

Priming cue encoding by manipulating transition frequency in explicitly cued task switching

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Explicitly cued task switching with multiple cues per task permits three types of transitions: cue repetitions (cue and task repeat), task repetitions (cue changes but task repeats), and task alternations (cue and task change). The difference between task alternations and task repetitions can be interpreted as a switch cost, but its magnitude varies substantially across experiments. We investigated how switch cost is affected by transition frequency (how often subjects repeat and switch tasks) with an experiment in which each transition had a frequency of .70 in separate sessions. Switch cost was smallest when task alternations were frequent and largest when task repetitions were frequent. Mathematical modeling of the data indicated that the different "switch costs" reflected priming of cue encoding for frequent transitions. Interpretations of our findings based on automatic priming from memory retrieval of past transitions and strategic priming from transition expectancies are discussed.

Task switching is used extensively to study executive control (Monsell, 2003). A typical task-switching experiment involves repeating and alternating tasks across trials, yielding a difference in response time (RT) and accuracy between task alternations and task repetitions known as a *switch cost*. One interpretation of the switch cost is that it reflects executive control processes that reconfigure the cognitive system when tasks are switched (e.g., Meiran, 1996; Rogers & Monsell, 1995). Another interpretation is that the switch cost arises from positive and negative priming in memory (e.g., Allport & Wylie, 2000; Schneider & Logan, 2005). These interpretations are not mutually exclusive, but both of them are concerned with what the switch cost represents, making it important to understand which factors affect switch costs in task-switching procedures.

The present study was motivated by a recent issue concerning the *explicit task-cuing* procedure, in which the task performed on each trial is indicated by a cue presented prior to the target stimulus (Sudevan & Taylor, 1987). An increased delay between the cue and the target (*stimulus onset asynchrony*, or SOA) often leads to a decreased switch cost, an effect interpreted by some authors as evidence for advance reconfiguration by executive control processes (e.g., Meiran, 1996). Such interpretations are based on a version of the explicit task-cuing procedure involving only one cue per task, which confounds cue repetition with task repetition (i.e., whenever the task repeats, the cue repeats; whenever the task changes, the cue

changes). To disentangle cue repetition from task repetition, some researchers have used multiple cues per task (e.g., Logan & Bundesen, 2003, 2004; Mayr & Kliegl, 2003), enabling three types of transitions: *cue repetitions* (cue and task repeat), *task repetitions* (cue changes but task repeats), and *task alternations* (cue and task change). The difference between task repetitions and cue repetitions can be interpreted as a repeated-cue-encoding benefit, whereas the difference between task alternations and task repetitions can be interpreted as a switch cost.

Logan and Bundesen (2003) and Mayr and Kliegl (2003) investigated the differences between transitions with multiple cues per task and arrived at different results and conclusions. Logan and Bundesen (2003) found a large repeated-cue-encoding benefit and little or no switch cost. On the basis of their results and formal modeling of the data, they argued that explicitly cued performance reflects cue-encoding effects and not executive control processes. In contrast, Mayr and Kliegl found a large repeated-cue-encoding benefit and a large switch cost. On the basis of their results, they argued that explicitly cued performance reflects two processes: cue-based retrieval of task rules from memory and application of task rules to the target (producing the repeated-cue-encoding benefit and the switch cost, respectively).

Many procedural differences could have contributed to the different patterns of data obtained by Logan and Bundesen (2003) and Mayr and Kliegl (2003); the cues, tasks, targets, and transition frequencies differed between the studies. Logan and Bundesen (2003, Experiment 3) used meaningful word cues for numerical judgments of single digits (e.g., *odd-even* and *parity* cued an odd-even judgment), with frequencies of cue repetitions, task repetitions, and task alternations of .25, .25, and .50, respectively. Mayr and Kliegl used arbitrary letter cues for perceptual judgments of colored forms (e.g., *G* and *S* cued a

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color judgment), with all transitions having a frequency of .33 because specific task alternations were omitted (see Mayr & Kliegl, 2003, p. 364). Logan and Bundesen (2004) investigated how cue type (meaningful vs. arbitrary cues) affected performance. Subjects performed two blocks of trials: One block involved meaningful word cues, and the other block involved arbitrary letter cues. Block order was counterbalanced across subjects. Word cues produced little or no switch cost, regardless of block order. Letter cues produced a sizable switch cost when they were used in the first block, but not in the second block. These results suggest that cue type was partly responsible for the different patterns of data obtained by Logan and Bundesen (2003) and Mayr and Kliegl.

What remains unclear is whether the switch cost was affected by any of the other procedural differences between past studies. The focus of the present study was on *transition frequency* (how often subjects repeat and switch tasks). Switch costs might vary as a function of transition frequency, but data on the issue are scarce. Meiran, Chorev, and Sapir (2000, Experiment 1) used the explicit task-cuing procedure with a single cue per task (permitting only cue repetitions and task alternations) to study the performance of different groups of subjects who experienced either equal frequencies of each transition or a higher frequency of cue repetitions (.67) than of task alternations (.33). Frequency condition did not interact significantly with transition or response–cue interval (SOA was fixed at 117 msec). In the *alternating runs* procedure, in which tasks are cued by the spatial position of the target in a predictable cycle (permitting task repetitions and task alternations), a few researchers have investigated the effect of increasing the frequency of task repetitions by manipulating run length (the number of consecutive trials with the same task). An examination of the data from Rogers and Monsell (1995, comparing the results from Experiments 3 and 6) hints at a slightly increased switch cost across different groups of subjects as the frequency of task repetitions increased from .50 to .75, but Monsell, Sumner, and Waters (2003, Experiment 1) observed no significant change in switch cost as the frequency of task repetitions increased from .50 to .75 to .88 in a within-subjects comparison.

The limited extant research on transition frequency suggests that it has little or no effect on switch cost, but it has rarely been manipulated systematically in a within-subjects design, and never in the explicit task-cuing procedure with multiple cues per task. To address this issue, we conducted an experiment similar to that in Logan and Bundesen (2003, Experiment 3), except that transition frequency was manipulated directly. Subjects repeated and alternated between two tasks: classifying single-digit targets as odd/even or as high/low with respect to 5. The odd/even task was cued by the words *odd–even* or the word *parity*, and the high/low task was cued by the words *high–low* or the word *magnitude*. Two cues per task permitted cue repetitions, task repetitions, and task alternations. The subjects experienced these transitions according to three

frequency conditions in separate experimental sessions: *cue repetitions frequent*, *task repetitions frequent*, and *task alternations frequent*. In each frequency condition, one type of transition occurred on .70 of the trials (providing the name for the condition), and each of the other types of transitions occurred on .15 of the trials. Each transition within each frequency condition could occur at five SOAs (0, 100, 200, 400, and 800 msec), allowing our analysis to extend beyond differences in mean RT to examine whether transition frequency alters the *time course function* (the change in RT with SOA) associated with performance.

METHOD

Subjects

Each of eighteen individuals from Vanderbilt University completed three experimental sessions in exchange for \$30.

Apparatus and Stimuli

The experiment was conducted using Dell Dimension computers connected to standard QWERTY keyboards and Sony Trinitron monitors. The tasks involved classifying single-digit targets as odd/even or as high/low with respect to 5. The odd/even task was cued by *odd–even* (37 × 7 mm) or *parity* (28 × 7 mm), and the high/low task was cued by *high–low* (37 × 7 mm) or *magnitude* (43 × 7 mm). The targets were the digits 1, 2, 3, 4, 6, 7, 8, and 9 (each 4 × 7 mm). The cues and targets were displayed in white font on a black background. Viewed at a distance of about 60 cm, 10 mm of the display subtended approximately 1° of visual angle.

Procedure

The subjects completed each experimental session in private rooms after providing informed consent before their first session. Instructions concerning the tasks, cues, targets, and response–key mappings were given before the experiment commenced. A reminder of the response–key mappings was posted below the computer screen for the duration of the experiment.

A session consisted of 10 blocks of trials (separated by self-paced rest periods) in a specific frequency condition. Each block included 101 trials, with the first trial involving the random selection of a task, cue, and SOA. The remaining 100 trials were constructed using a pseudorandom algorithm that generated the appropriate number of trials for each transition, equally divided among the five SOAs. For example, for each block in the cue-repetitions-frequent condition, 70 trials were cue repetitions (14 trials per SOA), 15 trials were task repetitions (3 trials per SOA), and 15 trials were task alternations (3 trials per SOA). The target associated with each trial was selected randomly. The distribution of transitions within each block was completely random, and all the blocks in a session and across subjects were generated independently. Data for all the frequency conditions were obtained in separate sessions for each subject, and the order in which the subjects experienced the frequency conditions was counterbalanced. Sessions were typically run on separate days, except for some subjects who had two sessions in 1 day that were separated by a few hours (e.g., morning and afternoon sessions).

Each trial began with a fixation display consisting of two plus signs (each 3 × 3 mm) arranged vertically in the center of the screen. After 500 msec, the screen was erased, and a cue was presented 5 mm below the position previously occupied by the top plus sign. After a variable SOA (0, 100, 200, 400, or 800 msec), a target was presented below the cue, 5 mm above the position previously occupied by the bottom plus sign. The cue and target remained on-screen until the subject responded by pressing the “Z” or “/” key. *Odd* and *high* responses were assigned to the “Z” key, and *even* and

low responses were assigned to the “/” key for all the subjects. After a response, the screen was erased for 500 msec; then the next trial commenced.

RESULTS

The first block of each session was considered practice, allowing the subjects to gain experience with the frequency condition and response–key mappings. The practice block, the first trial of each block, and trials with RT exceeding 3,000 msec (1.3% of all the trials) were excluded from all the analyses. Incorrect trials were excluded from the RT analysis. The mean number of correct observations per cell in the experimental design was 25 for the least frequent transitions and 120 for the most frequent transitions. Mean RT and accuracy (as a percentage of correct responses) across subjects for each combination of frequency condition, transition, and SOA are provided in Table 1, and mean RTs are plotted as points in Figure 1. The RT and accuracy data were submitted to separate 3 (frequency condition) \times 3 (transition) \times 5 (SOA) repeated measures ANOVAs (see Table 2 for a summary of these results). Planned contrasts were conducted using the relevant error terms from the ANOVAs.

Accuracy Analysis

Mean accuracy was 95.8% and did not differ among frequency conditions. Accuracy was lower for task alternations (94.0%) than for task repetitions (96.9%) and cue repetitions (96.3%) [$F(1,34) = 37.49, p < .01$], which did not differ [$F(1,34) = 1.42, p = .24$]. The difference in accuracy between task alternations and the average for task repetitions and cue repetitions was smaller when task alternations were frequent (1.3%) than when cue repetitions were frequent [2.6%; $F(1,68) = 5.76, p < .05$],

which was smaller than when task repetitions were frequent [4.0%; $F(1,68) = 6.82, p < .05$]. Within-subjects correlations between RT and accuracy did not suggest any speed–accuracy trade-offs; therefore, subsequent analyses focused on RT.

Response Time Analysis

Mean RT was longer when task alternations were frequent (879 msec) than when cue repetitions were frequent (777 msec) and when task repetitions were frequent (785 msec) [$F(1,34) = 13.60, p < .01$], which did not differ [$F(1,34) < 1$]. Mean RT for task alternations (885 msec) was longer than that for task repetitions (819 msec) [$F(1,34) = 25.44, p < .01$], which was longer than that for cue repetitions (737 msec) [$F(1,34) = 38.94, p < .01$]. Mean RT decreased as SOA increased, reflecting the time course function typically observed in explicitly cued performance.

The critical aspect of the RT data concerns the differences between transitions across frequency conditions. The difference between task alternations and task repetitions—the switch cost—was smaller when task alternations were frequent (12 msec) than when cue repetitions were frequent (75 msec) [$F(1,68) = 13.49, p < .01$], which was smaller than when task repetitions were frequent (112 msec) [$F(1,68) = 4.66, p < .05$]. The difference between task repetitions and cue repetitions—the repeated-cue-encoding benefit—was smaller when task repetitions were frequent (52 msec) than when task alternations were frequent (100 msec) and when cue repetitions were frequent (95 msec) [$F(1,68) = 9.47, p < .01$], which did not differ [$F(1,68) < 1$]. The differences between transitions decreased as SOA increased, in agreement with previous results (e.g., Meiran, 1996). There was also a significant three-way interaction (see Table 2), indicating that the

Table 1
Mean Response Time (RT, in Milliseconds) and Accuracy (Percentage of Correct Responses) Across Subjects at Each Stimulus Onset Asynchrony (in Milliseconds) as a Function of Frequency Condition and Transition (With Standard Errors)

Frequency Condition	Transition	Measure	Stimulus Onset Asynchrony									
			0		100		200		400		800	
			<i>M</i>	<i>SE</i>	<i>M</i>	<i>SE</i>	<i>M</i>	<i>SE</i>	<i>M</i>	<i>SE</i>	<i>M</i>	<i>SE</i>
Cue repetitions frequent	Cue repetition	RT	793	35	698	30	665	29	650	30	636	30
		Accuracy	96.6	1.0	96.9	0.9	96.8	1.0	95.9	1.2	96.8	0.9
	Task repetition	RT	927	52	831	46	777	46	710	39	672	39
		Accuracy	97.9	0.7	97.5	0.9	97.7	0.9	96.9	1.0	97.7	0.6
	Task alternation	RT	1,031	57	942	52	880	53	751	43	688	43
		Accuracy	93.9	1.3	94.6	1.4	94.1	1.5	94.8	1.7	95.1	1.6
Task repetitions frequent	Cue repetition	RT	845	46	748	36	672	31	664	36	636	29
		Accuracy	95.4	1.2	96.7	1.1	96.9	1.0	96.5	1.5	96.5	1.1
	Task repetition	RT	892	43	810	43	748	37	698	35	677	31
		Accuracy	97.2	0.7	96.8	0.8	96.4	1.0	96.3	1.0	96.5	1.1
	Task alternation	RT	1,046	50	971	51	880	47	764	40	726	41
		Accuracy	91.0	2.0	90.2	1.6	93.0	1.8	94.4	1.5	94.2	1.6
Task alternations frequent	Cue repetition	RT	964	56	886	53	776	48	696	39	719	43
		Accuracy	94.7	1.7	95.4	1.4	97.7	1.3	95.4	1.6	96.7	1.4
	Task repetition	RT	1,092	64	967	66	887	61	808	50	788	55
		Accuracy	95.8	1.8	96.5	1.9	96.5	1.9	96.9	1.4	97.3	1.2
	Task alternation	RT	1,077	61	982	57	912	57	839	56	794	54
		Accuracy	94.9	1.4	94.5	1.3	95.0	1.6	95.0	1.7	95.9	1.3

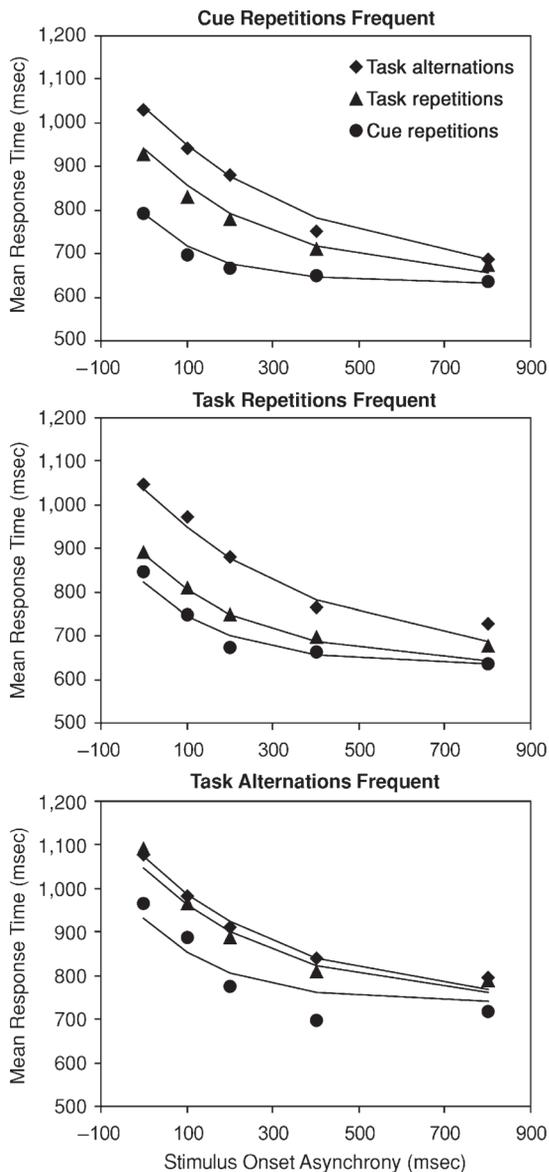


Figure 1. Mean response time across subjects at each stimulus onset asynchrony as a function of transition (task alternation, task repetition, and cue repetition) and frequency condition (top, middle, and bottom panels represent cue-repetitions-frequent, task-repetitions-frequent, and task-alternations-frequent conditions, respectively). Points represent observed data, and lines represent predictions of the six-parameter model.

time course function for each transition differed across frequency conditions; this aspect of the data will be examined in detail in the next section.

Modeling Analysis

The three-way interaction in the RT data suggests that transition frequency affects a process occurring during the SOA that differs among transitions. Logan and Bundesen (2003) argued that differences between transitions can

be attributed to differences in the process of encoding the cue during the SOA.¹ To examine the potential role of cue encoding in producing our pattern of results, we estimated cue-encoding times for each transition in each frequency condition.

Following Logan and Bundesen (2003), we assume that RT reflects the sum of cue encoding and residual processing times, with the contribution of cue-encoding time to RT varying as a function of SOA. Residual processing time is assumed to include target encoding, response selection, response execution, and remaining processes. Logan and Bundesen (2003) developed a model of the time course function in which performance is based on a probability mixture of two base RTs. When the cue has not been encoded, $RT = RT_{\text{Base}} + \mu$, where RT_{Base} represents an asymptotic base RT (residual processing time) and μ represents mean cue-encoding time. When the cue has been encoded, $RT = RT_{\text{Base}}$. Cue-encoding time is assumed to be distributed exponentially, and the cumulative distribution of cue-encoding times determines the probability that the cue has been encoded at a given SOA. Consequently, $RT = RT_{\text{Base}} + \mu$ with a probability of $\exp[-SOA/\mu]$, and $RT = RT_{\text{Base}}$ with a probability of $1 - \exp[-SOA/\mu]$, yielding the following equation when combined:

$$RT = RT_{\text{Base}} + \mu \cdot \exp[-SOA/\mu]. \quad (1)$$

To determine the best possible fit of Equation 1 to our data, we developed an 18-parameter model with a separate RT_{Base} and μ for each transition in each frequency condition. Using the Solver routine in Microsoft Excel to minimize the root-mean-squared deviation (RMSD) between observed and predicted values, the 18-parameter model fit the 45 RT data points with $RMSD = 15.86$ and product-moment correlation $r = .992$.

Examination of the best-fitting parameter values in the 18-parameter model (see Table 3) suggested that a simpler model could be derived from it, so we developed a 9-parameter model with a separate RT_{Base} for each frequency condition and two values of μ for each transition: μ_F for when the transition was frequent (μ_F) and μ_{IF} for when the transition was infrequent (μ_{IF}). The 9-parameter model fit the data with $RMSD = 20.18$ and $r = .987$. The 9-parameter model is nested within the 18-parameter model, allowing us to test the significance of the difference in goodness of fit. The correlation between observed and predicted values was not significantly larger for the 18-parameter model than for the 9-parameter model [$F(9,27) = 1.99$, $p = .08$], indicating that the latter model is sufficient to account for the data.

Examination of the best-fitting parameter values in the 9-parameter model (see Table 3) suggested two ways of producing a simpler model. First, RT_{Base} when cue repetitions were frequent (625 msec) was about the same as RT_{Base} when task repetitions were frequent (641 msec), indicating that they could be combined into a common RT_{Base} associated with frequent repetitions. Separate RT_{Base} parameters for frequent repetitions and frequent alternations could be

Table 2
Summary Table for the ANOVAs Conducted on
Mean Response Times and Accuracy

Effect	df	Response Time		Accuracy	
		<i>F</i>	<i>MS_e</i>	<i>F</i>	<i>MS_e</i>
Frequency condition (F)	2,34	6.84**	128,040.94	0.71	104.39
Transition (T)	2,34	63.91**	23,477.35	19.46**	32.29
SOA (S)	4,68	142.24**	12,695.73	3.28*	8.33
F × T	4,68	9.65**	6,589.54	6.59**	8.87
F × S	8,136	1.81	4,289.33	0.81	9.82
T × S	8,136	9.57**	4,025.25	1.49	11.73
F × T × S	16,272	3.52**	3,219.78	1.08	9.11

p* < .05. *p* < .01.

argued to reflect different levels of interference that affect residual processes such as response selection.²

Second, we noticed a conspicuous relationship between μ_F and μ_{IF} for each transition. For cue repetitions, task repetitions, and task alternations, the ratios of μ_F to μ_{IF} were .837, .814, and .823, respectively. Cue-encoding times appeared to exhibit the following simple relationship:

$$\mu_F = \mu_{IF} \cdot f, \tag{2}$$

where *f* represents a frequency priming factor with a mean value of .824 across transitions. In other words, cue encoding is faster by about .176 (i.e., 1 - *f*) when a transition is frequent than when it is infrequent. To assess whether Equation 2 provides an adequate account of the data, we developed a 6-parameter model with an RT_{Base} for fre-

quent repetitions, an RT_{Base} for frequent alternations, a separate μ_{IF} for each transition, and *f* (used to calculate μ_F for each transition). The 6-parameter model fit the data with *RMSD* = 21.07 and *r* = .986; its predictions are plotted as lines in Figure 1.³ The best-fitting parameter values were the following: RT_{Base} for frequent repetitions = 633 msec, RT_{Base} for frequent alternations = 740 msec, μ_{IF} for cue repetitions = 191 msec, μ_{IF} for task repetitions = 308 msec, μ_{IF} for task alternations = 403 msec, and *f* = .828 (see Table 3 for comparison with the 18- and 9-parameter models). The 6-parameter model is nested within the 18-parameter model (when specific values of μ are constrained to equal the values calculated using *f*), allowing us to test the significance of the difference in goodness of fit. The correlation between ob-

Table 3
Best-Fitting (and Calculated) Parameter Values
for the 18-, 9-, and 6-Parameter Models

Frequency Condition	Transition	Parameter	Number of Parameters in Model		
			18	9	6
Cue repetitions frequent	Cue repetition	μ	146	159	159
		RT_{Base}	635	625	633
	Task repetition	μ	262	310	308
		RT_{Base}	657	625	633
	Task alternation	μ	405	404	403
		RT_{Base}	623	625	633
Task repetitions frequent	Cue repetition	μ	197	190	191
		RT_{Base}	629	641	633
	Task repetition	μ	221	252	255
		RT_{Base}	667	641	633
	Task alternation	μ	373	404	403
		RT_{Base}	668	641	633
Task alternations frequent	Cue repetition	μ	267	190	191
		RT_{Base}	678	740	740
	Task repetition	μ	309	310	308
		RT_{Base}	748	740	740
	Task alternation	μ	299	332	334
		RT_{Base}	768	740	740
All	All	<i>f</i>	-	-	.828

Note—To enable comparison with the 18-parameter model, parameters that were absent in the 9- and 6-parameter models were calculated using parameters that were present in those models (see the text for details). Identical values within a column reflect the same parameter.

served and predicted values was not significantly larger for the 18-parameter model than for the 6-parameter model [$F(12,27) = 1.84, p = .09$], indicating that the latter model is sufficient to account for the data.⁴ The fit of the 6-parameter model suggests that when a transition is frequent, cue encoding for that transition is primed, which explains the observed interaction between frequency condition, transition, and SOA.

DISCUSSION

Our findings demonstrate that transition frequency strongly affects explicitly cued performance: Switch cost was small when task alternations were frequent, larger when cue repetitions were frequent, and even larger when task repetitions were frequent. Modeling of the time course functions in the data revealed a common frequency priming effect for all the transitions: Cue encoding was faster when a transition was frequent than when it was infrequent. We will consider two interpretations of the relationship between priming of cue encoding and transition frequency: automatic priming from memory retrieval of accumulated instances of past transitions and strategic priming from transition expectancies due to sensitivity to the frequency conditions.

Automatic priming of cue encoding is possible if the transition experienced on each trial is stored in memory and the presented cue activates cues for the next trial that are consistent with instances of past transitions (e.g., Logan, 1988). Activation of a forthcoming cue would prime subsequent cue encoding, resulting in a shorter RT on the next trial. Transition frequency would determine how many instances of each transition are available for retrieval from memory; if priming is a function of the relative frequencies of different transitions stored in memory, frequent transitions would produce greater priming than would infrequent transitions. For example, when task alternations are frequent, transitions such as *high–low to parity* and *high–low to odd–even* will be experienced more often than transitions such as *high–low to magnitude* and *high–low to high–low*. The *high–low* cue will become episodically associated with task alternations more than with task repetitions and cue repetitions. Consequently, when the *high–low* cue is presented, the *parity* and *odd–even* cues will become activated and will prime cue encoding on the next trial if one of those cues is presented.

Strategic priming of cue encoding is an alternative interpretation that is possible if subjects come to expect specific transitions, due to their sensitivity to the frequency conditions. The transition experienced on each trial could be stored in memory, as in the automatic priming account, and priming of cue encoding would result from activating cues for the next trial. Strategic priming differs from automatic priming in that the activation of cues arises from subjects' expectancies about the likelihood of specific transitions, not from the retrieval of instances of past transitions. Expectancies would change across frequency conditions as subjects learn the different sets of

cueing contingencies. The idea that transition expectancies can be altered already has support in the literature. Dreisbach, Haider, and Kluwe (2002) conducted experiments in which subjects' expectancies about transitions were manipulated by presenting a cue that indicated which task (or transition) was most probable on the current trial. Transitions occurred randomly, with equal frequencies across all trials. The main finding was that RT increased as probability decreased for both task repetitions and task alternations but switch costs were invariant when calculated from transitions with equal probabilities. Applied to our results, subjects' expectancies might become tuned to the different frequency conditions, resulting in strategic priming of expected cues that would facilitate cue encoding for frequent transitions, as compared with infrequent transitions. Our present results do not allow us to distinguish between strategic and automatic priming, but it is possible that both types of priming are involved in performance (Neely, 1977; Posner & Snyder, 1975).

Our modeling of transition frequency effects in explicitly cued task switching indicates that differences between transitions are related to priming of cue encoding. A direct implication is that differences between transitions may reflect differences in cue-encoding time, which raises uncertainty about interpreting "switch costs" as evidence for reconfiguration. It is possible that the difference between task alternations and task repetitions still reflects reconfiguration, in which case it is important to distinguish between the effects of executive control processes and those of more basic psychological processes. But an intriguing possibility is that an interaction of the latter processes may be all that is needed to explain task-switching performance.

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NOTES

1. Some authors have argued that the differences between transitions also reflect decay of the task set from the preceding trial, on the basis of the observation that switch cost decreases as the response-cue interval (RCI) increases (e.g., Meiran et al., 2000). Our experiment included an RCI of 1,000 msec, providing a reasonable amount of time for this decay. Furthermore, many researchers have demonstrated that there are strong SOA effects independent of RCI effects (e.g., Logan & Bundesen, 2003; Meiran et al., 2000); therefore, our modeling of cue encoding during the SOA is not compromised.

2. Logan and Bundesen (2003, 2004) argued that response selection could be accomplished via compound cue retrieval, with the encoded cue and target acting as joint retrieval cues for selecting a response. In their formal models, cue encoding was reflected in μ , and response selection was reflected in RT_{Base} . Schneider and Logan (2005) modeled the response selection component of RT_{Base} and suggested that decayed traces of past cues could accumulate in long-term memory and be retrieved to participate in compound cue retrieval. Activation of past cues could positively or negatively prime compound cue retrieval, resulting

in a shorter or longer RT_{Base} . Applied to our experiment, when cue repetitions or task repetitions are frequent, only a subset of cues will be experienced over short runs of trials, allowing dissipation of activation of past irrelevant cues, decreased interference in response selection, and a short RT_{Base} . When task alternations are frequent, all cues will be experienced over short runs of trials, resulting in recent activation of past irrelevant cues, increased interference in response selection, and a long RT_{Base} . These different levels of interference based on transition frequency could be modeled with separate RT_{Base} parameters, as was done in the present study.

3. The only noticeable discrepancy between the observed data and the model predictions in Figure 1 is the fit to cue repetitions in the task-alternations-frequent condition. The quality of the fit is not due to the 6-parameter model's having fewer parameters (the 18-parameter model has a similar fit) but is likely the result of instability in the time course function for that condition.

4. To examine the possibility that our results and model fits were distorted by long-term effects across sessions, we conducted an analysis involving only the first-session data. A repeated measures ANOVA with transition and SOA as within-subjects factors and frequency condition as a between-subjects factor mirrored the earlier analysis, except that the main effect of frequency condition was no longer significant [$F(2,15) = 1.40$, $MS_e = 660,329.77$, $p = .28$], the frequency condition \times transition interaction became marginally significant [$F(4,30) = 2.31$, $MS_e = 18,372.91$, $p = .08$], and the three-way interaction became marginally significant [$F(16,120) = 1.59$, $MS_e = 4,425.35$, $p = .08$]. These results are likely due to decreased statistical power and increased variability in the data. The pattern of differences between transitions was relatively unaffected, except that the switch cost in the cue-repetitions-frequent condition increased to equal that in the task-repetitions-frequent condition. All the models were fit to the reduced data set, and the 6-parameter model fit with $RMSD = 31.42$ and $r = .981$, which was not significantly worse than the 18-parameter model ($r = .989$) [$F(12,27) = 1.56$, $p = .16$]. The best-fitting parameter values in the 6-parameter model were slightly higher than those in the original fit, due to a longer overall RT, but the value of f was relatively unchanged between the new and the original fits (.811 and .828, respectively).

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