction (indicative of expectation-driven control), β = −12.21, *t* = −1.43 *p* = .151, were not significant. The three-way interaction was significant (β = 10.13, *t* = 4.25 *p* < .001), however, the pattern was unexpected. The magnitude of the Stroop effect increased as participants completed more trials (indicating control learning) when there was a precue (see Figure 3a). However, the Stroop effect was consistent regardless of the number of trials completed when there was no precue, indicating no significant control learning.

Unspeeded MI

The fixed effects estimates from the GLMM output are in Table 3. The main effect of trial type was significant, β = 91.45, *t* = 14.73 *p* < .001, indicating a typical Stroop effect. However, main effects of cue, β = −5.19, *t* = −.99 *p* = .323, and trial position, β = −1.94, *t* = −1.59, *p* = .112, were not significant. The Trial Type × Trial Position interaction was not significant, β = −2.10, *t* = −1.59, *p* = .112. However, the Trial Type × Cue interaction was significant, β = −19.81, *t* = −2.63 *p* = .009, such that the Stroop effect was smaller with the cue compared with without the cue (i.e., cue-induced MI-shift). Finally, the three-way interaction was not significant, β = 2.27, *t* = 1.64, *p* = .100, suggesting the learning slope was equivalent for cued and uncued lists (see Figure 3b).

Speeded MC

The fixed effects estimates from the GLMM output are in Table 4. We found a significant main effect of trial type (β = 115.17, *t* = 15.34, *p* < .001) and cue (β = −13.37, *t* = −4.23, *p* < .001), suggesting that overall RT was faster for congruent compared with incongruent and cued compared with uncued trials, respectively. Unlike the unspeeded MC list, we found a significant Trial Type × Trial Position interaction (β = 5.25, *t* = 3.21, *p* = .001), indicating that the overall Stroop effect increased as participants completed more trials indicative of control learning, and a significant Trial Type × Cue interaction (β = 50.10, *t* = 6.63, *p* < .001), suggesting a greater Stroop effect in cued than uncued lists. Finally, the three-way interaction was significant (β = −4.38, *t* = −2.15, *p* = .032), implying a trend whereby the difference between the cued and uncued Stroop effect was attenuated as participants experienced more trials within a list (see Figure 3c).

Speeded MI

The fixed effects estimates from the GLMM output are in Table 4. Again, the main effect of trial type was significant, β = 105.20, *t* = 11.66, *p* < .001, reflecting the Stroop effect. The main effect of trial position was not significant, β = 2.18, *t* = 1.75, *p* = .080. However, the Trial Type × Trial Position interaction was significant (β = −6.59, *t* = −4.33 *p* < .001) such that the Stroop effect decreased as participants completed more trials, consistent with control learning. The main effect of cue was not significant, β = 1.86, *t* = .36, *p* = .720. However, a significant Trial Type × Cue interaction (β = −32.62, *t* = −5.06, *p* < .001) showed that the Stroop effect was overall smaller for the cued than uncued condition, revealing a cue-induced MI-shift. In addition, a significant three-way interaction (β = 5.14, *t* = 4.14, *p* < .001) confirmed a significant slope difference between the cued and uncued lists with a steeper slope in the uncued lists (see Figure 3d).

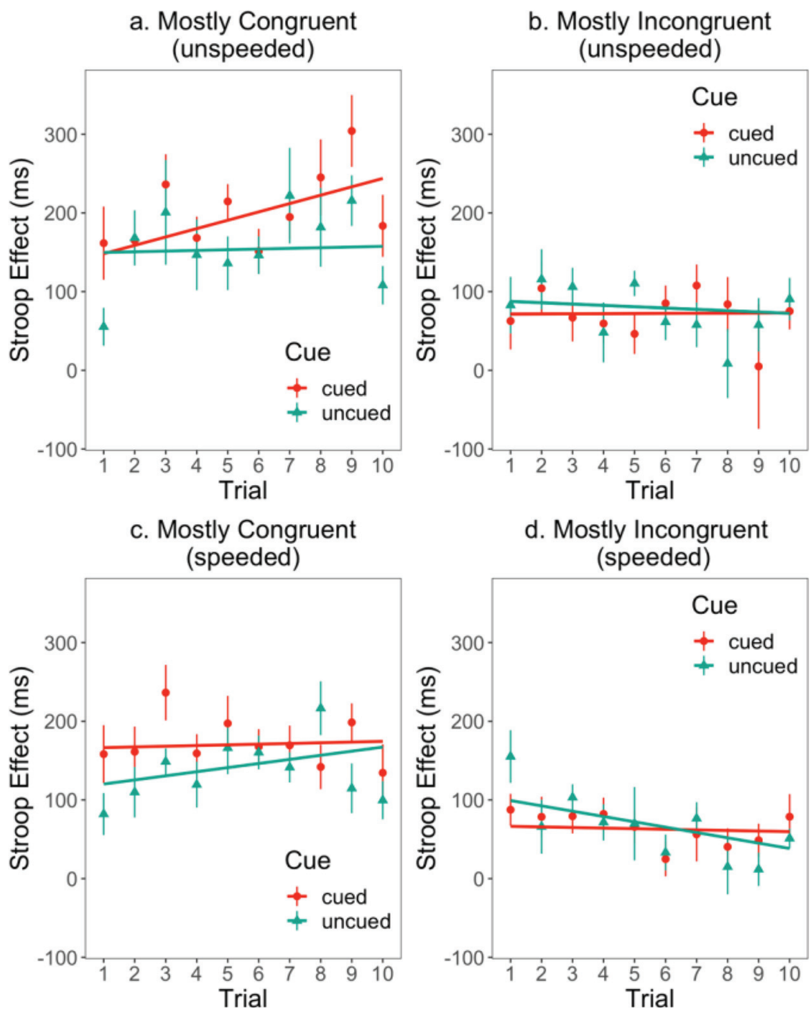
The model-predicted Stroop effects are plotted in Figure 3, illustrating the slopes for the unspeeded and speeded MC and MI lists. The model-predicted Stroop effects for the unspeeded MC list (see Figure 3a) showed an unexpected, reversed pattern such that the predicted Stroop effect increased as participants completed more trials only when the precue was provided (i.e., there was no such trend observed for uncued lists). The second GLMM analysis additionally confirmed the pattern that the slope was significantly greater than zero for the cued lists (β = 9.66, *t* = 3.22, *p* = .001), but it was not different from zero for the uncued lists (β = 2.77, *t* = 1.25, *p* = .210). For unspeeded MI lists (Figure 3b), there was no evidence of a cue-induced difference in the learning slope as evidenced by the lack of a three-way interaction. The second GLMM analysis confirmed that both cued (β = −.77, *t* = .38, *p* = .700) and uncued (β = −3.05, *t* = −1.51, *p* = .130) slopes were not different from zero.

For the speeded MC lists (Figure 3c), the slope was steeper in the uncued lists compared with the cued lists replicating Analysis 1. However, the second GLMM analysis[13] confirmed that neither cued or uncued slopes were different from zero (uncued: β = 5.27, *t* = 1.25, *p* = .210, cued: β = .51, *t* = .18, *p* = .86) in this condition. For the speeded MI lists, we found evidence for cue-influenced control learning as indicated by a difference in the learning slope for cued and uncued lists (i.e., a significant three-way interaction; see Figure 3d). The slope was steeper for the uncued than cued lists, suggesting that the Stroop effect decreased as participants completed more incongruent trials especially in uncued lists. The second analysis revealed that the slope was different from zero for the uncued lists (β = −5.87, *t* = −3.36, *p* < .001) but not different from zero for the cued lists (β = −3.20, *t* = −1.78, *p* = .075).

[13] The full model outcomes are available in the online supplemental materials.

Figure 3

Model-Predicted Stroop Effect (Solid Lines) as a Function of Cue and Trial Position of (a) Unspeeded Mostly Congruent (MC), (b) Unspeeded Mostly Incongruent (MI), (c) Speeded MC, and (d) Speeded MI Lists in Experiment 3 of Bugg et al. (2015)



Note. Each data point indicates the Stroop effect calculated from raw data. The color and shape of each point marker indicates the cue type (red/circle: cued, green/triangle: uncued). Error bars depict ±1 standard error. See the online article for the color version of this figure.

Discussion

Applying our novel analytical approach again, here we examined the signatures of expectation- and experience-driven control under conditions that encouraged use of the precue in a subset of the lists (i.e., speeded condition). There were several important findings highlighting the nature of adaptive weighting of expectation- and experience-driven control. First, we found the Trial Type × Cue interaction was significant in all conditions (except the unspeeded MC list), illuminating a cue-induced shift in control based on expectations. In contrast to Analysis 1, the model-predicted Stroop effects were smaller with the precue under both MI lists (unspeeded and speeded). Second, we found that the Trial Type × Trial Position interaction was significant for both MC and MI lists, but this was limited to the speeded condition. In other words, participants were able to learn a given conflict probability based on cumulative experience particularly when the stimulus presentation was speeded. This was somewhat surprising because the unspeeded condition in Experiment 3 was identical to Experiment 1 except that participants were given the speed cue (e.g., "SLOWER SPEED"). We speculate that, under the unspeeded instruction particularly with the "easier" MC cues, participants might have taken a break and disengaged from using the cue, but we reserve further discussion of the role of task demands for the General Discussion. Third and most interestingly, for the first time in the present study, we found a significant three-way interaction for MI lists which serves as evidence that control learning varied depending on whether a precue was available, and this interaction was observed in the speeded condition where precue use was encouraged by presenting the Stroop stimuli for a brief

Table 4
Generalized Linear Mixed Model Output of Speeded Condition in Experiment 3 of Bugg et al. (2015)

	Mostly congruent (MC) list				Mostly incongruent (MI) list			
Predictor	Estimates	95% CI	t	p	Estimates	95% CI	t	p
(Intercept)	506.57	[489.03, 524.12]	56.59	< .001	540.25	[525.21, 555.29]	70.39	< .001
Trial Type	115.17	[100.46, 129.89]	15.34	< .001	105.20	[87.52, 122.87]	11.66	< .001
Cue	−13.37	[−19.57, −7.17]	−4.23	< .001	1.86	[−8.37, 12.09]	0.36	.720
Trial Position	−0.95	[−2.13, 0.23]	−1.58	.114	2.18	[−0.26, 4.63]	1.75	.080
Trial Type × Trial Position	5.25	[2.04, 8.45]	3.21	.001	−6.59	[−9.57, −3.61]	−4.33	< .001
Trial Type × Cue	50.10	[35.99, 66.21]	6.63	< .001	−32.62	[−45.26, −19.98]	−5.06	< .001
Trial Type × Cue × Trial Position	−4.38	[−8.37, −0.38]	−2.15	.032	5.14	[2.71, 7.57]	4.14	< .001

Note. CI = 95% confidence interval.

duration. The slope difference suggests that participants might have heightened control immediately following the precue and maintained the heightened control within the cued MI list but in uncued MI lists the attentional control was gradually heightened as participants encountered incongruent trials. However, in contrast to the MI speeded condition, the three-way interaction was not significant in the MI unspeeded condition suggesting that participants used the precue to heighten control, but it did not change the control learning process.

To sum, the modeling results from speeded MC and MI lists best support Model 1 as they showed flat slopes for the cued lists and relatively steeper slopes for the uncued lists. This suggests that control learning did not occur in the presence of the precue in both list types. The reversed trend observed in unspeeded MC lists could be explained by Model 4, because the results showed that the slope was steeper when cued and not different from zero in the uncued condition. This may suggest that a certain level of demand on preparatory control is necessary for the adoption of expectation-driven control, and potentially such a demand may facilitate control learning and thereby experience-driven control. Finally, the results from the unspeeded MI lists support none of the proposed models. There was evidence for expectation-driven control in this condition (Stroop effect was overall smaller in presence of the cue), but the results do not support Model 1 because the cued *and* uncued slopes were not different from zero indicating a lack of control learning even in the uncued condition.

Analysis 3: Testing the Role of Motivation

The data from Experiment 4 ($N = 48$) of Bugg et al. (2015) were used for Analysis 3. In this experiment, in addition to being cued as to whether the upcoming list would be MC or MI, participants were also cued as to whether the upcoming list would be related to potential gain of low or high incentive (points). Incentives were earned (or not) as noted at the end of each list based on participants' performance within the list relative to a set of baseline lists at the beginning of the experiment. The mean-level analyses in Bugg et al. showed that participants used the precue to heighten control in MI lists when high incentives were expected but just as in Experiment 3, the cue-induced MI-shift was observed only for the first trial. The current analysis allows us to additionally examine whether incentives influence control learning and thereby experience-driven control, as well as the role of expectations (precues) in shaping this learning in MC and MI lists.

Results

Low-Incentive MC

The fixed effects estimates from the GLMM output are in Table 5. The main effect of trial type, $\beta = 109.96$, $t = 31.83$, $p < .001$, and trial position, $\beta = -3.77$, $t = -7.93$, $p < .001$, were significant indicating a typical Stroop effect as well as a practice effect such that overall RT decreased as more trials were experienced. The main effect of cue was not significant, $\beta = -3.92$, $t = -1.68$, $p = .093$, suggesting that overall RT was similar between the cued and uncued conditions. A significant Trial Type × Trial Position interaction, $\beta = 7.31$, $t = 6.87$, $p < .001$, revealed experience-driven control such that the overall Stroop effect increased as participants experienced more trials. In addition, the Trial Type × Cue interaction was significant, $\beta = 51.98$, $t = 10.95$, $p < .001$, highlighting expectation-driven control. The Stroop effect was greater for the cued than uncued lists. Finally, the three-way interaction was significant, $\beta = -4.75$, $t = -3.34$, $p < .001$, demonstrating that the learning slope for uncued lists was steeper than that for the cued lists.

Table 5
Generalized Linear Mixed Model Output of Low Incentive Condition in Experiment 4 of Bugg et al. (2015)

	Mostly congruent (MC) list				Mostly incongruent (MI) list			
Predictor	Estimates	95% CI	t	p	Estimates	95% CI	t	p
(Intercept)	562.22	[520.86, 603.59]	26.64	< .001	585.52	[576.23, 594.81]	123.56	< .001
Trial Type	109.96	[103.19, 116.73]	31.83	< .001	104.68	[93.70, 115.66]	18.68	< .001
Cue	−3.92	[−8.48, 0.65]	−1.68	.093	2.86	[−7.30, 13.01]	0.55	.582
Trial Position	−3.77	[−4.70, −2.84]	−7.93	< .001	−0.77	[−2.45, 0.92]	−0.89	.373
Trial Type × Trial Position	7.31	[5.23, 9.40]	6.87	< .001	−3.33	[−5.37, −1.30]	−3.21	.001
Trial Type × Cue	51.98	[42.68, 61.29]	10.95	< .001	−7.02	[−17.98, 3.94]	−1.26	.209
Trial Type × Cue × Trial Position	−4.75	[−7.54, −1.96]	−3.34	< .001	1.13	[−0.71, 2.97]	1.20	.230

Note. CI = 95% confidence interval.

Table 6

Generalized Linear Mixed Model Output of High Incentive Condition in Experiment 4 of Bugg et al. (2015)

	Mostly congruent (MC) list				Mostly incongruent (MI) list			
Predictor	Estimates	95% CI	*t*	*p*	Estimates	95% CI	*t*	*p*
(Intercept)	551.78	[542.05– 561.50]	111.21	<.001	567.23	[560.07, 573.40]	137.07	<.001
Trial Type	119.14	[110.69, 127.60]	27.63	<.001	99.60	[91.02, 107.78]	24.32	<.001
Cue	−16.54	[−21.05, −12.02]	−7.18	<.001	13.08	[7.75, 19.79]	3.50	<.001
Trial Position	−3.32	[−4.17, −2.48]	−7.74	<.001	−1.10	[−2.96, 0.74]	−1.37	.171
Trial Type × Trial Position	3.66	[1.60, 5.73]	3.48	<.001	−0.86	[−3.13, 1.34]	−1.00	.317
Trial Type × Cue	46.46	[39.19, 53.73]	12.53	<.001	−11.35	[−17.84, −3.77]	−2.69	.007
Trial Type × Cue × Trial Position	−1.48	[−4.05, 1.10]	−1.12	.261	−0.21	[−1.94, 1.27]	−0.25	.804

Note. CI = 95% confidence interval.

Low-Incentive MI

The fixed effects estimates from the GLMM output are shown in Table 5. The main effect of trial type, β = 104.68, t = 18.68, p < .001, was significant. However, the main effect of cue, β = 2.86, t = .55, p = .582, and trial position, β = −.77, t = −.89, p = .373, were not significant. The Trial Type × Trial Position interaction was significant, β = −3.33, t = −3.21, p = .001, indicating an experience-driven heightening of control such that the Stroop effect decreased as the number of trials completed increased. However, the Trial Type × Cue interaction, β = −7.02, t = −1.26 p = .209, and three-way interaction, β = 1.13, t = 1.20, p = .230, were not significant.

High-Incentive MC

The fixed effects estimates from the GLMM output are summarized in Table 6. For the high-incentive MC list, we found a significant main effect of trial type (β = 119.14, t = 27.63, p < .001), suggesting that overall RT was faster for the congruent compared with incongruent trials. Also, the main effect of cue (β = −16.54, t = −7.18, p < .001) was significant, showing that overall RT was faster in cued lists compared with uncued lists. A significant main effect of trial position (β = −3.32, t = −7.74, p < .001) indicated a practice effect such that overall RT was facilitated as participants completed more trials. The Trial Type × Trial Position interaction was also significant, β = 3.66, t = 3.48, p < .001, demonstrating that the Stroop effect increased as the amount of experience increased (i.e., control learning). In addition, the Trial Type × Cue interaction was significant, β = 46.46, t = 12.53, p < .001, showing a signature of expectation-driven control such that the Stroop effect was greater in cued lists than in uncued lists. However, the three-way interaction was not significant, β = −1.48, t = −1.12, p = .261.

High-Incentive MI

The fixed effects estimates from the GLMM output are shown in Table 6. For the high-incentive MI list, the same analysis was conducted revealing a significant main effect of trial type, β = 99.60, t = 24.32, p < .001, and cue, β = 13.08, t = 3.50, p < .001. The estimated coefficient for the main effect of the cue was positive indicating that participants slowed responses in cued lists compared with uncued lists. Interestingly, the Trial Type × Trial Position interaction was not significant, β = −.86, t = −1.00, p = .317. In contrast, the Trial Type × Cue interaction was significant, β = −11.35, t = 2.69, p = .007, reflecting that the Stroop effect was smaller for the cued compared with the uncued lists. The three-way interaction was not significant, β = −.21, t = −.25, p = .804, which highlights the fact that learning slopes for cued and uncued lists were not different.

The model-predicted Stroop effects are plotted in Figure 4, illustrating the slopes for the low-incentive and high-incentive MC and MI lists. The low-incentive lists largely replicated the pattern observed in Analysis 1. The three-way interaction was significant for the MC lists, but not for the MI lists. For the low-incentive MC lists (Figure 4a), the slope was greater than zero for the uncued lists (β = 7.02, t = 3.65, p < .001) but not different from zero for the cued lists (β = 2.60, t = 1.35, p = .180). For the low-incentive MI lists (Figure 4b), the slope was smaller than zero in the uncued lists (β = −4.75, t = −1.51, p = .002) but it was not different from zero in the cued lists (β = −.88, t = −.60, p = .547). For the high-incentive lists, the three-way interaction was not significant in either MC (Figure 4c) or MI lists (Figure 4d). The second GLMM analysis[14] revealed that the slope was greater than zero in the uncued (β = 4.11, t = 2.14, p = .032) but not in the cued (β = 1.89, t = .90, p = .370) high-incentive MC lists. For the high-incentive MI lists, the slope was not different from zero for either uncued (β = −1.21, t = −.73, p = .46) or cued (β = −.33, t = −.23, p = .82) lists.

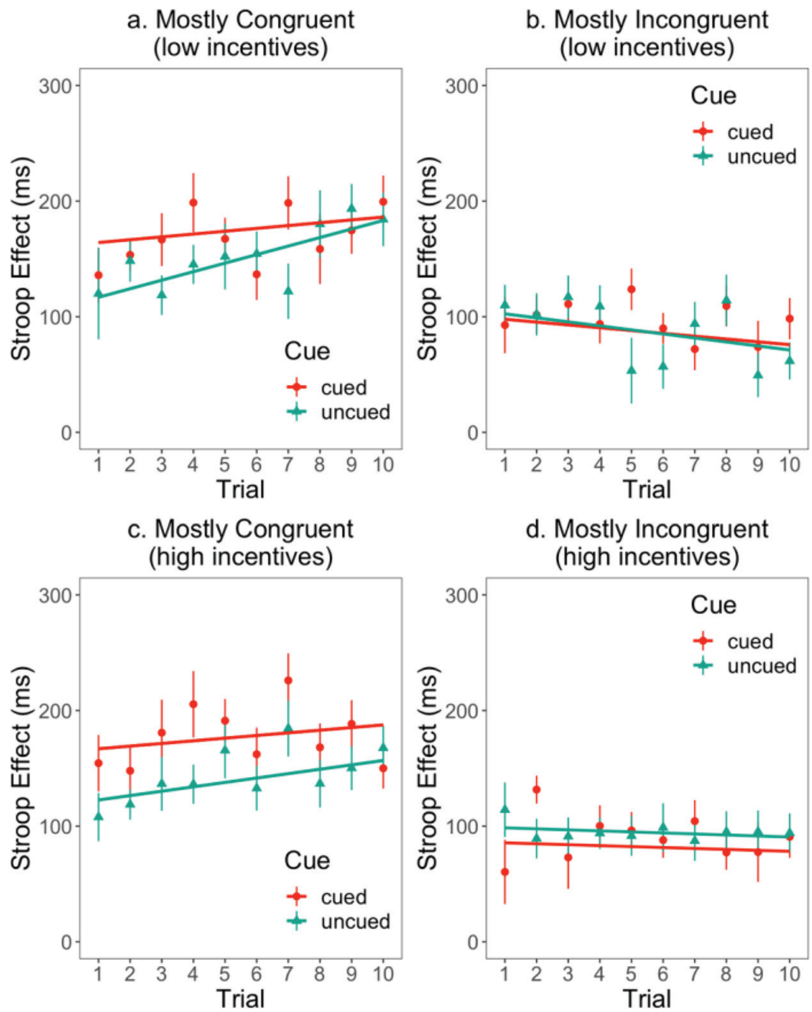
Discussion

We tested how expectation- and experience-driven control is modulated by the amount of expected incentives (i.e., motivation) by examining slopes of learning for each combination of list type (MC vs. MI) and incentives (low vs. high). Unlike the mean-level analyses of Bugg et al. (2015) that suggested the cue-induced MI shift under the high incentive condition was restricted to the first trial of the list, we found that the MI shift was not limited to the first trial. Instead, it was consistently observed throughout the list (see Figure 4d), as in the MC condition. This suggests that, under expected high incentives, participants used the precue at the beginning of the list to heighten (MI) or relax (MC) control and seemed to rely on the cued information throughout the list (i.e., heavily weight expectations). This interpretation is reinforced by the lack of a three-way interaction for either high incentive MC or MI lists although there was an overall cue-induced MC and MI shift (i.e., change in the Stroop effect based on the cue). This pattern also shows a contrast to the modeling outcomes from the speeded condition of Analysis 2 where both the three-way (cue-influenced control learning) and Trial Type × Cue interactions (cue-induced shifts) were significant. For low incentive conditions, the analysis

[14] The full summary of the additional GLMM analysis is available in the online supplemental materials.

Figure 4

Model-Predicted Stroop Effect (Solid Lines) as a function of Cue and Trial Position of (a) Low Incentives Mostly Congruent (MC), (b) Low Incentives Mostly Incongruent (MI), (c) High Incentives MC, and (d) High Incentives MI Lists in Experiment 4 of Bugg et al. (2015)



Note. Each data point indicates the Stroop effect calculated from raw data. The color and shape of each point marker indicates the cue type (red/circle: cued, green/triangle: uncued). Error bars depict ±1 standard error. See the online article for the color version of this figure.

replicated key findings of Analysis 1, showing that participants instantly relaxed attentional control following the MC cue but not following the MI cue resulting in an absence of a cue-induced attentional shift in the latter condition.

The GLMM results indicated that the data from high incentive MC lists best support Model 5 (see Figure 1), given that the expectation- and experience-driven control showed an additive effect. However, the data from high incentive MI lists are not perfectly consistent with any of the proposed models because both uncued and cued slopes were not different from zero suggesting the absence of experience-driven control. The low incentive MC and MI lists are best explained by Models 1 and 2, respectively, just as in Analysis 1.

A very interesting observation was that when high incentives were available in the MI lists, we found evidence of weak experience-driven control (e.g., flat slopes indicating a lack of control learning). One could interpret this such that, once the context (e.g., high incentive) was mapped to a control setting (e.g., expectation-driven), participants tended to stick to the mapped control setting instead of switching regardless of environmental input (e.g., accumulated conflict information via experience). On this view, it is possible that the lack of control learning could be due to the participants' tendency to stick with using the cue under high incentives.

So far, we have shown that the signature of control learning (i.e., slope) varies based on the availability of the precue as well as the demand for preparatory control and motivation. In uncued lists, this signature can be taken as a relatively pure index of experience-driven control. In cued lists, this signature represents the potentially conjoint influences of experience-driven and expectation-driven control since

Table 7
Generalized Linear Mixed Model Output of Cue Conditions ("MC Cue," "Valid Cue," "MI Cue," Versus "Uncued") in Experiment 5 of Bugg et al. (2015)

Predictor	Estimates	95% CI	t	p
(Intercept)	620.89	[616.01, 625.77]	249.34	<.001
Trial Type	111.82	[106.46, 117.18]	40.90	<.001
MC Cue	3.10	[−1.27, 7.42]	1.41	.158
Valid Cue	2.99	[−0.54, 6.53]	1.66	.097
MI Cue	4.53	[0.36, 9.41]	2.83	.070
Trial Position	0.10	[−0.27– 0.47]	0.53	.598
Trial Type × Trial Position	0.42	[−0.25, 1.09]	2.35	.216
Trial Type × MC Cue	27.86	[22.46, 33.26]	10.22	<.001
Trial Type × Valid Cue	−2.77	[−7.30, 1.76]	−1.20	.230
Trial Type × MI Cue	7.50	[3.08, 11.92]	3.33	<.001
Trial Type × MC Cue × Trial Position	−1.06	[−1.92, −0.21]	−2.45	.014
Trial Type × Valid Cue × Trial Position	0.16	[−0.93, 0.62]	−0.39	.693
Trial Type × MI Cue × Trial Position	−1.21	[−1.99, −0.43]	−3.04	.002

Note. The interpretation of the cuing effects should be made in comparison with the uncued list, which served as the reference group in this model. Additionally, note that the Trial Type × Trial Position interaction represents that interaction within the reference group (uncued lists). MC = mostly congruent; MI = mostly incongruent; CI = 95% confidence interval.

the precue was always valid (i.e., the MI precue was always followed by an MI list and the MC precue was always followed by the MC list). To address this limitation, Bugg et al., in their Experiment 5, tested pure expectation-driven control by examining the effect of MC and MI cues while holding experience constant (50% congruent) between lists. The results showed that participants used the MC cue to relax attention but there was no evidence that participants used the MI cue to heighten attention. In addition, the cue-induced shift in attentional control was only evident for the first half of trials but not for the second half of the trials, implying a decay in expectation-driven control over time.

In the following analysis, by using the data from Experiment 5 of Bugg et al. we tested a signature of pure expectation-driven control that was never directly examined previously. Unlike the former analyses, where the primary interest was testing differences in trajectories of experience-driven control (control learning) between cued and uncued lists (slopes), Analysis 4 aimed to investigate the isolated effect of the precue while the experience was fixed rather than when experience covaried with the precue.

Analysis 4: Testing the Pure Effect of Expectation-Driven Control

Experiment 5 of Bugg et al. (2015) examined the effects of precues when proportion congruency (experience) was fixed to 50% across lists and a misleading precue (80% matching [MC], 80% conflicting [MI]) or a valid cue (50% matching/conflicting) was presented, and these conditions were compared with uncued lists. Selectively in the first half of trials, the mean Stroop effect was larger when participants were presented with a MC compared with a MI precue even though the actual proportion congruency was equivalent highlighting a pure expectation-driven modulation of control. This modulation was driven by a difference between the MC cued lists and the validly cued lists (the difference between the MI cued lists and the validly cued lists was nonsignificant). Here, we reanalyzed Experiment 5 (N = 35) of Bugg et al. (2015) by using GLMM. The experimental design was identical to previous studies except there were 20 trials per list (compared with 10 trials per list in Experiment 1–4). In the model, we submitted all 20 trials to analysis (rather than analyzing the first half [first 10 trials] separately from the second half [second 10 trials] as in Bugg et al., 2015) and the precue type (MC cue, MI cue, valid cue, uncued) was coded as a categorical variable by having the uncued condition as a reference condition.

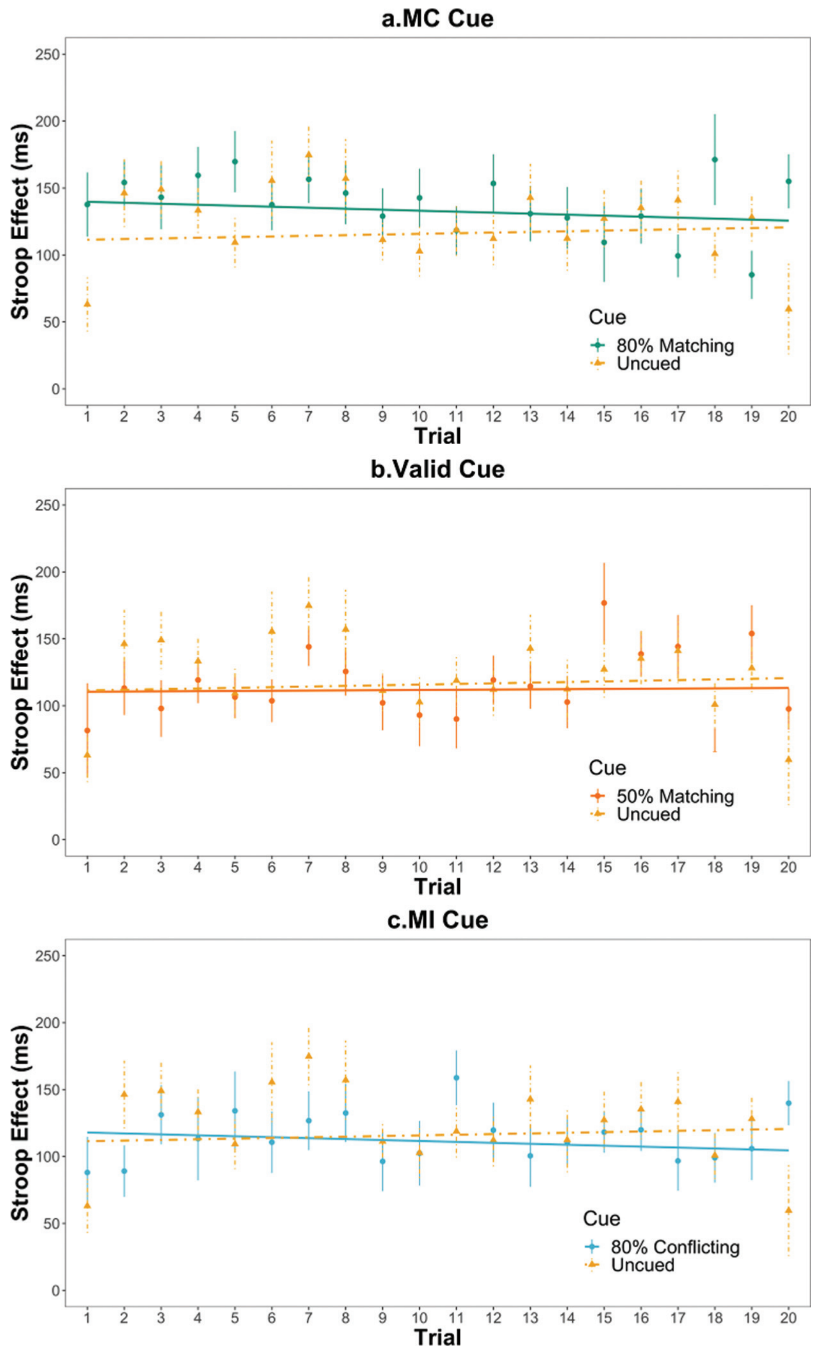
Results

The fixed effects estimates from the GLMM output are shown in Table 7. The GLMM analysis revealed that the main effect of trial type was significant, β = 111.82, t = 40.90, p < .001, revealing a typical Stroop effect. Compared with the uncued condition, there was not an effect of cuing for the MC cue, β = 4.53, t = 1.82, p = .070, MI cue, β = 3.10, t = 1.41, p = .158, or valid cue, β = 2.99, t = 1.66, p = .097, suggesting that the overall RT was not modulated by the precue. The main effect of trial position, β = .10, t = .53, p = .598, and the Trial Type × Trial Position interaction, β = .42, t = 2.35, p = .216, were not significant indicating the lack of experience-driven modulation in control in the reference group (uncued condition). The Trial Type × Cue interaction was significant with the MC cue, β = 27.86, t = 10.22, p < .001, suggesting that the magnitude of the Stroop effect was larger with the cue compared with the uncued condition. Interestingly, the same interaction with the MI cue was also significant, β = 7.50, t = 3.33, p < .001, with a positive beta estimate, suggesting that the Stroop effect was larger when followed by the MI cue compared with that of the uncued condition.[15] Unlike the misleading cues, with the valid 50% congruent cue, the Trial Type × Cue interaction was not significant, β = −2.77, t = −1.20, p = .230. Of primary interest, the three-way interaction of Trial Type × Cue × Trial Position was significant with

[15] At first glance, this may seem surprising considering that the MI cue is expected to heighten control. It is helpful to remember that the beta estimate for the Trial Type × Cue interaction indicates the difference in the Stroop effect between cued and uncued lists when trial position is zero (i.e., zero experience; see Footnote 11). If one extends the blue/solid (cued MI) and yellow/dashed (uncued) lines to position zero in Figure 5c (see also Figure 6c the), the blue/solid line is above the yellow/dashed line (meaning a larger Stroop effect for MI cued than uncued). The positive beta estimate might also be an artifact of the linear assumption that we had taken in the GLMM analysis, as Figure 5c suggests that initially (in Trial Positions 1 and 2) the cueing effect was in the right direction for the MI condition (see also Figure 6c).

Figure 5

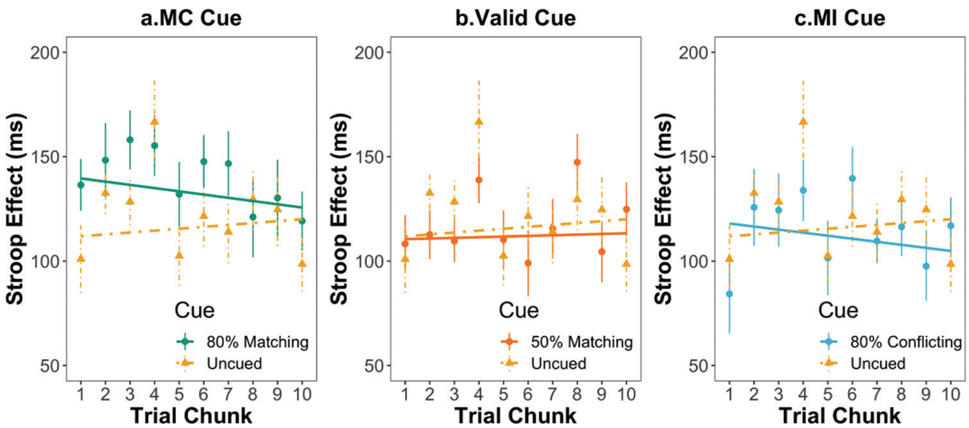
Model-Predicted Stroop Effect as a Function of Cue and Trial Position for (a) Mostly Congruent (MC) Cue, (b) Valid Cue, and (c) Mostly Incongruent (MI) Cue in Experiment 5 of Bugg et al. (2015)



Note. Each data point indicates the Stroop effect calculated from raw data. The solid and dashed lines indicate the cued (80% matching, 50% matching, & 80% conflicting) and uncued conditions, respectively, in Panels a - c. Error bars depict ±1 standard error. See the online article for the color version of this figure

Figure 6

Model-Predicted Stroop Effect as a Function of Cue and Trial Chunk for (a) Mostly Congruent (MC) Cue, (b) Valid Cue, and (c) Mostly Incongruent (MI) Cue in Experiment 5 of Bugg et al. (2015)



Note. Each data point indicates the Stroop effect calculated from raw data. The solid and dashed lines indicate the cued (80% matching, 50% matching, & 80% conflicting) and uncued conditions, respectively, in Panels a - c. Error bars depict ±1 standard error. See the online article for the color version of this figure.

the MC cue, β = −1.06, *t* = −2.45, *p* = .014, and the MI cue, β = −1.21, *t* = −3.04, *p* = .002, but not with the valid cue, β = .16, *t* = −.39, *p* = .693.

The three-way interactions are illustrated in Figure 5. As Figure 5a shows, with the MC cue, the Stroop effect was initially large but decreased as the list progressed, resulting in a larger cuing effect in the initial part of the list. With the MI cue (Figure 5c), the Stroop effect also decreased as the list progressed. There was no effect of the valid cue as the overlapping trend lines in Figure 5b indicate.

The second GLMM analysis was conducted to examine individual slopes separately. The results showed that all slopes were not different from zero, MC cue (β = −1.14, *t* = −1.56, *p* = .118), MI cue (β = .28, *t* = .50, *p* = .618), valid cue (β = .09, *t* = .19, *p* = .853), and uncued (β = −.23, *t* = −.41, *p* = .679). The results of the individual slope analyses, especially for MC cued lists, were surprising, given the significant Trial Type × Cue × Trial Position interaction (see Table 7). To examine whether the lack of steepness in the individual slopes might be attributable to the noisiness of the individual trial position estimates, we combined adjacent trials (e.g., Trials 1 and 2) so that each chunked trial unit had more observations (resulting in a total of 10 positions as in Analyses 1–3).[16] Figure 6 illustrates the three-way interactions with the chunked trial position.

The model outcome with the chunked trial position mirrored the original results (see full results from Table S21 in the online supplemental materials). The individual slope analysis showed that, with the chunked trials, the slope was significantly steeper than zero for MC cued lists (β = −2.46, *t* = −2.38, *p* = .018). However, slopes with MI cue, valid cue, and uncued lists were not different from zero (see Table S22 in the online supplemental materials for the full summary).

Discussion

We reanalyzed Experiment 5 of Bugg et al. (2015) where the experience was matched across all lists to be 50% congruent, and a precue provided invalid information such that 80% of upcoming trials will be conflicting or matching, or valid information (50% congruent). The results of Bugg et al. suggested that expectation-driven control influenced performance in the initial trials, whereas experience-driven control dominated in the later trials. We investigated these patterns further with GLMM and found several interesting patterns that were not revealed from the mean-level analysis in the original report. With the MC cue (Figures 5a and 6a), the Stroop effect initially increased indicative of a relaxation of control and then gradually decreased as experience accumulated (as participants learned the list was 50% congruent). Given that experience did not change over the course of the list (i.e., the entire list was 50% congruent), we believe the initial shift and later decay can be interpreted as a waxing and waning of the expectation-driven control. With the MI cue, the model-predicted Stroop effect showed that the changes were less pronounced immediately following the precue and were relatively gradual thereafter as can be seen by the decreases in the Stroop effect with increasing trial position (Figure 5c). This pattern is clearly contrasting to the typical effects of the MI cue as illustrated in the model-predicted Stroop effects from Analyses 2 and 3 (in Figures 3d and 4d) that showed immediate changes in the Stroop effect following the precue when there was a significant cue-induced shift in the MI list (speeded & high incentive MI conditions). However, the raw data plotted in Figures 5c and 6c raise the possibility that there was an initial heightening of control immediately following the MI cue (as is apparent at Trial Position 1 and Trial Chunk 1, respectively) but it was not

[16] We thank Giacomo Spinelli for suggesting this approach. For completeness, we also re-analyzed the data from Analysis 1–3 using the chunked trials approach and the results are available in the online supplemental materials (Table S15–S20). The results replicated the original pattern of results but some beta estimates, those originally not significant, became significant (three-way interaction of MI lists in Analysis 1, Trial Type × Cue interaction of unspeeded MC lists in Analysis 2, steepness of slope of uncued speeded MC lists in Analysis 2).

Table 8
Summary of Model Output in Analyses 1–3

Data set	Condition	Predictor	MC Estimated coefficient	MC p	MC Model	MI Estimated coefficient	MI p	MI Model
Analysis 1 (Experiment 1 and 2 of Bugg et al., 2015)		Trial Type × Cue	98.90	<.001	Model 1	−8.99	.125	Model 2
		Trial Type × Trial Position	10.10	<.001		−2.95	.003	
		Trial Type × Cue × Trial Position	−9.11	<.001		1.53	.126	
Analysis 2 (Experiment 3 of Bugg et al., 2015)	Unspeeded	Trial Type × Cue	−12.21	.151	Model 4	−19.81	.009	—
		Trial Type × Trial Position	0.83	.642		−2.10	.112	
		Trial Type × Cue × Trial Position	10.13	<.001[a]		2.27	.100	
	Speeded	Trial Type × Cue	50.10	<.001	Model 1	−32.62	<.001	Model 1
		Trial Type × Trial Position	5.25	.001		−6.59	<.001	
		Trial Type × Cue × Trial Position	−4.38	.032		5.14	<.001	
Analysis 3 (Experiment 4 of Bugg et al., 2015)	Low incentive	Trial Type × Cue	51.98	<.001	Model 1	−7.02	.209	Model 2
		Trial Type × Trial Position	7.31	<.001		−3.33	.001	
		Trial Type × Cue × Trial Position	−4.75	<.001		1.13	.230	
	High incentive	Trial Type × Cue	46.46	<.001	Model 5	−11.35	.007	—
		Trial Type × Trial Position	3.66	<.001		−0.86	.317	
		Trial Type × Cue × Trial Position	−1.48	.261		−0.21	.804	

Note. — = Data do not fit in any of the proposed models. The model refers to the predicted model that is most consistent with the GLMM outcomes (see Figure 1 for reference). MC = mostly congruent, MI = mostly incongruent.
[a] Estimated β parameter showed a reversed direction.

captured by the linear model. We consider this possibility further in the General Discussion.

General Discussion

The present study had two major goals. One was to examine the learning processes underlying the LWPCE (experience-driven control). The second and main goal was to reveal whether such learning processes are influenced by precued knowledge about prospective conflict (expectation-driven control). First, we summarize the main findings informing how cognitive control is shaped by the adaptive weighting of experience and expectations.

In Analyses 1–4, we demonstrated the unique signatures of experience-driven control (control learning) and expectation-driven control, and their interaction by modeling slopes of the Stroop effect as a function of the accumulated experience in MC and MI lists and comparing the slopes between uncued and cued conditions. The modeling results revealed several important observations that have never been illuminated in prior studies that used mean level analyses. To begin with, we summarize three major findings. First, the analyses revealed evidence of control learning underlying the LWPCE for the first time. In our modeling results, the Trial Type × Trial Position interaction[17] showed that the Stroop effect exhibited a gradual increase or decrease as experience accumulated in MC and MI lists, respectively (see Table 8). This incremental pattern suggests that participants relaxed or heightened the extent of attentional control by continuously updating information about upcoming conflict from experience via learning processes.

Second, we found different signatures of control learning depending on the presence of a precue in select data sets.[18] In the modeling output, we were able to verify this by evaluating the Trial Type × Cue × Trial Position interaction. With the precue, the learning effect was often absent or weak, showing a relatively stable Stroop effect regardless of the amount of experience. This pattern fits well with our initial prediction of Model 1[19] (see Figure 1), which illustrates a dominant expectation-driven control when the precue is available. However, it is notable that the extent to which experience-driven control was modulated by the precue was more consistently evident in MC lists compared with MI lists as the latter list type showed a marginal or nonsignificant three-way interaction in all but one of the MI data sets (see Table 8), which is more consistent with Model 2. Although the three-way interactions in MI lists often failed to reach statistical significance, the predicted RT consistently illustrated a relatively flatter slope (i.e., Stroop effect as a function of trial position) with the cue compared with without the cue (consistent with Model 1). Therefore, the lack of interaction may reflect a lack of statistical power as the effect of the cue on the Stroop effect tended to be weaker in MI lists.[20] This may have made it difficult to detect a modulating effect of the cue on patterns of control learning.

[17] The Trial Type × Trial Position interaction was significant in a meaningful direction in the following conditions: MC and MI lists in Analysis 1, speeded condition of Analysis 2, low incentive condition of Analysis 3, and MC list only in high incentive condition in Analysis 3.

[18] In MC lists, the three-way interaction was significant in Analysis 1, the speeded condition of Analysis 2, and the low incentives condition in Analysis 3. In MI lists, the interaction was significant in the speeded condition of Analysis 2.

[19] Our interpretation that the overall data fit with the prediction of Model 1 is based on a relatively strict interpretation of the data, namely that in the cued condition the slope was not different from zero. However, there often was a nonsignificant slope in the expected direction for the cued condition, which raises the possibility that the slope is real, but detecting the effect may require more power than the individual analyses reported in this manuscript can offer especially considering experience-driven learning is reduced in cued conditions. If the slope is real, then a different model (e.g., Model 3) may be the better fitting model. We thank Giacomo Spinelli for pointing this out.

[20] Supporting this view, the chunked trial position analysis (see Table S15 and S16 in the online supplemental materials), which is presumably a more powerful approach because the individual cells (each chunked trial position) are based on more observations, revealed that Model 1 might be the best fitting model for MI lists in Analysis 1 (three-way interaction was significant, β = 3.45, $t = 1.98$, $p = .048$, and Trial Type × Cue interaction was marginally significant, β = −11.05, $t = −1.91$, $p = .056$).

Lastly, in Analysis 2 and 3, the expectation-driven control varied based on the demand on preparatory control as well as the magnitude of projected incentives. In specific, we found that both MC and MI lists showed a robust cuing effect (Trial Type × Cue interaction) when the use of the precue was encouraged (speeded lists in Analysis 2 and high incentive lists in Analysis 3). In contrast, when the use of the precue was relatively not encouraged (unspeeded lists in Analysis 2 and low incentive lists in Analysis 3), the cuing effect was weaker or even absent. These results confirm the initial observations of Bugg et al. (2015) but extend them by showing that, in contrast to the conclusion of Bugg et al., the cue-induced shift in MI lists was not limited to the first trial (Bugg et al. found a cuing effect on the first trial but not in the analysis comparing mean Stroop effects for the entire list). Taken together, these three major findings provide converging evidence to support the notion that the weighting of experience- and expectation-driven control appears to be dependent on the demand on preparatory control as well as motivation to utilize the cue.

Speed Versus Incentives

In the experiments that yielded data for Analysis 2 and Analysis 3, speed and incentive manipulations were used to facilitate the adoption of the precue by participants. Although both manipulations had the same general purpose, they seem to be tapping slightly different operating principles. For example, in the speeded condition of Analysis 2, the cue was intended to have participants preload (especially in MI lists) a "focused" attentional setting prior to the stimulus (e.g., color word) onset because the stimulus was expected to remain on the screen for a brief time. On the other hand, in the high incentive condition of Analysis 3, the cue primarily aimed to increase the level of participants' motivation by having them actively gathering and utilizing information that would benefit performance including the precue. Therefore, it is possible that speed and incentive manipulations are fundamentally different in terms of whether the use of the precue was caused by external factors such as experimental structure or internal factors such as motivation. However, the mean level analyses of Bugg et al. could not inform this possibility. In line with this possibility, the modeling outputs of Analysis 2 and Analysis 3 showed contrasting patterns (see model-predicted Stroop effects in Figures 3 and 4). In Analysis 2 speeded condition, there was evidence for cue-influenced control learning in MC and MI lists such that the difference between the cued and uncued slopes was significant (flatter for cued). In Analysis 3 high incentive condition, although the precue shifted the Stroop effect in MC and MI lists, the uncued and cued slopes were parallel to each other in both list types (i.e., there was no evidence for cue-influenced control learning). This is theoretically interesting because it suggests that, under prospective high incentives, the cue heightened control while concurrently enabling control learning, whereas in the speeded conditions, the cue heightened control but attenuated control learning (such that the effect of the cue was more apparent early in the list before experience caught up in the uncued condition). Another interesting finding from Analysis 3 is that both cued and uncued slopes in high incentive MI lists were not different from zero, indicating the absence of control learning. One possible post hoc explanation is that, when highly motivated, people rely more on explicitly presented knowledge (i.e., certainty) and such heavy reliance on the explicit source of information (expectations) counteractively prevents recruitment of experience-driven control.

Asymmetric Effect of Precue

In the present study, we found a persistent MC-shift but mixed evidence of an MI-shift (see Table 8). This asymmetric cuing effect is not completely unexpected given similar results have been reported in the literature, including in the data used in the present analyses (Bugg et al., 2015; Correa et al., 2009; Ghinescu et al., 2010; Gratton et al., 1992; Liu & Yeung, 2020; see also Bugg & Diede, 2018). What causes this asymmetric influence of the precue remains an open question.

The original and follow-up studies (Bugg et al., 2015; Bugg & Diede, 2018) discussed two possibilities that could explain the lack of MI-shift (i.e., Trial Type × Cue interaction). First, in an MI list, it is possible that participants might have already reached the ceiling in minimizing word reading in the current paradigm even without the cue, leaving no extra room for adjustment in attentional control. Second, it is also plausible to assume that participants simply did not use the cue because they thought the cue was not useful. In line with this, Gratton (1992) provided a similar explanation such that the lack of an MI-shift could be due to a ceiling effect or low demand of the cue use. Recently, Aben et al. (2017) suggested an alternative explanation interpreting the asymmetry as a consequence of different timescales of control between MC and MI lists. According to them, attentional control operates on a longer timescale in frequent conflict contexts (MI lists) and therefore a cue-induced heightening of attentional control could not be achieved in a relatively short time scale after the cue was provided in 10-trial lists. They also attributed the prevalent MC-shift to the fact that attentional control works in a relatively shorter timescale in rare conflict contexts (MC lists), thus it allows the cue-induced adjustment in control within a range of 10 trials. This is an interesting possibility. The new analyses performed herein suggest this explanation may not be complete because, when the MI-shift was observed, it was more evident during the early trials within the list.

Although all the prementioned explanations provide reasonable accounts, empirical evidence is still lacking primarily because the prior cuing literature has been focused on the role of the precue as an information carrier rather than understanding how people actually use the cue. In Bugg et al. (2015), some efforts were made to further explore the absence of an MI-shift by encouraging precue use in Experiments 3 and 4. By using the same data sets, but applying GLMM, the current analyses revealed that an MI-shift was observable when the use of the precue was encouraged, thereby providing support for the view that participants may have otherwise defaulted to not utilizing the precue.

Motivation or willingness to use the precue seems to play a role in MC lists as well. In Analysis 2 unspeeded MC lists, we observed an unexpected pattern showing a gradual relaxation in control in the cued lists (evidence for control learning) but lack of such an effect in uncued lists. Although it is speculative, when the perceived demand of control is *relatively* low (as in MC unspeeded lists when MC speeded lists also exist), the precue might facilitate control learning that otherwise would not occur without the cue. Regardless of whether this speculation is true, the asymmetric pattern comparing speeded and unspeeded conditions provides a hint of a minimum amount of task (cue) demand that may be a prerequisite to produce the MC shift.

Why do MI lists require a stronger motivation or demand to encourage use of the precue compared with MC lists although the precue is presumably more beneficial in high conflict contexts? We speculate that the answer may reflect decision making principles centered on tradeoffs between reward and cost. It has been suggested that people tend to perceive cognitive effort as a cost in the decision-making process, namely the "law of least mental effort" (Braver et al., 2014; Kool et al., 2010; Shenhav et al., 2013). According to this view, if the perceived subjective value of goal-directed behavior (e.g., naming the color) is greater than the perceived cost related to the effort, people are willing to make an effortful choice. What this account illustrates aligns well with the lack of MI-shift that we observed in Analysis 1, in the unspeeded lists in Analysis 2, and in the low incentive lists in Analysis 3, and other cuing studies. It is possible that participants did not use the precue in these MI lists because the perceived value of the expected cognitive effort associated with utilizing the precue was less than that of the color naming behavior in this high conflict context. However, when high incentives were provided as in Analysis 3, the perceived value of using the precue may have been greater than that of the color naming behavior and thus participants made a costly choice by adopting the precue. Additional empirical validation must follow in future studies.

The Role of Cue Validity

In Analysis 4, we examined isolated effects of expectations by reanalyzing the data set of Experiment 5 in Bugg et al. (2015) that used the invalid cues (in addition to a validly cued and an uncued condition) while keeping the experience constant at 50% congruent. Consistent with the original finding of Bugg et al. (2015), we found a significant slope difference between uncued and misleading cue conditions. Both MC and MI cues showed negative slopes. The negative slope with the MC cue (Figures 5a and 6a) suggests that participants temporarily relaxed control followed by the MC cue, but gradually abandoned relying on the cued information as they accumulated experience. However, the slope was also negative with the MI cue (Figures 5c and 6c), meaning the model predicted that the Stroop effect would decrease over the course of the list, suggesting that participants maintained the heightened control state during the entire list. The negative slope was surprising because we initially expected that the Stroop effect would decrease immediately following the cue and then gradually increase toward the end of the list as they abandoned the cue (with accumulated experience). There are a few possible explanations for the negative slope with the MI cue. First, it is possible that the negative slope could be an artifact of the linear model that we used in the GLMM analysis. Supporting this idea, the raw data points in Figure 5c (or Figure 6c) at Trial Position 1 (or Trial Chunk 1) indicate that there was an initial heightening of control following the MI cue, but this was not captured by the model. Alternatively, it is possible that the negative slope reflects the true nature of expectation-driven control following an MI cue, but it was not revealed earlier in Analyses 1–3 because there was not enough room for control to be exerted further (i.e., ceiling effect) in the MI lists used in those analyses. If this is true, the flat slope that we reported earlier with the valid MI cue could have been a negative slope if there was room for additional control heightening. Lastly, we speculate that the negative slope may reflect the asymmetry in shifting attentional control. Abrahamse et al. (2013) found that the LWPC effect was smaller when participants performed traditional (long) lists in the MI-MC compared with MC-MI order, a pattern called the *asymmetrical list shifting effect*. Drawing on this effect, it is possible that participants had a hard time detecting the list PC (that half the trials were congruent/incongruent) and/or relaxing control after they initially heightened control following the MI cue (as indicated by trial Chunk 1 in Figures 5c and 6c), resembling the MI-MC shift. Though additional data are needed to further examine these possibilities, the results of Analysis 4 showed that expectations alone affect control and may change one's perceptions of experience, thereby influencing the development of an optimal control strategy.

Limitations and Future Directions

Although our results provide novel insights into how the cognitive control system achieves an optimal behavioral outcome through adaptive weighting of expectations and experience, as illustrated by the trial-to-trial changes in the Stroop effect under cued and uncued conditions, which has never been investigated previously, there are several limitations that could be potentially addressed by future studies. First, in the present analyses, many conditions were never directly compared (e.g., MC vs MI, speeded vs. unspeeded, high incentives vs. low incentives, etc.) because those comparisons were outside the scope of our primary goals and complex models with additional factors often fail to converge especially with a limited sample size. However, with a larger data set, future studies will be able to run a complex model to directly test how adaptive weighting of expectation- and experience-driven control interact with factors such as PC or incentives.

Second, there may be additional models that merit consideration beyond the five models we specified in the introduction section.[21] For example, precues might induce an immediate shift in expectation-driven control (as in Models 1, 3, and 5) and simultaneously boost experience-driven control learning (as in Model 4). More generally, models that embrace the theoretically plausible possibility that precue usage may vary across trials independent of variations owing to experience-driven control learning should be considered in future research. For example, it is possible that participants might get better at translating their expectations into attentional biasing strategies across trials. Alternatively, it may be that sustaining a heightened state of control in response to an MI precue may be difficult such that use of the precue decays across trials, or the precue may simply be forgotten. Indeed, the precue was always presented once at the beginning of the list in the studies we modeled. To prevent the retrospective forgetting of the cued information, future studies might consider modifying the way that the precue is presented, for instance it could remain on the screen during the task. This may yield stronger or longer-lasting effects of the cue (e.g., in MI lists) or be more likely to lead to cue-influenced control learning (changes in the slope in the presence vs. absence of the cue). Additionally, we recognize that the assumption of a linear relationship between the amount of

[21] We thank Tobias Egner and Giacomo Spinelli for suggesting consideration of these other model possibilities.

experience and corresponding changes in control might not reflect the true nature of learning. Indeed, it is possible that the signature of experience-driven control would be better captured with a nonlinear function, such as a typical learning curve that is well fitted by an exponential function (Ebbinghaus, 1885/1913). Similarly, it is possible that the signature of expectation-driven control may also be better captured by a nonlinear function. For example, in Analysis 4, the best-fitting line for the MI precue may be one that shows an initial dip (implying an initial heightening of control [consistent with the first trial chunk]) followed by a peak (implying some relaxation of control) and subsequently a gradual reheightening of control.

Third, the present analyses were limited to the abbreviated lists paradigm and the color-word Stroop task. Therefore, generalization to longer-list paradigms and other tasks remains to be tested. With respect to list length, we are only picking up on the initial stages of experience-driven control learning in our 10-item (or 20-item as in Analysis 4) lists. The learning dynamics would likely look different in longer lists, for example, the rate of control learning would possibly asymptote at some point.

Fourth, as Bugg et al. (2015) acknowledged, the design of the experiments does not allow us to break down what we referred to as experience-driven control learning into various sources (i.e., conflict probabilities, contingencies, temporal rhythms, control states, etc.). Therefore, we cannot pinpoint what exactly is learned trial-to-trial that changes the magnitude of the Stroop effect. However, there is evidence from the abbreviated list paradigm showing that when there are four inducer items (i.e., four colors/words that are MC or MI within the MC and MI lists) as in the present lists, performance differences are also detected on diagnostic trials (i.e., stimuli comprised of differing colors/words that are 50% congruent in MC and MI lists) consistent with the view that the lists induce differences in control at the list level (Cohen-Shikora et al., 2018). Future studies could shed further light on this question by examining whether there are unique signatures of learning (i.e., slopes) depending on the source using the analytic approach we developed, and relatedly whether evidence for cue-influenced control learning varies depending on the information communicated by the cue. The cues in the present study explicitly informed participants of the conflict probability within a list. Informing participants of contingencies (i.e., when you encounter BLUE it will usually be in blue ink) instead could have different effects (e.g., there may not be a cuing effect) and may interact differently with control learning.

One source whose putative role we were able to explore more directly in the current study was episodic binding (e.g., Giesen et al., 2019; Schmidt et al., 2020), and namely the extent to which our effects are better described by episodic contributions (repetition of word-distractor pairings within a list) as opposed to control or control learning.[22] The fact that the slopes for control learning tended to be steeper in MC and MI lists is potentially consistent with such an account and could reflect that there are more likely to be repetitions of the same word-distractor pairing in MC lists than MI lists (given there are only four possible congruent pairings compared with 12 possible incongruent pairings). To examine such episodic contributions, we performed three steps. First, we used the combined data set from Analysis 1, which represents the basic LWPC manipulation, and we examined the LWPC effect when prior exact repetitions were excluded. The results showed that the LWPC effect remained intact (typical pattern) and robust even in a quite restrictive case where we excluded exact repetitions occurring as many as eight trials back in the list (see Figure S8 in the online supplemental materials). Second, we ran a GLMM analysis to examine the contribution of prior repetitions ($n-1$, $n-2\ldots n-9$) to the LWPC effect (see Table S10 in the online supplemental materials). The key results were that (a) the LWPC effect remained significant regardless of the inclusion of prior repetitions and (b) the $n-1$ and $n-2$ repetition effects were significant. This means that although episodic effects may be at play in the present paradigm, at least for exact repetitions that occur one or two trials back, controlling for such effects does not eliminate the LWPC effect. Based on these results, it seems hard to claim that the experience effect (LWPC) reflects episodic binding instead of learning. However, because the learning component is really captured more directly by the slopes, in the third step the same GLMM models as originally reported for Analysis 1 (and then all subsequent analyses) were run after excluding exact repetitions (as in Analysis 3 of Schmidt et al., 2020). The results of these new analyses mirrored the original models (that did not exclude exact repetitions; see Table S11–S14 in the online supplemental materials for the full summary). Collectively, the findings of these additional analyses suggest the experience-based adjustments underlying the LWPC effect result from a learning process as opposed to episodic repetition effects, and the learning process is driven by experiences with conflict (past experiences with control) and not simply repetition of recent trials.[23]

Despite those limitations, our findings convey novel information that informs understanding of the flexible and adaptive nature of cognitive control. We suggest that the modeling approach introduced in the present study, in conjunction with the abbreviated-lists paradigm, could be broadly used to examine dynamic signatures of cognitive control including the learning of control based on experiences that accumulate across time, a goal that is not readily achieved and/or possible with a traditional mean level analysis.

Conclusion

The purpose of this study was to examine the learning processes that underlie the LWPCE and whether prior knowledge about upcoming conflict via explicit precues influences such learning processes. Applying a novel analytic approach, we showed for the first time a gradual increase and decrease in the Stroop effect as experience unfolded in uncued MC and MI lists, revealing a signature of experience-driven learning that underlies differences in control between lists (i.e., the LWPCE). However, when a precue was presented to signal the upcoming conflict, we observed evidence that the cue influenced the signature of learning, in addition to shifting overall Stroop effects (e.g., larger in MC and smaller in MI lists). Specifically, the evidence for learning was often absent or weak, showing a relatively stable Stroop effect regardless of the amount

[22] We thank Luis Jiménez for raising this possibility and encouraging us to run additional analyses to test for episodic effects.

[23] It is worth noting that this conclusion is nonetheless compatible with the possibility that LWPC effects may reflect adjustments that are based on relatively recent learning (of control) based on conflict experiences within a list and not an accumulation of all prior experiences within the list (see, e.g., Colvett et al., 2020; Jiménez & Méndez, 2013).

of experience within the list. This pattern was more consistently observed in MC than in M Ilists, although not exclusively so, and the pattern suggests that in the cued lists control was mainly driven by explicit knowledge of conflict probability (i.e., expectations) and not the adaptive learning processes. In addition, our analyses also revealed that increased task demands (speeded) and motivation (high incentives) tended to shift the weighting in favor of expectations based on the precue, including in MI lists where Bugg et al. (2015) had previously found cuing effects to be limited to the first trial. We suggest that the present findings provide a proof-of-principle so to speak demonstrating that the analytical approach introduced and applied for the first time herein could be widely applied in future studies to enhance our understanding of (a) hidden learning processes that underlie cognitive control and (b) how control is optimized via the adaptive weighting of learning and external knowledge (experience and expectations).

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