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The Effects of Sleep Deprivation on Item and Associative Recognition Memory

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Sleep deprivation adversely affects the ability to perform cognitive tasks, but theories range from predicting an overall decline in cognitive functioning because of reduced stability in attentional networks to specific deficits in various cognitive domains or processes. We measured the effects of sleep deprivation on two memory tasks, item recognition ("was this word in the list studied") and associative recognition ("were these two words studied in the same pair"). These tasks test memory for information encoded a few minutes earlier and so do not address effects of sleep deprivation on working memory or consolidation after sleep. A diffusion model was used to decompose accuracy and response time distributions to produce parameter estimates of components of cognitive processing. The model assumes that over time, noisy evidence from the task stimulus is accumulated to one of two decision criteria, and parameters governing this process are extracted and interpreted in terms of distinct cognitive processes. Results showed that sleep deprivation reduces drift rate (evidence used in the decision process), with little effect on the other components of the decision process. These results contrast with the effects of aging, which show little decline in item recognition but large declines in associative recognition. The results suggest that sleep deprivation degrades the quality of information stored in memory and that this may occur through degraded attentional processes.

Keywords: diffusion model, reaction time and accuracy, total sleep deprivation, drift rate, recognition memory

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Sleep deprivation has profound effects on human brain functioning. For example, sleep deprivation is associated with large-scale changes in the activity of neurotransmitters and neuromodulaters, such as dopamine (Volkow et al., 2009) and adenosine (Urry & Landolt, 2014). Sleep deprivation leads to significant shifts in the dominant frequencies in the waking EEG (Torsvall & Akerstedt, 1987). Furthermore, it changes evoked potentials, indicative of altered stimulus processing (Corsi-Cabrera, Arce, Del Río-Portilla, Pérez-Garci, & Guevara, 1999). Not surprisingly, sleep deprivation also has substantial impact on cognitive performance (Jackson & Van Dongen, 2011). Yet, the effects of sleep deprivation on different cognitive tasks are ostensibly widely different (Lim & Dinges, 2010). Cognitive, pharmacological, neuroimaging, and genetic approaches have been put to use in the search for underlying mechanisms. This search has been hampered, however, by reliance on methods not specifically designed to test the effects of sleep deprivation and use of global outcome measures (Whitney & Hinson, 2010).

Recently there has been a focus on experimental and modeling studies of component processes of cognitive functioning (Gunzelmann, Gluck, Price, Van Dongen, & Dinges, 2007; Chee & Chuah, 2008; Ratcliff & Van Dongen, 2009; Tucker, Whitney, Belenky, Hinson, & Van Dongen, 2010). This has yielded new insights, indicating that distinct cognitive processes can be differentially affected by sleep deprivation (Jackson et al., 2013). One (qualitative) theory about the underlying mechanism posits that the effects of sleep deprivation are use-dependent, involving degraded information processing in neuronal networks that are most intensively used during performance of the task at hand (Van Dongen, Belenky, & Krueger, 2011). The diffusion decision model (Ratcliff, 1978; Ratcliff & McKoon, 2008; Ratcliff, Smith, Brown, & McKoon, 2016) provides an account of decision making that has been explicitly related to neuroscience measures (Forstmann, Ratcliff, & Wagenmakers, 2016; Gold & Shadlen, 2007; Smith & Ratcliff, 2004) and as such offers measures that can be related to neuronal processing theories.

There has been a long history of the use of item and associative tasks to examine processing and representation in memory. In an item recognition task, words or pictures are presented and the subject is to decide if the test item was in the study list. In associative recognition, pairs of words are presented and the subject is to decide if a test pair was composed of words studied together or whether the words were from different study pairs. Murdock (1974) reviewed and distinguished these as different forms of memory that operated in different ways and required different model-based approaches. Following the early work, a

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number of studies have provided evidence for this distinction (Clark & Shiffrin, 1992; Hockley, 1991, 1994; Hockley & Cristi, 1996; Humphreys, 1976, 1978; Malmberg & Xu, 2007). Theories that attempted to deal with item and associative recognition and recall have produced integrated models that have common representations for all the kinds of information but different retrieval mechanisms (Gillund & Shiffrin, 1984; Murdock, 1982; Shiffrin & Steyvers, 1997). More recently, in research in aging, a sharp distinction has been drawn between item and associative recognition. The general finding is that associative recognition declines with age but item recognition is largely spared (Balota, Dolan, & Duchek, 2000; Craik, 1983, 1986, 1994; Gordon & Clark, 1974; Naveh-Benjamin, 2000; for further discussion see Ratcliff, Thapar, & McKoon, 2011; McKoon & Ratcliff, 2012). The generality of the associative recognition decline relative to item recognition was supported by Old and Naveh-Benjamin (2008) in a meta-analysis of data from 90 studies.

There is an extensive body of literature on sleep deprivation and memory, but most of the research has focused on the role of sleep in memory consolidation after the memories have been acquired. Yet, obtaining sufficient sleep beforehand may also be important, in order to be able to encode memories effectively (Walker & Stickgold, 2006), retain them reliably during task performance (Habeck et al., 2005), and recall them accurately when probed (e.g., Tantawy, Tallawy, Farghaly, Farghaly, & Hussein, 2013; Mograss, Guillem, Brazzini-Poisson, & Godbout, 2009). Vice versa, acute sleep deprivation appears to degrade some or all of these aspects of memory task performance (e.g., Nilsson, Bäckman, & Karlsson, 1989). The underlying mechanisms, however, have not been fully elucidated. At the neuronal level, it remains unknown whether the effects of sleep deprivation are global and nonspecific, or local and specific (Chee & Van Dongen, 2013). Insight into this issue may be gained by considering item recognition and associative recognition tasks, which have clearly defined shared and distinct features and may or may not be affected by sleep deprivation differentially.

If forming associations is more difficult or associations in memory are more fragile (i.e., more easily disrupted), then associative recognition should show more decline during sleep deprivation than item recognition. To date there have been few studies of item or associative recognition memory and sleep deprivation, and no head to head comparison has been made. For item recognition, Harrison and Horne (2000) presented two lists of 12 pictures (at 10 s per picture) and followed this with a test list of 48 pictures, half old and half new. Subjects were asked whether they had seen each test picture before (recognition). If so, they were then asked to specify whether it was included in List A or List B (i.e., list discrimination or in their terms, temporal memory). There was no significant effect of sleep deprivation on recognition (though d' fell from about 2.8 to 2.3) but there was a decline in list discrimination performance. This pattern suggests that item recognition may not decline with sleep deprivation, but tasks that require binding (item to list context as in Harrison and Horne or item to item as in associative recognition) may decline. Other studies using a few lists of pictures have found declines in recognition memory (Mograss, Guillem, Brazzini-Poisson, & Godbout, 2009; Williams, Gieseking, & Lubin, 1966). But there have not been studies like those in the list-learning memory area with multiple lists and comparisons other than the Harrison and Horne (2000) study that compare different forms of memory.

Diffusion Model

The diffusion model is designed to explain the cognitive processes involved in making simple two-choice decisions. The model separates the quality of evidence entering a decision from the decision criteria and from nondecision processes. This allows a direct comparison across tasks and across subject groups in components such as the quality of evidence used in the decision process and how much evidence is needed for a decision. The model can be seen as decomposing accuracy and reaction time (RT) data for correct and error responses into distinct cognitive processes. The model has provided successful explanations of performance in many paradigms in cognitive psychology and different subject populations. For example, it has been used to examine processing in children (Ratcliff, Love, Thompson, & Opfer, 2012), sleep-deprived individuals (Ratcliff & Van Dongen, 2009), aphasic individuals (Ratcliff, Perea, Colangelo, & Buchanan, 2004), hypoglycemic individuals (Geddes et al., 2010), individuals with depression (White, Ratcliff, Vasey, & McKoon, 2010), and individual differences (Pe, Vandekerckhove, & Kuppens, 2013; Ratcliff, Thapar, & McKoon, 2010; Schmiedek et al., 2007). It has also been used to examine decision processes in neurophysiology (Forstmann et al., 2016), including single-cell recordings (Hanes & Schall, 1996; Ratcliff, Cherian, & Segraves, 2003), EEG (Philiastides, Ratcliff, & Sajda, 2006), MEG (Wenzlaff, Bauer, Maess, & Heekeren, 2011), and fMRI (Heekeren, Marrett, & Ungerleider, 2008).

In the decision process of the diffusion model, information about a stimulus is accumulated over time from a starting point z toward one of two response criteria, or boundaries, a and 0 (see Figure 1). A response is executed when the amount of accumulated evidence reaches one of the boundaries. The rate at which information is accumulated is labeled "drift rate" (v) and it is determined by the quality of the information available from the match between a test probe and memory. Within-trial variability (noise) in the accumulation of information from the starting point to the boundaries results in processes with the same mean drift rate terminating at different times (producing RT distributions) and sometimes terminating at the wrong boundary (producing errors).

The total RT for a stimulus is the time taken by this decision process plus other, nondecision, processes (e.g., test probe encoding and accessing memory with it, and response execution). Nondecision processes are combined into one distribution in the model, the time taken by them (mean value T_{er}). Drift rates, boundaries, and nondecision times are the three main components of the model used in understanding differences between tasks, among subject populations, from experimental manipulations such as sleep deprivation, and due to individual differences.

The values of the components of processing are assumed to vary from trial to trial, under the assumption that subjects cannot accurately set the same parameter values from one trial to another (e.g., Laming, 1968; Ratcliff, 1978). Across-trial variability in drift rate is normally distributed with SD η, across-trial variability in starting point is uniformly distributed with range s_z, and across-trial variability in the nondecision component is uniformly distributed with range s_t. This across-trial variability allows the model to

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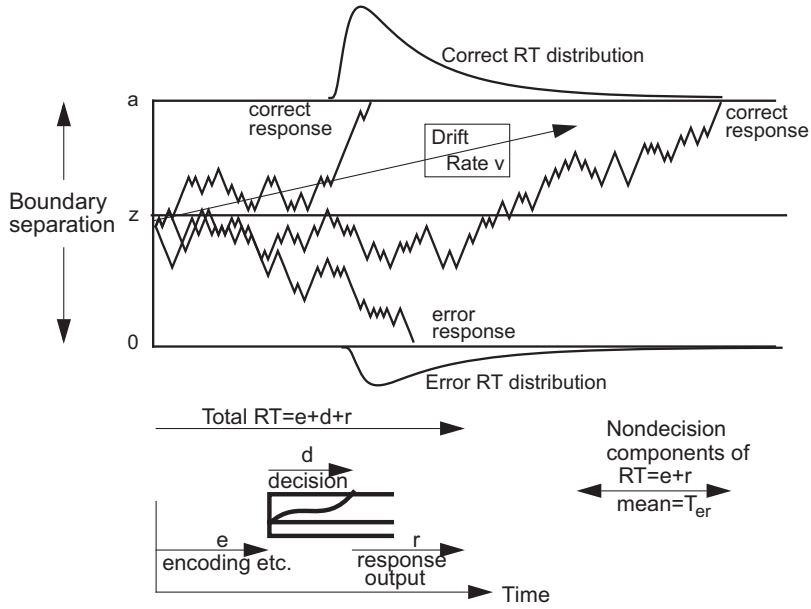

Figure 1. An illustration of the diffusion model.

fit the relative speeds of correct and error responses (Ratcliff, Van Zandt, & McKoon, 1999). In signal detection theory, which deals only with accuracy, all sources of across-trial variability would be collapsed onto one parameter, namely variability in evidence across trials. In contrast, in diffusion model fitting, the separate sources of across-trial variability are identified. If simulated data are fit by the model, then, for example, variability in drift rate is not incorrectly recovered as variability in starting point (Ratcliff & Tuerlinckx, 2002). Partly the success of parameter identifiability comes from the requirement that the model is fit to both the correct and error RT distributions, which provides tight constraints on the model (see Ratcliff, 2002).

In almost all RT studies, some proportion of responses are spurious contaminants (e.g., Ratcliff, 1979, 1993). These have previously been explicitly modeled in applications of the diffusion model (Ratcliff & Tuerlinckx, 2002) as random delays in processing. Thus, predicted RTs are a mixture of pure diffusion model processes and of diffusion model processes with a delay added (usually 0% - 2%), which means that contaminant processes are just as accurate as processes without contaminants. In Ratcliff and Van Dongen (2009) we used a different assumption, and that was that contaminants were random guesses (Vandekerckhove & Tuerlinckx, 2008) that were uniformly randomly distributed over the range from the shortest to the longest RT for each response category. Thus the predicted RT distribution was a probability mixture of diffusion model processes and random guesses. Random guesses can be distinguished from the assumption of an added random delay, because random guesses reduce accuracy in the most accurate conditions, as was seen for some subjects in Ratcliff and Van Dongen's study. Here we fit the model with both contaminant assumptions. In both cases, the proportion of contaminants was estimated to be small. Note that recovery of diffusion

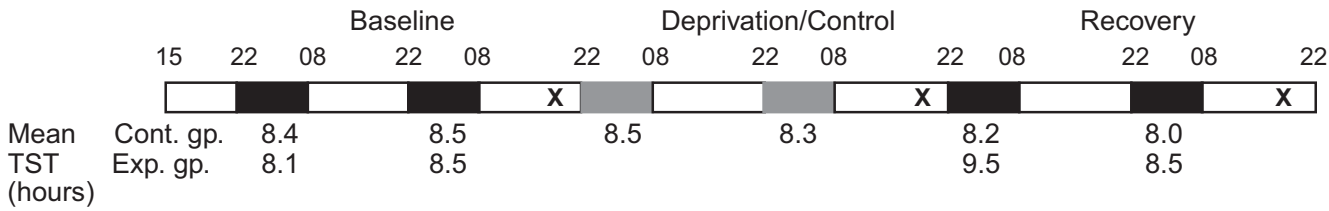

Figure 2. Subjects stayed in the laboratory continuously from 15:00 on Day 1 until 22:00 on Day 7. Black areas represent 10-hr nocturnal periods in bed for sleep (22:00–08:00). Gray areas represent 10-hr nocturnal periods in bed for sleep (22:00–08:00) for the control group only; the sleep deprivation group was kept awake continuously for a total of 62 hours. X's indicate the three administrations of the item and associative memory tasks (at 17:00): after 9 hours of scheduled wakefulness during baseline; after 57 hours of continuous wakefulness in the sleep deprivation group or 9 hours of scheduled wakefulness in the control group; and after 9 hours of scheduled wakefulness following 2 nights of recovery sleep. The top row of numbers represents time of day, the second row is mean total sleep time (TST) for the control group and the bottom row is mean total sleep time for the experimental group (as measured with polysomnography; Butkov, 2002).

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Table 1
Accuracy and Mean RT

Task	Condition	"Old" or "Intact" Stimuli			"New" or "Rearranged" Stimuli		
		Pr correct	Mean correct RT (ms)	Mean error RT (ms)	Pr correct	Mean correct RT (ms)	Mean error RT (ms)
Item Recognition	Sleep: baseline	.674	907	1001	.852	943	931
	Sleep: deprived	.608	884	954	.655	941	887
	Sleep: recovery	.654	844	947	.859	855	932
	Control	.734	898	1027	.872	937	959
	Control	.686	860	945	.830	848	961
	Control	.678	834	915	.842	841	892
Associative Recognition	Sleep: baseline	.722	908	975	.719	1004	1015
	Sleep: deprived	.588	939	927	.655	990	941
	Sleep: recovery	.698	870	949	.723	944	920
	Control	.775	898	988	.751	1020	1041
	Control	.730	860	929	.814	943	905
	Control	.717	828	842	.811	888	947

model parameters is reasonably robust to the assumed form of the contaminant distribution - for example, if exponentially distributed contaminants were simulated and the parameter recovery algorithm assumed uniformly distributed contaminants, the model parameters would be recovered well (Ratcliff, 2008). Results are shown for the random delays assumption.

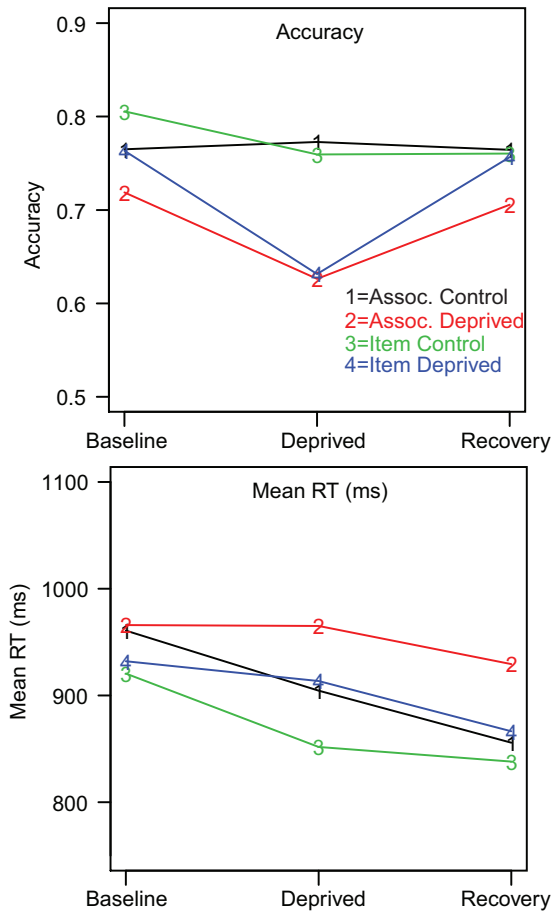

Figure 3. Plots of mean accuracy and mean correct RT in each session for item and associate recognition, for the sleep deprived and control groups. See the online article for the color version of this figure.

Method

Subjects

A total of 26 subjects, ages 22–37 years (10 were women) completed the study. Subjects were screened with physical exam, urine and blood chemistry, and questionnaires, to be physically and psychologically healthy and free of traces of drugs. They were good sleepers (getting between 6 and 10 hours a night) and had no sleep or circadian disorder as assessed by history, questionnaires, wrist actigraphy (Ancoli-Israel, 2005), and baseline polysomnogram (Butkov, 2002). They had normal or corrected to normal vision. They had not traveled between time zones and had not been engaged in shift work in the prior 1 month. Subjects were required to maintain their habitual sleep schedule in the week before the study and to avoid napping, as monitored by sleep/wake logs, time-stamped voice recording of bedtimes and rising times, and wrist actigraphy (wrist-worn activity monitoring). They were instructed to abstain from drugs, smoking, alcohol, and caffeine in the week before the study. Compliance was verified with urine and breathalyzer tests on the first day in the laboratory. The study was approved by the Institutional Review Board (IRB) of Washington State University, and all subjects gave written informed consent.

Experimental Design

Subjects were in the laboratory for 6 consecutive nights (7 days). They were randomized to a total sleep deprivation condition (13 subjects) or a control condition (13 subjects). On Days 1 and 2, all subjects had baseline sleep (10 hours in bed each night; 22:00–08:00). On Day 3, subjects in the experimental condition began 62 hours of continuous wakefulness. That day at 17:00, while 9 hours awake, they took their baseline test. Two days later at 17:00, while 57 hours awake (48 hours after Test 1), they took their second test. After the 62 hours of wakefulness, subjects were allowed two recovery nights (10 hours in bed each night). At 17:00 on the last day (48 hours after Test 2), they took their recovery test. Control subjects were tested on the

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Table 2
Diffusion Model Parameters for Item Recognition

Condition	a	T_{er}(sec)	η	s_z	p_o	s_t(sec)	z	v	χ^2
Control 1	.161	.639	.224	.060	.003	.177	.070	.222	61.7
Control 2	.151	.604	.282	.020	.003	.159	.073	.196	65.0
Control 3	.138	.607	.219	.063	.003	.153	.070	.197	66.0
Sleep 1 (baseline)	.171	.615	.229	.077	.003	.173	.077	.195	69.9
Sleep 2 (deprived)	.151	.569	.175	.058	.007	.305	.071	.084	75.5
Sleep 3 (recovery)	.157	.594	.230	.072	.008	.188	.076	.228	51.0

Note. a = boundary separation; z = starting point; T_{er} = nondecision component of response time; η = standard deviation in drift across trials; s_z = range of the distribution of starting point (z); s_t = range of the distribution of nondecision times; p_o = proportion of contaminants; χ^2 = chi-square; v = the mean of absolute values of drift rates for studied items and new items from Table 3.

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same days and at the same time of day, but they had sleep (10 hours in bed; 22:00–08:00) each night throughout the study.

Subjects continually stayed inside the isolated, environmentally controlled laboratory during the study, and were behaviorally monitored at all times by trained research assistants. The laboratory was temperature controlled (21°C) with fixed light levels (<100 lux) during scheduled wakefulness and lights off during scheduled sleep periods. Each person had an isolated room for sleep and performance testing. Meals were provided every 4 waking hours. Between test bouts and meals, subjects were permitted only nonvigorous activities. Subjects were monitored throughout the experiment, and no visitors, phone calls, live TV or radio, or Internet access were allowed. Besides the memory tasks, a number of other performance tests were administered throughout the experiment (Whitney, Hinson, Jackson, & Van Dongen, 2015). Figure 2 shows details of the design, including the mean number of hours of sleep for the two groups as measured with polysomnography (Butkov, 2002).

All sleep periods were recorded with digital polysomnography (Nihon Kohden, Foothill Ranch, CA), and total sleep times were assessed per the criteria of the American Academy of Sleep Medicine (Iber, Ancoli-Israel, Chesson, & Quan, 2007). The data in Figure 2 show that all subjects were well-rested after the two baseline nights, and the sleep deprivation group shows the expected increase in sleep duration in the first recovery night (night 5) following the 62-hr sleep deprivation period. Subjects were kept awake with nonvigorous activities and social interaction. This method has been used many times in previous studies; for a demonstration that the sleep deprivation intervention was successful, see Whitney et al. (2015).

Procedure

Cognitive performance was tested on an item and associative recognition memory task. The design is within subjects for sessions and memory tasks (and variables within tasks) and between subjects for the sleep deprivation and control groups. The task had 15 study-test blocks. For each block, the study list consisted of eight high-frequency and eight low-frequency word pairs, each displayed for 3 s in the upper left corner of an LCD monitor, followed by a 100-ms blank screen and then the next pair. From a viewing distance of 57 cm, the median edge-to-edge width of the word pairs was 6.0 degrees and the height was 0.5 degrees. The words were shown in clearly visible, light characters presented against a dark background. Half of the high-frequency pairs were presented once and half twice; likewise, half of the low-frequency pairs were presented once and half twice. The pairs were presented in random order. Each study block was immediately followed by one of two types of test blocks: three-item recognition or 12 associative recognition blocks. No word was repeated within a session, but the same pools were used from session to session with completely different randomizations (so a new word in item recognition in one session could be a member of an intact pair in associative recognition in the next session). The test type was cued after the study list so that subjects could not differentially encode the stimulus and the test type was randomized across lists.

Item recognition test blocks consisted of the 32 words from the 16 word pairs plus 32 new words that had not appeared in the study pairs, presented in random order. Subjects were asked to press the ?/ key on the keyboard if the test word had been in any of the immediately preceding study pairs, and the Z key if not. These keys were also labeled "Yes" and "No", respectively. The test words remained on the screen until a response was made. After each response there was a 500-ms blank screen and then the next item was presented.

Associative recognition test blocks consisted of 16 pairs of words, all of which had appeared in a study pair: four intact low-frequency pairs, four intact high-frequency pairs, four rearranged low-frequency pairs, and four rearranged high-frequency pairs. Subjects were asked to press the ?/ ("Yes") key if the two words of a test pair had occurred in the same pair in the study list and the Z ("No") key if the words had occurred in different pairs. The words in the test pairs always occupied the same position as in the study list: If a word was the first of a pair in the study list, it was the first of a test pair, whether the pair was intact or rearranged. For each test pair, the first word was displayed for 300 ms and then the second word was presented immediately below the first. This was done to reduce the variability in RTs that could occur if reading times included both words. Both words remained on the screen until a response was made.

Table 3
Drift Rates for Item Recognition

Condition	v_{HF1}	v_{LF1}	v_{HF2}	v_{LF2}	v_{HFN}	v_{LFN}
Control 1	.082	.154	.143	.292	−.260	−.402
Control 2	.007	.146	.131	.346	−.199	−.349
Control 3	.067	.175	.082	.345	−.180	−.333
Sleep 1 (baseline)	.087	.113	.140	.264	−.205	−.361
Sleep 2 (deprived)	.020	.063	.092	.116	−.070	−.142
Sleep 3 (recovery)	.073	.178	.145	.334	−.239	−.401

Note. HF = High Frequency; LF = Low Frequency; 1 = One Presentation; 2 = Two Presentations; N = New Item.

Table 4
Diffusion Model Parameters for Associative Recognition

Condition	a	T_{er}(sec)	η	s_z	p_o	s_t(sec)	z	v	χ^2
Control 1	.162	.596	.124	.056	.001	.306	.069	.145	86.2
Control 2	.170	.554	.180	.061	.002	.212	.069	.182	67.1
Control 3	.155	.559	.205	.041	.001	.290	.068	.183	68.2
Sleep 1 (baseline)	.171	.594	.197	.067	.001	.310	.075	.141	80.6
Sleep 2 (deprived)	.157	.558	.130	.052	.006	.369	.075	.065	97.8
Sleep 3 (recovery)	.176	.514	.159	.085	.001	.284	.077	.122	87.6

Note. a = boundary separation; z = starting point; T_{er} = nondecision component of response time; η = standard deviation in drift across trials; s_z = range of the distribution of starting point (z); s_t = range of the distribution of nondecision times; p_o = proportion of contaminants; v = the mean of absolute values of drift rates for intact and rearranged items from Table 5.

During both types of test blocks, subjects were instructed to respond as quickly and accurately as possible, but not so quickly that they started hitting the wrong key by mistake. If a response time was under 280 ms, a TOO FAST message was flashed on the screen for 1,500 ms (to discourage fast guessing), followed by a blank screen for 500 ms, then the next item. Subjects were not informed until after the study list about which type of test list they would be given for that block.

Subjects were given practice blocks of each type of test before beginning the experimental trials, and were given reminders of task instructions at the beginning of each test block. They were also informed that they could take a brief break between blocks of trials.

Results

Experimental Data

Summaries of the accuracy and RT data for the experimental and control groups for the three sessions are shown in Table 1 and Figure 3. Responses from the first block of each session, short (<280 ms) and long (>2,500 ms) outlier RTs in all blocks (less than 9.0% of the data in the sleep deprivation session and less than 3.6% of the data in the other sessions), and the first response in each test list were eliminated. For both item and associative recognition, response proportions were very similar for the experimental and control groups in the baseline and recovery sessions, but in the sleep deprivation session, the subjects showed a drop in accuracy relative to the control subjects.

We performed an analysis of variance with control versus sleep deprived subjects as a between-subjects variable (condition) and the three sessions as a within subjects variable (session). The mean accuracy values and mean correct RTs were averaged over old and new responses for item recognition and over intact and rearranged responses for associative recognition. For item recognition, there was a significant effect on accuracy for session, $F(2, 48) = 19.6$, $p < .05$ and the interaction between condition and session was significant, $F(2, 48) = 9.5$, $p < .05$. These showed a drop in accuracy for the sleep deprived session relative to the control and baseline and recovery sessions. There was a significant effect on mean RT across sessions only, $F(2, 48) = 11.8$, $p < .05$, which showed an overall effect on RTs. This could be interpreted as a practice effect.

For associative recognition, there was a marginally significant effect on accuracy for session, $F(2, 48) = 3.0$, $p = .058$ and the interaction between condition and session was significant, $F(2, 48) = 4.4$, $p < .05$. These showed a drop in accuracy for the sleep deprived session relative to the control and baseline and recovery sessions. There was a significant effect on mean RT across sessions only, $F(2, 48) = 7.2$, $p < .05$, which again could be interpreted as a practice effect.

It is notable that there was no moderate increase in RT for the sleep deprived session relative to the baseline and recovery sessions and the control condition, given the relatively large drop in accuracy. For both item and associative recognition, mean RT for the sleep deprived session was about the same as for the baseline condition, but for the control subjects, the matched condition showed a drop of 60 ms (though the interaction was not significant).

Diffusion Model Fits

The model was fit to the data for each task and every session for each subject by minimizing a chi-square value obtained from observed and predicted frequencies of observations between RT

Table 5
Drift Rates for Associative Recognition

Condition	v_{IHF1}	v_{RHF1}	v_{ILF1}	v_{RLF1}	v_{IHF2}	v_{RHF2}	v_{ILF2}	v_{RLF2}
Control 1	.031	−.154	.133	−.118	.164	−.160	.250	−.150
Control 2	−.025	−.274	.098	−.191	.176	−.238	.283	−.223
Control 3	−.055	−.319	.117	−.193	.148	−.267	.328	−.145
Sleep 1 (baseline)	.030	−.202	.109	−.142	.113	−.193	.252	−.088
Sleep 2 (deprived)	−.018	−.143	−.015	−.075	.067	−.081	.146	−.037
Sleep 3 (recovery)	.032	−.182	.088	−.151	.089	−.142	.174	−.116

Note. I = Intact; R = Rearranged; HF = High Frequency; LF = Low Frequency; 1 = One Presentation; 2 = Two Presentations.

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quantiles, using a general simplex minimization routine (Nelder & Mead, 1965). In this procedure, the values of all the parameters, including the variability parameters, are estimated simultaneously, fitting the model to all the data from all the conditions of an experiment. The minimization routine adjusts the parameters of the model until it finds the parameter estimates that give the minimum chi-square value (see Ratcliff & Childers, 2015; Ratcliff & Tuerlinckx, 2002).

With the best-fitting parameter values, the model accounted well for the data, as shown by the chi-square values (averaged over subjects) in Tables 2 and 4. These values are only a little higher than the critical values, namely, 71.0 for item recognition ($df = 53$) and 93.9 for associative recognition ($df = 73$). Ratcliff, Thapar, Gomez, and McKoon (2004) discussed the quality of fits of the

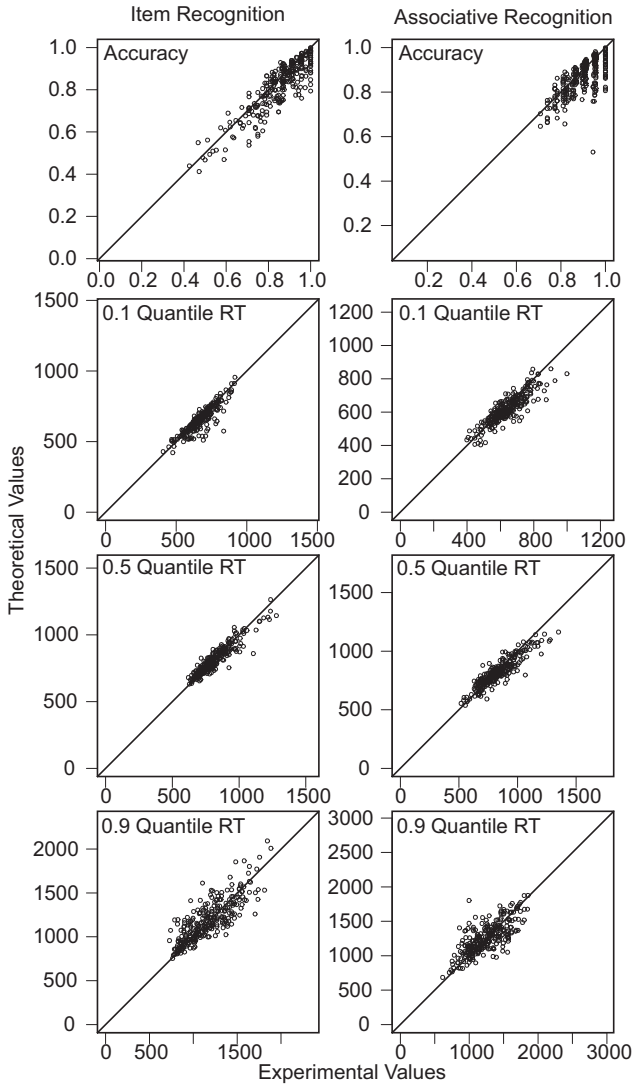

Figure 4. Plots of accuracy and the .1, .5 (median), and .9 RT quantiles for correct responses (*x*-axis) and predicted values from fits of the diffusion model (*y*-axis) for item and associative recognition (for RTs, only values from conditions with greater than 15 responses are plotted).

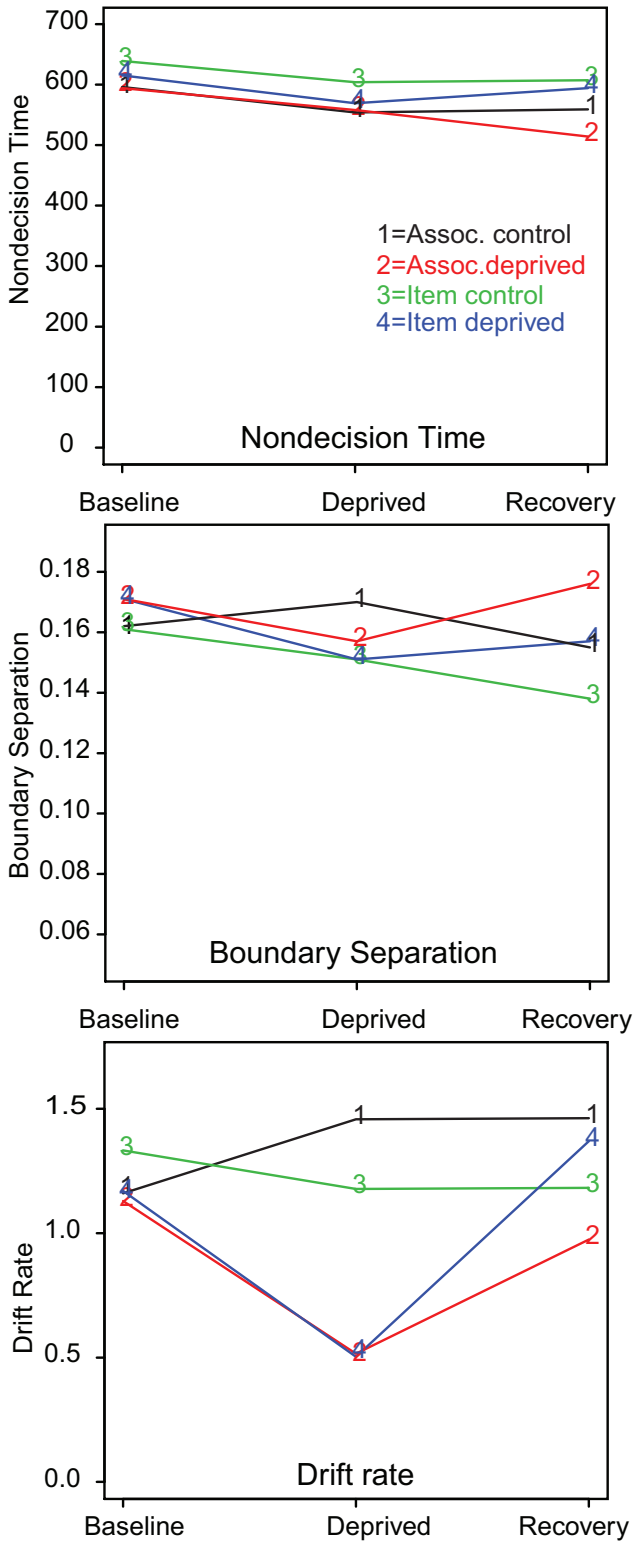

Figure 5. Plots of drift rate, boundary separation, and nondecision time as a function of session for item and associate recognition, for the sleep deprived and control groups. See the online article for the color version of this figure.

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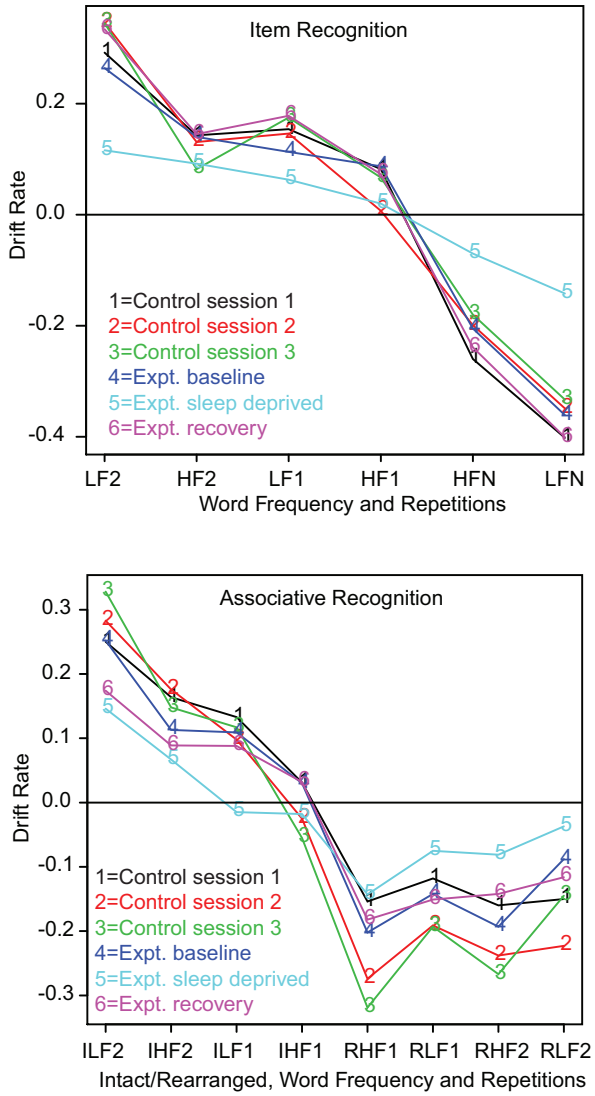

Figure 6. Plots of drift rates for the individual conditions and sessions. For item recognition, LF = low frequency; HF = high frequency; 2 = two presentations; 1 = one presentation, and *N* = new. For associative recognition, the first letter I = intact; and R = rearranged; LF = low frequency; HF = high frequency; 2 = two presentations; and 1 = one presentation. See the online article for the color version of this figure.

diffusion model to data, as indicated by chi-square values, and showed that small shifts in the proportions of responses between quantiles within a condition or between conditions (for predictions vs. observations) could account for contributions to chi-square as large as the critical values. Thus, the chi-square values represent reasonable fits of the model to the data. Tables 2-5 show the means for the best-fitting parameters values averaged over subjects.

Goodness of fit is illustrated in Figure 4, with theoretical values for correct responses for accuracy and the .1, .5, and .9 quantile RTs plotted against the empirical values for each subject for item recognition (left column) and associative recognition (right column). Because these experiments had relatively low numbers of observations per condition, only values representing more than 15 observations are plotted (about 270 points in each case). For associative recognition, there was a maximum of 23 observations per condition, which means that only quantile RTs with accuracy greater than .65 are shown and for item recognition, there was a maximum of 24 observations per condition for old items and 48 for new items (the first item in each list was discarded). The choice proportions show 57 deviations between predictions and data (out of 624) greater than 10% for associative recognition and 52 for item recognition (out of 468). Given that the standard deviation in response proportion for .95 accuracy and 23 observations is 0.05 and for .80 accuracy and 23 observations is 0.08, we would expect this many deviations of this size. For the .1 RT quantiles for correct responses, there are only 14 and 12 deviations of more than 100 ms, and for the .5 quantile RTs, only 23 and 7 deviations of more than 100 ms for associative and item recognition, respectively. In general, there are few systematic biases in the predictions given the relatively low numbers of observations per condition (see Ratcliff & Childers, 2015, for examples of variability in parameter estimates and power with as few as 80 total observations per subject).

For mean drift rates (the mean of: the drift rates for old items and minus the drift rates for new items), nondecision time, and boundary separation, Figure 5 shows the best-fitting values, averaged over subjects. In this figure, the drift rates are the absolute values averaged over trial types (see Tables 3 and 5 for separate values). Differences in accuracy and RT over the experimental conditions (old vs. new, intact vs. rearranged, repetitions and word frequency) were accounted for by differences in drift rates (Tables 3 and 5).

Parameter Estimates

For the parameter estimates of the diffusion model, the main results to note are the drop in drift rate for both item and associative recognition in the sleep deprivation session; and little effect on nondecision time or boundary separation, but with a small decrease in both over sessions (a practice effect).

The parameter values represent the behavior of components of cognitive processing in the experiment, and we use their values to interpret the effects of sleep deprivation on performance in the two-choice tasks. Two-way mixed-effects ANOVAs of each of the

Figure 7 (opposite). Scatter plots, histograms, and correlations for drift rates for the control group and the sleep deprived group. The diagonal plots are histograms of the values. The panels above and to the right of the diagonal show the correlations, and the sizes of the digits represent the sizes of the correlation. The panels below and to the left of the diagonal show the scatter plots, with each dot representing an individual subject. The lines are lowess smoothers (from the R function). The identity of the comparison in each off-diagonal plot or correlation is obtained moving vertically and horizontally from the task labels in the corresponding diagonal plots. "B", "S" and "R" represent the baseline, sleep deprived (or control second session) and recovery sessions. "Item" and "Assoc" represent item and associative recognition memory, respectively. See the online article for the color version of this figure.

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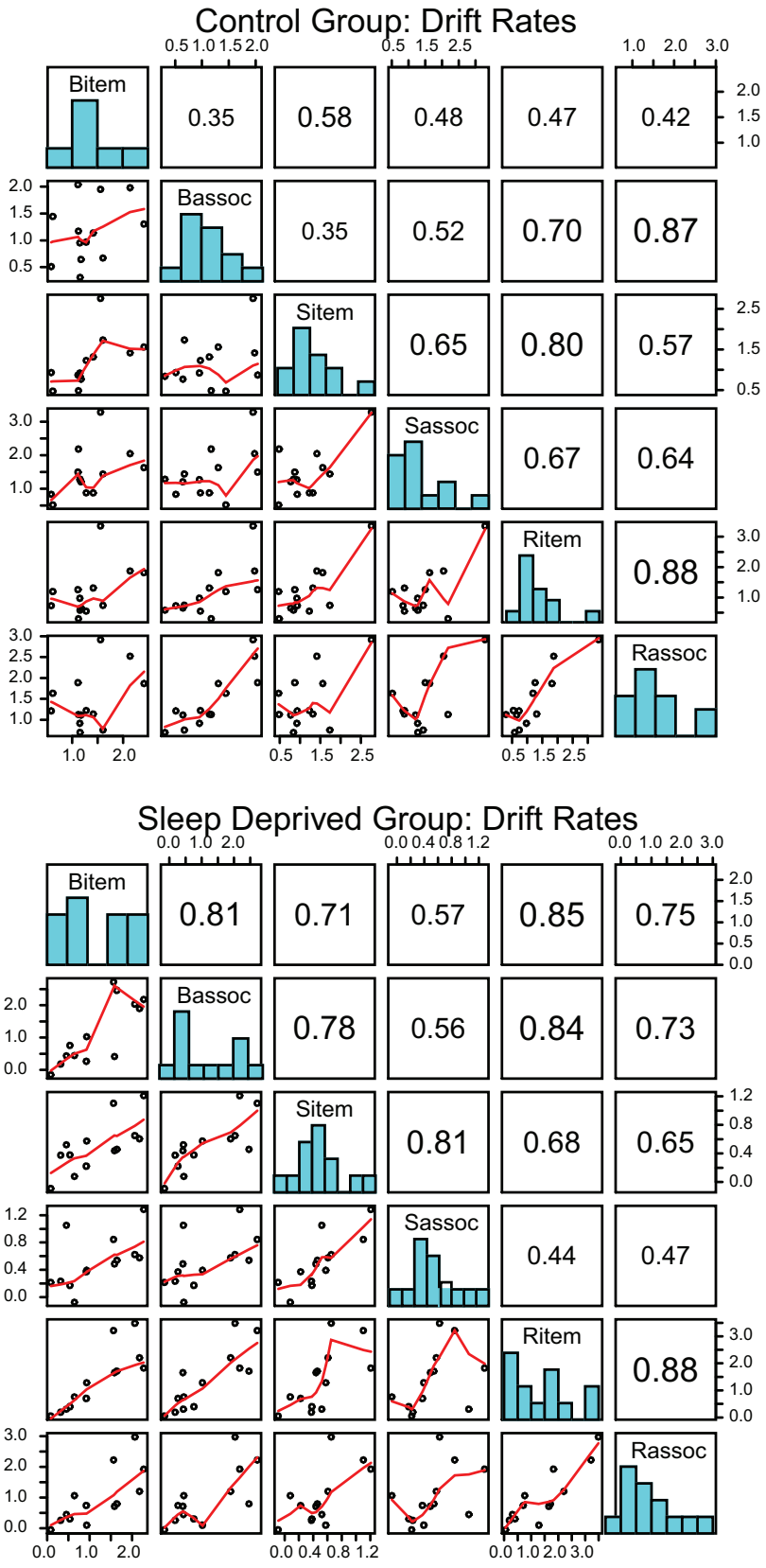

Figure 7 (opposite)

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parameters for the three sessions by experimental and control groups were performed. The degrees of freedom for all the F's are 2 and 48. The mean values of the parameter used in these analyses are shown in Tables 2 and 4.

For drift rate, there was a main effect of session for item recognition ($F = 7.2$, $p < .05$) but not associative recognition ($F = 1.6$), and for both types of recognition there was an interaction between session and group ($F = 6.8$, $p < .05$ and 5.9, $p < .05$). In both cases, this represented a fall in drift rates for the sleep deprived group. For boundary separation, there was a main effect of session for item recognition ($F = 5.4$, $p < .05$) and an interaction between group and session for associative recognition ($F = 5.9$, $p < .05$). These effects can be seen in Figure 5, but the differences are relatively modest in size. There was a difference in nondecision time across sessions, with a significant main effect ($F = 4.6$, $p < .05$ and 3.7, $p < .05$). This represents a practice effect across sessions. The interaction of session with group for across-trial variability in drift rate was significant ($F = 4.1$, $p < .05$ and 3.9, $p < .05$), showing that across-trial variability in drift rate was lower for the sleep deprivation condition (Tables 2 and 4). This could also represent a scaling effect, with mean and *SD* both being reduced in this condition (Ratcliff, Thapar, & McKoon, 2010). Across-trial variability in starting point showed a main effect across sessions for item recognition ($F = 3.8$, $p < .05$), but not for associative recognition ($F = 2.2$, $p > .05$).

It is possible that sleep deprivation might induce a bias to respond "new" or "rearranged" if the subjects become more conservative about making a response about the presence of the item or presence of the intact relationship between the test pair of words. Figure 6 shows plots of the separate drift rates in Tables 3 and 5, and these show that the zero point of drift rate (the drift criterion) does not change with sleep deprivation.

The primary effect of sleep deprivation was a drop in drift rate for both types of recognition. Also, across-trial variability in drift rate was lower in the sleep deprivation session. Furthermore, there were effects on boundary separation and nondecision time, which can be interpreted as practice effects.

Predictions for the effect of the decrease in drift rate in the model for accuracy and mean RT were generated using parameters similar to those in the model fits (Tables 2–5). Using $a = 0.16$, $T_{er} = 0.55$, $\eta = 0.18$, $s_z = 0.06$, $p_o = 0.001$, and $s_t = 0.3$, for drift rate $v = 0.07$, accuracy = 0.63 and mean RT = 967 ms, and for drift rate $v = 0.14$, accuracy = 0.74 and mean RT = 928 ms. Thus an 11% change in accuracy corresponds to about a 39 ms change in mean RT, consistent with the sizes of the effects in Figure 3.

Contaminant Assumptions

In Ratcliff and Van Dongen (2009), the assumption that some proportion of responses were random guesses was needed in fitting the data from the numerosity discrimination task. To check whether this assumption would improve the fits of the model to the data from the two memory tasks in the present study, we refit the data with the random contaminant assumption. The main result was that the estimated proportion of contaminants was small and had a mean of 1% or less for each group and task (in the sleep deprivation session, there was one subject with 6.1% contaminants in item recognition and one with 3.3% contaminants in associative recognition, but the means were 0.6% and 0.7% respectively). This resulted in parameter estimates for the two sets of fits with the different contaminant assumptions that were almost identical.

Individual Differences

Thirteen subjects in the sleep deprivation group and 13 in the control group is a small number of subjects with which to conduct individual differences studies. But we have a reasonable amount of power if the pairwise correlations between the six conditions replicate (i.e., 15 pairs). We cannot tell if one correlation is larger than another, but we can tell if a parameter correlates across sessions and tasks. Figures 7, 8, and 9 show correlations and scatter plots between pairs of parameter values, and histograms of the parameter values. Drift rates correlated strongly across tasks and across sessions for both groups of subjects with a mean correlation of 0.65 and with the lowest pairwise correlation of 0.35. This implies that someone with good memory in item recognition has good memory in associative recognition in both the control subjects and the experimental subjects (and for those in the sleep deprivation session). Boundary separation showed the same pattern with a mean correlation of 0.54 and with the lowest pairwise correlation of 0.20. Nondecision time showed a weaker pattern with the mean correlation of 0.43 but with this there were some negative correlations with the lowest value −0.26 (this was probably due to one large value of nondecision time shown in Figure 9 - the effect of such a deviant score would be expected because of the low number of observations in each comparison).

Of particular interest is the comparison of the sleep deprivation conditions with the baseline and recovery sessions. If sleep derivation differentially disrupts memory performance for individuals, the correlations for the sleep deprived sessions with the baseline and recovery sessions should be reduced relative to the correlations between the baseline and recovery sessions. In fact, the mean correlations for drift rates between the sleep deprivation session and the baseline and recovery sessions were 0.63 and 0.63, while the mean correlation between the baseline and recovery sessions was 0.81. Thus the sleep deprivation condition produced correlations with the baseline and recovery sessions that are a little lower than the correlation between the baseline and recovery sessions, but the correlation is still very high, showing little disruption in the relative effect of sleep deprivation across subjects. Generally, all these comparisons show consistent individual differences across tasks and sessions (see also Patanaik, Zagorodnov, Kwoh, & Chee, 2014).

Discussion

The experimental data from this study were fit with the diffusion decision model, which fits accuracy and RT distributions for correct and error responses. In the diffusion model in designs in which difficulty is manipulated within lists, differences in performance between conditions that vary in difficulty (once- vs. twice-presented words, high- vs. low-frequency words) are accounted for by differences in drift rates. Boundary settings cannot change between easy items and difficult items because the settings cannot change as a function of test item type once the accumulation of information has begun. To change the settings before accumulation

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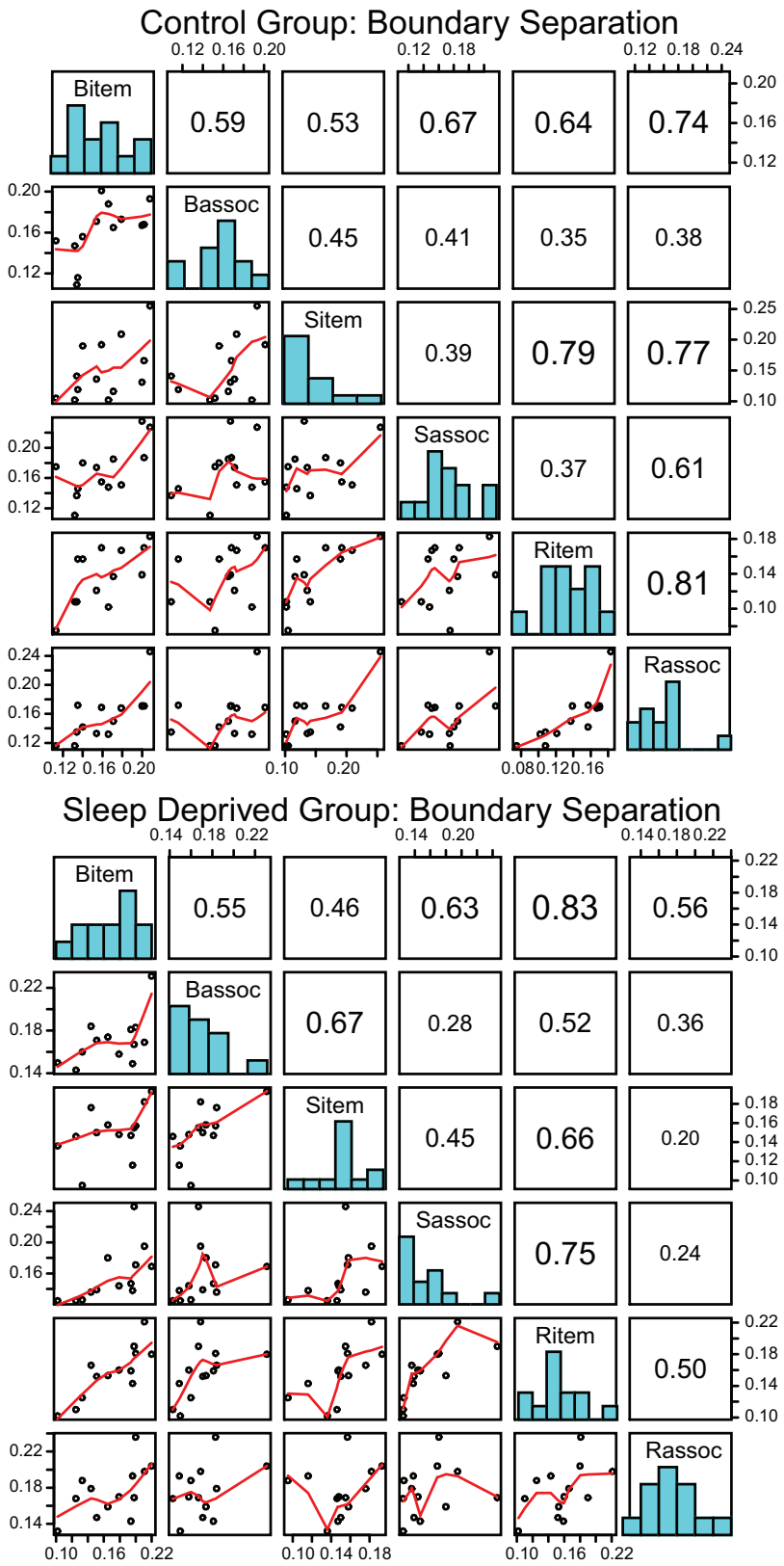

Figure 8. Scatter plots, histograms, and correlations for boundary separation. Details are the same as for Figure 7. See the online article for the color version of this figure.

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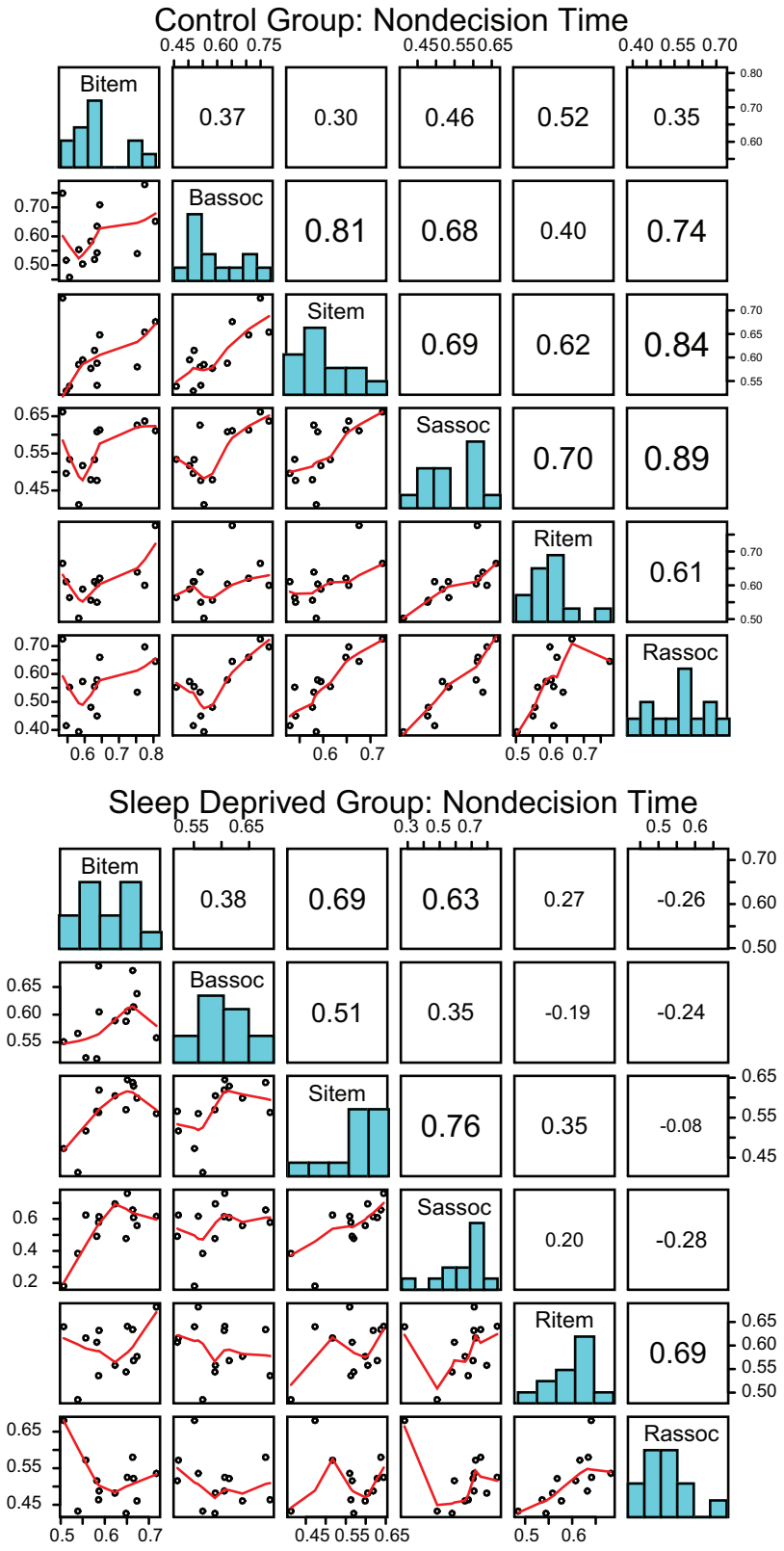

Figure 9. Scatter plots, histograms, and correlations for nondecision time. Details are the same as for Figure 7. See the online article for the color version of this figure.

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began would require knowing whether a test item was easy or difficult, something that cannot be known until after information has been accumulated. As expected, differences in accuracy and RT between once- and twice-presented words and high- and low-frequency words were all explained by differences in drift rates. Note that all parameters of the model were allowed to vary between sessions, because practice could alter any of the parameters.

The diffusion model analysis indicates that the quality of stored information in memory that drives the decision process is reduced in the sleep deprivation condition relative to the control group and relative to the baseline and recovery sessions. This implicates reduced quality of encoding during study of the word lists, reduced maintenance (retention) of stored information in memory, or reduced ability to retrieve information from memory (or combinations of these) as the main processes affected by sleep deprivation. Because item and associative information require somewhat different retrieval processes, a deficit in encoding or maintenance is the more plausible.

There were mainly nonsignificant effects of sleep deprivation on boundary separation and nondecision time, and results were most consistent with practice effects on these components of processing (cf. Dutilh, Kryptos, & Wagenmakers, 2011; Dutilh, Vandekerckhove, Tuerlinckx, & Wagenmakers, 2009; Petrov, Van Horn, & Ratcliff, 2011; Ratcliff, Thapar, & McKoon, 2006). The only other systematic effect was a decrease in across-trial variability in drift rate for the sleep deprivation condition in both item and associative recognition. These results suggest that other decision-making processes are not significantly affected by sleep deprivation in these tasks.

Ratcliff and Van Dongen (2009) examined the effects of sleep deprivation on performance in a numerosity discrimination task using a diffusion model analysis. They found a drop in drift rates for the sleep deprived condition along with an increase in the number of contaminants (though there were large individual differences), as well as smaller but significant changes in boundary separation and across-trial variability in both nondecision time and starting point. The present study replicated the drop in drift rates, but the other effects were not obtained. This may be due to smaller numbers of observations - two tasks were presented per 45 min. session, while in Ratcliff and Van Dongen (2009) the one task took the whole session. The effect of sleep deprivation on drift rate has also been observed (Ratcliff & Van Dongen, 2011) on a psychomotor vigilance test (PVT), which is a simple RT task designed to measure sustained attention (Lim & Dinges, 2008). Having found this effect again in our present study of two types of recognition memory tasks, we may see a trend emerging, suggesting that reduced drift rate may be a universal feature of the impact of sleep deprivation on cognitive performance.

Recent studies have suggested that memory task performance deficits during sleep deprivation are due to deficits in attentional processing and memory maintenance, whereas memory encoding and retrieval seem to be relatively unaffected by sleep deprivation (Rakitin, Tucker, Basner, & Stern, 2012; Wee, Asplund, & Chee, 2013). However, evidence to the contrary, namely that the encoding phase *is* affected by sleep deprivation, has also been reported (Tucker et al., 2011). The present study sheds some light on these issues through a head-to-head comparison of item and associative recognition memory (though the Tucker and Wee studies address somewhat different working memory processing). We found that the effects of sleep deprivation on diffusion model parameters were similar for the two types of recognition memory, suggesting shared mechanisms underlying the effects of sleep deprivation on the two tasks. This was corroborated by consistency (correlation) of model parameter changes due to sleep deprivation for the two tasks. There is overlap between brain regions activated during memory task performance and brain regions associated with attentional processes, raising the possibility that performance deficits in memory tasks are due to attentional deficits (Jackson & Van Dongen, 2011). Indeed, our results are more consistent with an explanation of performance impairment in terms of degraded attentional processes than in terms of item or associative memory impairment per se.

A recently proposed, qualitative theory posits that the effects of sleep deprivation are use-dependent, involving degraded information processing in neuronal networks that are most intensively used during performance of a given task (Van Dongen, Belenky, & Krueger, 2011). In the context of this theory, our quantitative diffusion modeling results suggest that attentional processes are the most intensively used processes in both recognition memory tasks. Sleep deprivation is well known to degrade task performance in tasks with a high attentional demand (Lim & Dinges, 2008).

It is noteworthy in this regard that our present results differ from those found earlier in aging, which reduces drift rates in associative recognition but not item recognition (Ratcliff, Thapar, & McKoon, 2011). In contrast with sleep deprivation, therefore, the breakdown of associative memory in aging may not be related to nonspecific impairment in attention, but rather to impairment of specific processes involved in associative memory. Using a battery of neuropsychological tests, Harrison and colleagues compared a group of young adults subjected to 36 hours of sleep deprivation to a group of healthy, alert, non-sleep-deprived people aged about 60 years (Harrison, Horne, & Rothwell, 2000). They observed that 36 hours of sleep deprivation in the young adult group produced effects on prefrontal cortex-mediated performance similar to those found in the nonsleep deprived older group. Our findings and those of others (Tucker, Stern, Basner, & Rakitin, 2011) are inconsistent with the idea that the effects of sleep deprivation on cognitive performance are comparable to those of aging.

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Call for Nominations

The Publications and Communications (P&C) Board of the American Psychological Association has opened nominations for the editorships of the *Journal of Experimental Psychology: Animal Learning and Cognition, Neuropsychology,* and *Psychological Methods* for the years 2020 to 2025. Ralph R. Miller, PhD, Gregory G. Brown, PhD, and Lisa L. Harlow, PhD, respectively, are the incumbent editors.

Candidates should be members of APA and should be available to start receiving manuscripts in early 2019 to prepare for issues published in 2020. Please note that the P&C Board encourages participation by members of underrepresented groups in the publication process and would particularly welcome such nominees. Self-nominations are also encouraged.

Search chairs have been appointed as follows:

- *Journal of Experimental Psychology: Animal Learning and Cognition*, Chair: Stevan E. Hobfoll, PhD
- *Neuropsychology,* Chair: Stephen M. Rao, PhD
- *Psychological Methods,* Chair: Mark B. Sobell, PhD

Candidates should be nominated by accessing APA's EditorQuest site on the Web. Using your browser, go to https://editorquest.apa.org. On the Home menu on the left, find "Guests/Supporters." Next, click on the link "Submit a Nomination," enter your nominee's information, and click "Submit."

Prepared statements of one page or less in support of a nominee can also be submitted by e-mail to Sarah Wiederkehr, P&C Board Editor Search Liaison, at swiederkehr@apa.org.

Deadline for accepting nominations is Monday, January 8, 2018, after which phase one vetting will begin.