The Effects of Sleep Deprivation on Information-Integration Categorization Performance

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Background: Sleep deprivation is a serious problem facing individuals in many critical societal roles. One of the most ubiquitous tasks facing individuals is categorization. Sleep deprivation is known to affect rule-based categorization in the classic Wisconsin Card Sorting Task, but, to date, information-integration categorization has not been examined.

Study Objectives: To investigate the effects of sleep deprivation on information-integration category learning.

Design: Participants performed an information-integration categorization task twice, separated by a 24-hour period, with or without sleep between testing sessions.

Participants: Twenty-one West Point cadets participated in the sleep-deprivation group and 28 West Point cadets participated in a control group.

Measurements and Results: Sleep deprivation led to an overall performance deficit during the second testing session—that is, whereas participants allowed to sleep showed a significant performance increase during the second testing session, sleepless participants showed a small (but nonsignificant) performance decline during the second testing session. Model-based analyses indicated that a major contributor to the sleep-deprivation effect was the poor second-session performance of a subgroup of sleep-deprived participants who shifted from optimal information-integration strategies at the end of the first session to less-optimal rule-based strategies at the start of the second session. Sleep-deprived participants who used information-integration strategies in both sessions showed no drop in performance in the second session, mirroring the behavior of control participants.

Conclusions: The findings suggest that the neural systems underlying information-integration strategies are not strongly affected by sleep deprivation but, rather, that the use of an information-integration strategy in a task may require active inhibition of rule-based strategies, with this inhibitory process being vulnerable to the effects of sleep deprivation.

Keywords: Category learning, procedural learning, striatum, sleep consolidation, sleep deprivation

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SLEEP DEPRIVATION IS A COMMON SITUATION EXPERIENCED BY INDIVIDUALS IN MANY PROFESSIONS, INCLUDING THOSE WHO PERFORM CRITICAL ROLES in society. These people include medical doctors, firefighters, parents, and members of the military.[1-4] One of the most important and ubiquitous tasks faced by individuals in these important roles is that of categorization. Quick and accurate categorization is fundamental to survival and is critical in many professions for which sleep deprivation is common. For example, accurately categorizing an individual with chest pain as suffering from a heart attack could save the individual's life, whereas categorizing the person as suffering from indigestion could lead to death. Similarly, for a soldier, accurately categorizing an individual as an enemy combatant or a civilian can be crucial for survival.

Category learning involves laying down a memory trace that improves the efficiency of responding. It is now widely accepted that mammals have multiple memory systems, each of which is associated with different neural circuits.[5-7] The predominant view is that different memory systems are better suited for learning different types of category structures.[8-10]

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Two category learning domains that are of particular interest are rule-based and information-integration categories.[8,11,12] Rule-based categories are those for which the optimal decision rule is cannot be verbalized. For example, if all members of 1 category are large, and all members of the other category are small, then the optimal strategy would be to determine the size of the target stimulus and to apply the following verbal rule: "If the stimulus is small place, it in category A; if the stimulus is large, place it in category B." One of the most well-known and highly studied rule-based category learning tasks is the Wisconsin Card Sorting Task.[13]

Unlike rule-based categories, the optimal decision rule for information-integration categories is that it cannot be verbalized but, instead, requires a predecisional integration of information from 2 or more stimulus dimensions (usually expressed in different physical units). An example of information-integration categories composed of circular sine-wave gratings is shown in Figure 1. The optimal strategy (denoted by the solid diagonal line) cannot be verbalized because it involves a linear integration of information from dimensions expressed in incommensurable units (ie, orientation and spatial frequency).

Optimal rule-based category learning is thought to be mediated by a hypothesis-testing system.[8,10-12,14,15] The hypothesis-testing system reasons in an explicit fashion and is dependent on conscious awareness. Optimal information-integration category learning is thought to be mediated by a procedural system.[8,10-12,14,15] Unlike the hypothesis-testing system, the procedural learning system is not consciously penetrable and, instead, operates by

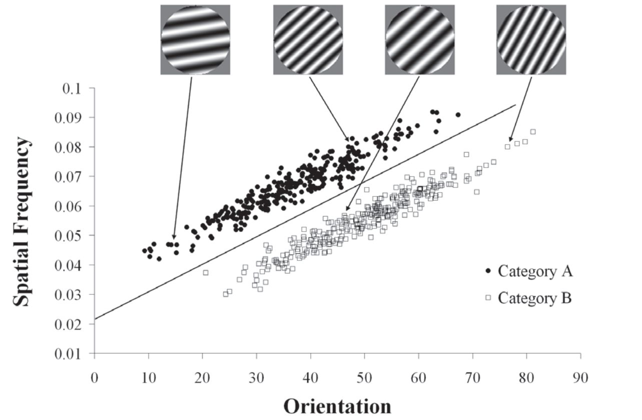

Figure 1—Scatterplot of the stimulus used in the experiment. The filled symbols denote stimuli from Category A, and the open symbols denote stimuli from Category B. The diagonal line indicates the optimal decision bound. Four sample stimuli and their associated locations in the scatterplot are included.

associating regions of perceptual space with actions that lead to reward. The hypothesis-testing and procedural systems rely on distinct neural substrates. The hypothesis-testing system relies on working memory and executive attention processes[16,17] and appears to be dependent on a neural circuit involving dorsolateral prefrontal cortex, anterior cingulate, the head of the caudate nucleus, and medial-temporal-lobe structures.[14,18-21] The procedural system is implemented by a circuit involving inferotemporal cortex and the posterior caudate nucleus.[8,14,21-23]

The current view is that the hypothesis-testing and procedural systems are operative on every trial of a categorization task and that there is a competition between these 2 systems to determine which system generates the output on a given trial.[8] There is also an initial bias in the overall system toward the use of rule-based strategies. Thus, although the output of the procedural system might yield optimal information-integration performance in the long run, learning in this system is more gradual and incremental, and experience with the task is required before this system begins to dominate. Finally, there is also strong evidence that taxing a participant who is solving an information-integration task often leads the participant to "fall back" on rule-based strategies.[24-29] For example, if the feedback is delayed or if the response requirements are changed, participants have been shown to revert to rule-based strategies when procedure-based strategies were being used. It will be of interest in the current study to determine whether sleep deprivation might have similar effects.

Sleep deprivation has been shown to adversely affect rule-based category learning. Specifically, Herscovitch, Stuss, and Broughton[30] found that sleep-deprived individuals were impaired in the Wisconsin Card Sorting Task, with the ratio of perseverative errors within a category to total perseverative errors increasing after sleep deprivation. To our knowledge, no studies have examined the effects of sleep deprivation on information-integration categorization (although studies have examined the effect of sleep deprivation on procedural motor learning tasks.[31] Many real-world categorization problems likely involve information integration and are performed by professionals who often operate under sleep-deprived conditions. For example, the classification of radiographs into those that contain or do not contain a tumor may involve information integration. Analogously, the operation of complex machinery, such as military fighter planes or heavy construction machinery, likely involves information integration. These classification problems are difficult to verbalize and are often made quickly (and generally accurately) by individuals who are deprived of sleep. The goal of this work is to examine the effects of sleep deprivation on information-integration categorization in a laboratory setting.

Because conscious control processes are affected by sleep deprivation, and since rule-based categorization is mediated by conscious control processes, it is not surprising that rule-based deficits emerge with sleep deprivation. Predictions are less clear with respect to information-integration categorization. Performance in information-integration tasks is thought to proceed outside of conscious awareness and is thought to be mediated by fairly automatic, stimulus-response learning processes, at least when participants are using information-integration strategies to solve the task. In that sense, one reasonable hypothesis is that there will be no information-integration categorization deficit. On the other hand, it may be the case that sleep-deprived individuals fall back on rule-based strategies, in which case, performance deficits would be observed.

In the next (second) section, we outline the experimental methods used in the current study. The third section is devoted to the results. A major strength of our empirical paradigm is that we can complement analyses of performance measures, based on the accuracy of responding, with computational models that can be used to clarify individual strategies applied to the task.[32] Although accuracy analyses are informative, they tell us little about the specific response strategies utilized by participants. It is well known[8] that a given accuracy rate can be achieved by qualitatively different response strategies, and, hence, qualitatively different category learning systems, the processing of which is mediated by different neural circuits. For example, if we observe that a participant achieves 75% accuracy in a block of trials, we do not know whether that participant used a procedural learning strategy or a hypothesis-testing strategy. Because each of these strategies is thought to be mediated by different neural circuits (summarized above), it is highly informative to apply computational models that instantiate each type of categorization strategy. The fourth (and final) section is devoted to a summary and discussion of the results.

METHODS

Participants

Twenty-one West Point cadets participated in the Sleepless (sleep deprivation) group (16 men, 5 women; mean age, 20.3 years; range, 19-26 years), and 28 West Point cadets participated in a Control group (23 men, 5 women; mean age, 19.5 years; range, 18-22 years). The 2 samples did not differ in age ($P = 0.12$) or sex ratio ($P = 0.61$), but they were tested at different time points. Participants in the Sleepless group where tested in 2 sessions separated by 24 hours. Each participant was monitored continuously to ensure that no participant slept. Participants in the Control group where tested in 2 sessions separated by 24 hours and were allowed to engage in a normal night's sleep during the intervening time. All participants in both groups were tested between 0600 and 1200. All participants had normal or corrected-to-normal vision. The Institutional Review Board of The University of Texas, Austin, and the United States Military Academy approved the study, and informed consent was obtained from all participants.

Stimuli and Stimulus Generation

Four sample stimuli are shown in Figure 1, along with a scatterplot of the full stimulus set. Each stimulus was a circular sine wave grating with a fixed orientation and spatial frequency. Each stimulus belonged to 1 of 2 categories "A" or "B." The stimuli were generated by drawing 300 random samples from each of 2 bivariate normal distributions along the 2 stimulus dimensions with mean vectors μ_A and μ_B (in orientation-frequency stimulus space) and common variance-covariance matrix Σ:

μ_A = [37.1 0.067]', μ_B = [49.9 0.055]'and $\Sigma_A = \Sigma_B$ = [121 0.104 0.104 0.0000978].

Orientation was defined in degrees counterclockwise from horizontal, and frequency was defined in cycles per degree.

Procedure

Day 1

Participants were not allowed to consume alcohol 24 hours prior to the study or to consume caffeine between 00:00 and 06:00 before the first or second day. They were instructed to engage in normal sleep-wake cycles the night before testing, and sleepless participants were peer monitored during this period. Participants in the Control and Sleepless conditions completed five 100-trial blocks of category learning on Day 1. Each block of 100 trials contained 50 category A and 50 category B stimuli. These stimuli were randomly sampled (without replacement) from the full set of 300 A and 300 B stimuli defined above. Participants were informed that there were 2 categories and that they should pay attention to both the speed and accuracy of their responses. On each trial, participants were asked to categorize a single stimulus into 1 of 2 categories by pressing either the "n" or "m" key on the keyboard. A typical trial proceeded as follows. A stimulus was presented centered on the screen along with the message "Categorize this stimulus as 'N' or 'M.'" Stimulus presentation was response terminated. Once the participant generated a response, the stimulus was removed and a 750-ms feedback screen ("correct" or "wrong") was presented. Feedback was followed by a 1250-ms blank screen (intertrial interval) and initiation of the next trial. The total time to complete the task ranged from 30 to 40 minutes.

After testing, participants in the Sleepless group were accompanied by a monitor at all times. During the evening and night, they ate a meal and engaged in both physical and mental activities, such as walking, bowling, videogames, and board games to keep them awake. After testing, participants in the Control group were told to engage in normal sleep that evening. Testing was conducted over a weekend when West Point cadets generally engage in sports activities (eg, rugby).

Day 2

Both groups of participants ate breakfast, and, 24 hours after initial testing, participants in both groups completed an additional three 100-trial blocks in the same category-learning task. Again, each block consisted of 50 A and 50 B stimuli randomly sampled (without replacement) from the full set of 300 A and B stimuli. Participants were informed that the task was identical to that completed on Day 1. The timing of each trial was identical to that from Day 1, but the duration of the task was shortened. The total time to complete the task ranged from 20 to 30 minutes.

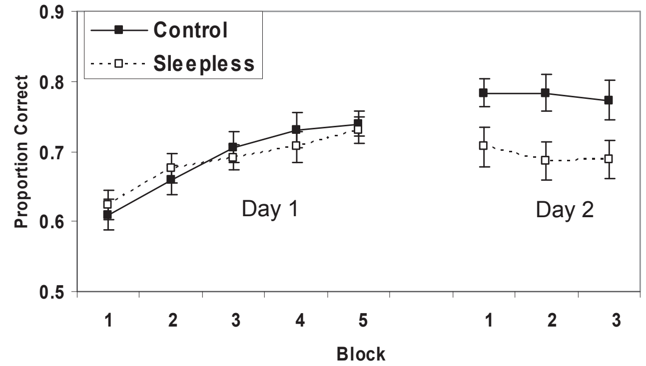

Figure 2—Proportion correct for the Sleepless group (squares) and the Control group (circles). Standard error bars are included.

RESULTS

The results are organized into 2 sections. First, we focus on standard statistical analyses of the categorization accuracy data. In this section we examine several measures of learning, retention, and asymptotic performance. Second, we introduce and apply a series of model-based analyses that provide a window into the types of strategies that participants are using. Accuracy analyses tell us little about the types of strategies that participants use and how those are affected by sleep deprivation.

Accuracy-Based Analyses

To ensure that only participants who learned the initial category structures in Day 1 were included in the analyses, a learning criterion of 58% accuracy or greater on the final block of Day 1, or on every block except the final block, was applied. This criterion of 58% represents chance performance based on a binomial distribution with 100 trials. Data from 5 Control participants and 1 Sleepless participant were excluded from all subsequent analyses based on this criterion. The average learning curves for the Control and Sleepless conditions across the 5 blocks of trials from Day 1 and the 3 blocks of trials from Day 2 are displayed in Figure 2.

Day 1 Performance

A 2-group x five 100-trial block analysis of variance (ANOVA)was conducted on the Day 1 accuracy rates to determine whether there were any Day 1 learning effects and whether these differed across groups. The block effect was significant ($F_{4,164}$ = 17.43, P < 0.001, mean squared error [MSE] = .005), suggesting that both groups of participants showed a performance increase across the first day of training. The group effect and the interaction were both nonsignificant [both F values < 1.0]. In addition, there was no performance difference in the final block of Day 1 (t < 1.0). Thus, before introducing the sleep-deprivation ma-

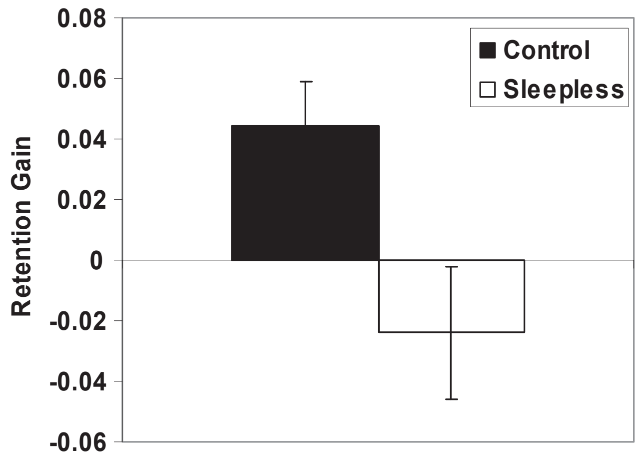

Figure 3—Retention gain defined as the change in accuracy from the final block of Day 1 to the first block of Day 2 (Day 2 Block 1 - Day 1 Block 5). Standard error bars are included.

nipulation, both participant groups showed a clear performance increase, reaching asymptote at .74 and .73 proportion correct in the final block for the Control and Sleepless groups, respectively, and, importantly, there were no performance differences between groups on Day 1.

Day 2 Performance

A 2-group x three 100-trial block ANOVA was conducted on the Day 2 accuracy rates to determine whether there were any sleep-deprivation effects on Day 2 performance and whether any additional performance improvement took place in either group. The block effect ($F < 1.0$) and the interaction ($F < 1.0$) were both nonsignificant. However, there was a significant main effect of group ($F_{1,41} = 6.26$, $P < 0.05$, MSE = .038), suggesting that overall Sleepless participants (.69) performed worse than Control participants (.78). Thus, the sleep-deprived group performed worse than the control group, but neither group showed any additional performance improvement.

In the next 2 sections we examine 2 additional aspects of performance. First, we examine final block performance, then we examine the amount of information retained from Day 1 to Day 2 by comparing performance on the first block of Day 2 with the final block of Day 1. Specifically, we subtracted performance on the final block of Day 1 from performance on the first block of Day 2. Thus, positive values denote a retention gain, and negative values denote a retention loss. In our view, retention gains and absolute performance measures are both important indicators. Retention gains allow us to determine whether a participant's performance improves over a 24-hour period with or without sleep, whereas the absolute performance measure (ie, Day 2, Block 1 accuracy) allows us to determine how a 24-hour period with or without sleep affects the accuracy of responding.

Day 2 Final Block Performance

To determine how sleep deprivation affected performance at the end of the task, we compared performance during the final block of Day 2 with the chance performance level of .58 (determined from a binomial distribution). Although Sleepless participants performed worse than Controls during Day 2, it is important to note that they did not simply give up and respond randomly. During the final block of Day 2, Sleepless participants performed significantly above the chance level of .58 (.69) ($t_{19} = 3.90$, $P < 0.001$), as did Control participants (.77) ($t_{22} = 6.90$, $P < 0.001$). Thus, although sleep deprivation led to worse overall Day 2 performance relative to Controls, both groups showed above-chance performance at the end of Day 2, suggesting that sleep deprivation did not lead participants to simply abandon the task.

Day 2 Retention

To examine the effect of sleep deprivation on the amount of information retained from Day 1 to Day 2, we compared performance on the first block of Day 2 with the final block of Day 1. These retention-gain data are displayed in Figure 3. In the Control group, performance improved by 4.3% from the final block of Day 1 (74.0% accuracy) to the first block of Day 2 (78.3% accuracy). This increase was significant based on a 2-tailed t-test comparison with 0 ($t_{22} = 3.03$, $P < 0.01$), suggesting some improvement in performance as a result of being allowed to sleep between tasks. By contrast, in the Sleepless group, performance declined by 2.4% from the final block of Day 1 (73.1% accuracy) to the first block of Day 2 (70.7% accuracy). This decline was not significantly different from 0 ($t_{19} = 1.11$, NS). In addition, these retention scores did differ significantly across the Sleepless and Control groups ($t_{41} = 2.67$, $P < 0.05$).

To summarize the accuracy-based analyses, we found no Day 1 performance differences between the Control and Sleepless groups. This was expected, since both groups of participants were allowed to sleep before Day 1 testing, but is still important to verify. Despite the same performance profiles on Day 1, Sleepless participants performed significantly worse on Day 2 than did Control participants. Even so, Sleepless participants did not simply give up on the task but, rather, continued to perform well above chance, and their initial Day 2 performance was not significantly lower than their final Day 1 performance. The Control participants showed some evidence of improvement across the 24-hour delay, improving by 4.3% from the final block of Day 1 to the first block of Day 2. Although it does offer some insight, the current experimental design does not allow us to definitively determine whether this improvement reflected learning consolidation that might be mediated by sleep. This question will be examined in future research.

Model-Based Analyses

The accuracy-based analyses suggest that sleep deprivation led to a performance decline during Day 2 relative to the Control group. However, it is critical to provide some insights into the locus of this deficit. Given the fact that the use of information-integration versus rule-based strategies to solve information-integration categorization leads to large performance differences, it would be advantageous to determine whether the effects of sleep deprivation differed as a function of the type of learning strategy that participants utilized on Day 1. To address this issue, we applied a series of decision-bound models[32,33] to the final block of data from Day 1 separately for each participant. One set of decision-bound models assumed that the participant used an information-integration classification strategy, and the other set of models assumed that the participant used a rule-based classification strategy (see the Appendix for details) [a]. These models make no detailed process assumptions, in the sense that a number of different process accounts are compatible with each of the models.[34,35] For example, if an information-integration model fits significantly better than a rule-based model, then we can be confident that participants did not use a rule-based strategy, but we cannot specify which specific information-integration strategy was used (eg, a weighted combination of the two dimensions versus more holistic processing). Because information-integration strategies are mediated by memory and neural systems different from those of rule-based strategies, these analyses not only will provide information about sleep-deprivation effects on classification strategies, but could potentially shed light on the underlying neurobiology that is affected by sleep deprivation.

We begin by calculating the number of Control and Sleepless participants whose final block of Day 1 data was best fit by an information-integration or rule-based strategy. For the Control group, 14 participants' data was best fit by an information-integration model, and 9 participants' data was best fit by a rule-based model. For the Sleepless group, 13 participants' data was best fit by an information-integration model, and 7 participants' data was best fit by a rule-based model. These participant frequencies did not differ across participant groups ($\chi^2_1 < 1.0$). Although it might seem surprising that only 60% to 65% of participants' data was best fit by an information-integration model when the optimal decision rule requires information-integration, this is consistent with the results of previous studies conducted in our lab.[12]

To reiterate, Control and Sleepless participants were divided into 2 subgroups, depending upon whether each participants Day 1, Block 5 data was best fit by an information-integration model or a rule-based model. The average learning curves for the Control information-integration, Control rule-based, Sleepless information-integration, and Sleepless rule-based participant groups across the 5 blocks of trials from Day 1 and the 3 blocks of trials from Day 2 are displayed in Figure 4.

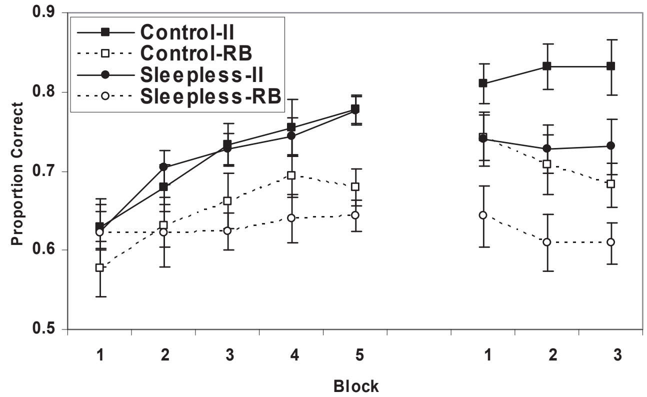

Figure 4—Proportion correct by Participant group and model (information-integration [II] vs rule-based [RB] that provided the best account of the final block of trials from Day 1. Standard error bars are included.

Day 1 Performance

A 2-group x 2-model type x five 100-trial block ANOVA was conducted on the Day 1 accuracy rates to determine whether there were any Day 1 learning effects and whether these differed across conditions. Both the effect of block ($F_{4,156} = 13.50$, $P < 0.001$, MSE = .005) and model type ($F_{1,39} = 13.66$, $P < 0.001$, MSE .021) were significant. The results suggest that performance improved with training and that information-integration participants performed better than rule-based participants.

Taken together, these findings mirror those from the accuracy data in the sense that we found no Day 1 performance differences across Control and Sleepless groups. However, the model analyses suggest that Control and Sleepless participants using information-integration strategies by the end of Day 1 demonstrated a clear performance advantage over participants using rule-based strategies.

Day 2 Performance

Again, with the model type (information-integration or rule-based) being determined by the model that best fit the data from Day 1, Block 5, a 2-group x 2-model type x three 100-trial block ANOVA was conducted on the Day 2 accuracy rates. The main effects of group ($F_{1,39} = 8.14$, $P < 0.01$, MSE = .030) and model type ($F_{1,39} = 12.64$, $P < 0.001$, MSE = .030) were significant, with Control participants (.77) performing better than Sleepless participants (.68) and information-integration participants (.78) performing better than rule-based participants (.67). The model type-by-block interaction was nearly significant ($F_{2,78} = 2.80$, $P = 0.067$, MSE = .003). Although this should be interpreted with caution due to the marginal significance, this interaction was characterized by no change in performance across blocks for the information-integration participants ($F < 1.0$) (Day 2, Block 1 = 78%; Day 2, Block 3 = 78%) and a significant performance decrement across blocks for the rule-based participants ($F_{2,30} = 3.61$, $P < 0.05$, MSE = .003), with a drop in performance from 69% in Day 2, Block 1 to 65% in Day 2, Block 3.

Day 2 Final Block Performance

To determine how model type and participant group affected performance at the end of the task, we compared performance during the final block of Day 2 with the chance level of .58. Performance was well above .58 for Control information-integration participants ($t_{13} = 7.26$, $P < 0.001$), Control rule-based participants ($t_8 = 3.67$, $P < 0.01$), and Sleepless information-integration participants ($t_{12} = 4.25$, $P < 0.001$). Performance was not above .58 for Sleepless rule-based participants ($t_6 = 1.12$, $P = 0.31$). Thus, all participant groups achieved above-chance performance after 800 trials of experience over 2 days of training, except for the Sleepless participants who were using the less-optimal rule-based strategies at the end of Day 1.

Day 2 Retention

We also examined the effects of model type on retention gains for Control and Sleepless participants whose Day 1, Block 5 data were best fit by either an information-integration strategy or a rule-based strategy. These are displayed in Figure 5A. For the Control participants using an information-integration strategy, performance improved by 3.3% from the final block of Day 1 (77.7% accuracy) to the first block of Day 2 (81.0% accuracy). This effect was marginally significant based on a 2-tailed test ($t_{13} = 1.83$, $P = 0.09$) but was significant based on a 1-tailed test. For the Control participants using a rule-based strategy, per-

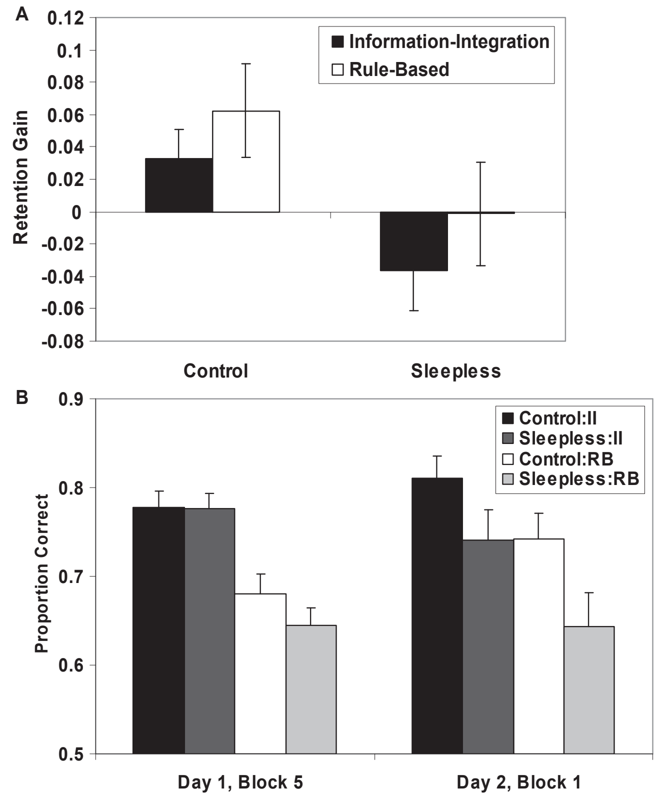

Figure 5—A. Retention gain defined as the change in accuracy from the final block of Day 1 to the first block of Day 2 (Day 2 Block 1 - Day 1 Block 5) for Sleepless and Control participants whose Day 1 Block 5 data was best fit by an information-integration (II) model or a rule-based (RB) model. Positive values denote a performance gain and negative values denote a performance loss. B. Proportion correct during Day 1, Block 5, and Day 2, Block 1 for the same subject groups. Standard error bars are included

formance improved significantly by 6.2% from the final block of Day 1 (68.0% accuracy) to the first block of Day 2 (74.2% accuracy) ($t_8 = 2.49$, $P < 0.05$). For the Sleepless participants using an information-integration strategy, performance declined (albeit nonsignificantly) by 3.6% from the final block of Day 1 (77.7% accuracy) to the first block of Day 2 (74.1% accuracy) ($t_{12} = 1.25$, NS). Finally, for the Sleepless participants using a rule-based strategy, performance remained essentially constant, dropping by 0.1% from the final block of Day 1 (64.4% accuracy) to the first block of Day 2 (64.3% accuracy) ($t < 1.0$).

This pattern of results is interesting because it sheds some light on the retention analyses presented before application of the models. Based on only accuracy, without the model breakdown, we found that the Control participants showed a significant retention gain, whereas Sleepless participants showed a slight (nonsignificant) retention loss. Once the models were included, it became clear that the retention data are better predicted by incorporating the type of strategy that the participant is using at the end of Day 1. Control participants using rule-based strategies showed a retention gain, but the magnitude of that gain went to 0 with sleep deprivation. On the other hand, participants using information-integration strategies showed a retention gain only under control conditions; participants who were sleep deprived showed a retention loss.

Despite the effects of condition and model type on the magnitude of retention gains (or losses), it is important to keep in mind that rule-based participants were performing significantly worse during the final block of Day 1. Thus, despite the fact that rule-based participants showed retention gains, a finding that is interesting in and of itself, their actual performance during the first block of Day 2 was poor. Figure 5B displays the proportion correct for each group during Day 1, Block 5 and Day 2, Block 1. Most importantly, notice that Day 2, Block 1 performance is nearly identical for the Sleepless information-integration participants and the Control rule-based participants, despite the fact that the former group showed a retention loss and the latter group showed a retention gain.

Day 2, Block 1 Decision-Bound Modeling Results

There is 1 aspect of the model analyses that is of particular interest and worthy of additional study. Note that, from Figure 4 and from the analyses reported above, that Control information-integration and Sleepless information-integration participants' performance did not differ statistically on Day 1. However, notice that, during the initial block of Day 2, Sleepless information-integration participants were performing at a lower lever than Control information-integration participants and at a level that was the same as that of Control rule-based participants. One possible explanation is that Sleepless information-integration participants were more likely to fall back on rule-based strategies in Day 2 (ie, following sleep deprivation), whereas Control information-integration participants (who were allowed to sleep) were not. As a test of this hypothesis, we fit the information-integration and rule-based decision-bound models to the first block of trials from Day 2 for only those Control and Sleepless participants whose Day 1, Block 5 data were best fit by an information-integration model (ie, the Control information-integration and Sleepless information-integration participants). Thus, this analysis focused exclusively on the subset of participants in both groups who were using the task-appropriate strategy (ie, information-integration) by the end of the first experimental session. Of the 14 Control information-integration participants, 12 continued to utilized information-integration strategies (referred to as Control information-integration–information-integration participants), 1 shifted to a conjunctive rule-based strategy, and 1 shifted to a unidimensional rule-based strategy (collectively referred to as Control information-integration–rule-based participants).[b] Of the 13 Sleepless information-integration participants, 9 continued to utilize information-integration strategies (referred to as Sleepless information-integration–information-integration participants), 1 shifted to a conjunctive rule-based strategy, and 3 shifted to a unidimensional rule-based strategy (collectively referred to as Sleepless information-integration–rule-based participants). Thus, Sleepless information-integration participants were numerically more likely than Control information-integration participants to shift to rule-based strategies on Day 2, and the Sleepless participants who did shift were numerically more likely to shift to a unidimensional rule-based strategy. Unidimensional strategies are simple strategies and yield poor performance (ie, are highly suboptimal) in information-integration tasks. Conjunctive strategies are also suboptimal but generally yield much higher accuracy rates than do unidimensional rules.

To determine how Day 2 accuracy was affected by the type of strategy used on the first block of Day 2, we computed the retention gain (ie, the difference between Day 2, Block 1 accuracy and Day 1, Block 5 accuracy) for the Control information-integration–information-integration, Control information-integration–rule-based, Sleepless information-integration–information-integration, and Sleepless information-integration–rule-based participants. These data are displayed in Figure 6A. The pattern is clear. Sleepless information-integration–rule-based participants—that is, those sleep-deprived participants using information-integration strategies at the end of Day 1 but using rule-based strategies at the beginning of Day 2—showed a large and significant ($t_3 = 4.37$, $P < 0.05$) performance decline, whereas Sleepless, information-integration–information-integration participants showed a small but nonsignificant decline ($t < 1.0$). Thus, the retention cost observed in Figure 5A for the Sleepless group was being driven by the retention cost for those participants who shifted from an information-integration strategy at the end of Day 1 to a rule-based strategy at the beginning of Day 2. Interestingly, the retention gain observed in Figure 5B for the Control group was being driven by the retention gain for those participants who continued to use an information-integration strategy at the beginning of Day 2. These Control information-integration–information-integration participants showed a retention gain ($t_{11} = 2.72$, $P < 0.05$), whereas the Control information-integration–rule-based participants showed a large (but nonsignificant) retention loss ($t_1 = 3.67$, $P = 0.17$). Despite the large absolute effect, the latter test was not significant because only 2 Control participants shifted from an information-integration strategy at the end of Day 1 to a rule-based strategy at the beginning of Day 2, and, therefore, these data should be interpreted with caution.

For completeness, Figure 6B displays the proportion correct for each group during Day 1, Block 5 and Day 2, Block 1. These data simply reinforce what was observed in Figure 6A. There is a large performance gain when information-integration strategies are used in both sessions and people are allowed to sleep. There is relatively little performance change when information-integration strategies are used in both sessions but people are not allowed to sleep. Finally, if people shift from information-integration strategies at the end of Day 1 to rule-based strategies in Day 2, then Day 2 performance suffers regardless of whether or not people were allowed to sleep.

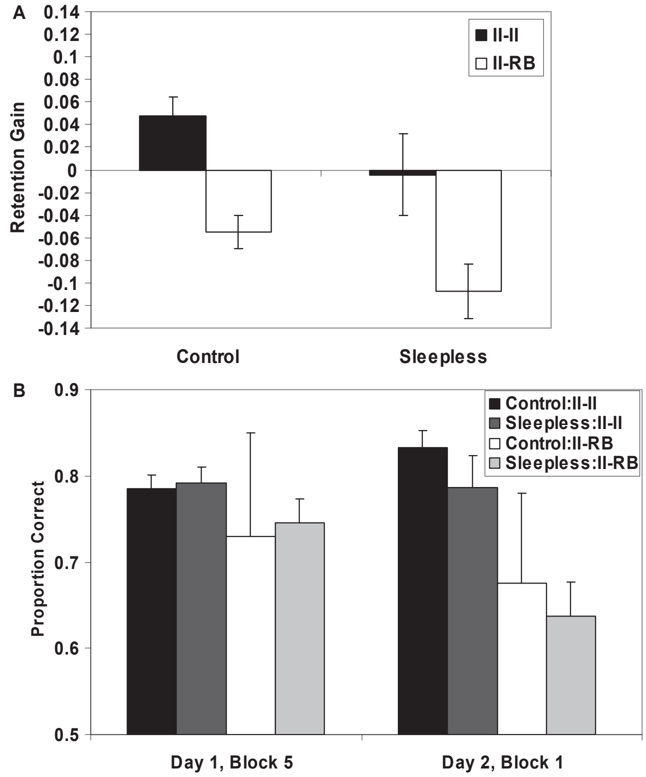

Figure 6—A. Retention gain defined as the change in accuracy from the final block of Day 1 to the first block of Day 2 (Day 2 Block 1 - Day 1 Block 5) for Sleepless and Control participants whose Day 1, Block 5 data was best fit by an information-integration (II) model. Retention gains are plotted separately for participants whose Day 2 Block 1 data was best fit by an information-integration model (II-II) or a rule-based (II-RB) model. B. Proportion correct during Day 1, Block 5, and Day 2, Block 1 for the same subject groups. Standard error bars are included

DISCUSSION

This article reports the results of the first-ever study of the effects of sleep deprivation on information-integration categorization. Following 500 trials of initial information-integration categorization training, 1 group of participants was totally sleep deprived (for 24 hours) and was then given 300 additional trials of exposure to the task. A second group of control participants were exposed to the same procedures but were allowed to sleep normally during the 24-hour period. Sleep led to a significant performance increase on Day 2 relative to Day 1, whereas sleep deprivation led to a nonsignificant performance decline on Day 2 relative to Day 1. In addition, sleep deprivation led to a large and consistent information-integration performance deficit relative to the control situation in which the subjects were allowed to sleep. Thus, although optimal information-integration categorization is thought to be mediated by a system that is outside the realm of cognitive control and that proceeds relatively automatically, sleep-deprivation effects were observed.

Had strategy analyses not been conducted, we would have come to the simple, but somewhat counterintuitive, conclusion that sleep deprivation adversely affects processing in a relatively automatic procedural-category learning system. However, including the strategy analyses suggests a clearer, more parsimonious interpretation that is consistent with the underlying neurobiology of information-integration category learning. Three aspects of the model-based analyses are critical. First, sleep-deprived participants who used information-integration strategies at the end of Day 1 performed much better on Day 2 than did sleep-deprived participants who used rule-based strategies at the end of Day 1 (Figure 4). This suggests that the effects of sleep deprivation are much smaller for participants who were better able to engage the relatively automatic procedural-categorization system during Session 1. Even so, sleep-deprived participants using information-integration strategies at the end of Day 1 performed worse during Day 2 than did control participants using information-integration strategies and performed at about the same level as control participants using rule-based strategies. This leads to the next important point—namely, that the Day 2 performance deficit for sleep-deprived individuals using information-integration strategies at the end of Day 1 appears to be due to the fact that a small number of these participants fail to continue using information-integration strategies in Day 2. Instead, these participants fall back on simple (and highly suboptimal) unidimensional rule-based strategies and, thereby, show a large (and significant) performance drop from Day 1 to Day 2 (Figure 6). On the other hand, sleep-deprived participants who use information-integration strategies during Day 1 and continue to use them during Day 2 show no performance drop and show a performance pattern that is similar to that observed for control participants using information-integration strategies in Day 1 and 2.

Finally, although sleep-deprived participants who used rule-based strategies at the end of Day 1 performed poorly on Day 1, they did not show a large retention loss on Day 2. In fact, they showed only a 0.1% drop in performance from the end of Day 1 to the beginning of Day 2. This finding is inconsistent with the previous literature that suggests that sleep deprivation impairs explicit processing. To provide additional insight into this issue, we examined the retention gain for sleep-deprived participants who used rule-based strategies at the end of Day 1 and during the first block of Day 2. Only 4 participants met this criterion, so these data should be interpreted with some caution. In support of the previous literature, these participants showed an average retention loss of 3%. Clearly, further work is needed to more fully understand the effects of sleep deprivation on rule-based processing, including testing on a task in which optimal performance requires rule-based processing.

The current results raise an important consideration, namely, the role of cognitive control in *inhibiting* the application of a suboptimal strategy in service of task performance. This study clearly demonstrates that those individuals using rule-based strategies in a task in which information-integration strategies are optimal suffer in performance (for similar findings see Maddox and Ashby[12]). What was not previously known was whether or not this involved the active inhibition of the suboptimal rule-based strategy, which itself is thought to rely on engagement of an executive control system that is mediated by the prefrontal cortex in concert with other cortical and subcortical regions.[8] These results suggest that use of an information-integration strategy in a task may require active inhibition. Consistent with this possibility are the results of previous studies that have demonstrated that tasks requiring executive control are those most vulnerable to the effects of sleep deprivation.[36] Although other interpretations are possible, this interpretation is in line with results from a recent study conducted in our lab (Schnyer, Maddox, Davis, Ell, Pacheco, & Verfaellie, unpublished data). In this study, patients with damage to the frontal cortex were found to exhibit a deficit in a similar information-integration category learning task. Model-based analyses indicated that the deficit was localized only to patients with damage to the frontal cortex who utilized rule-based strategies to solve the information-integration task. Those patients with damage to the frontal cortex who used information-integration strategies performed at the same level as healthy controls. Although the prefrontal cortex has been shown to be critical for cognitive control, it is important to note that tasks requiring engagement of an executive control system also involve thalamic and other brain regions, making it difficult to tie the deficits seen here solely to the changes in the functioning of the prefrontal cortex due to sleep deprivation.

One weakness of the present study is that we did not monitor the amount of sleep obtained by the control participants between the first and second testing session. Thus, it is possible that some of the control participants did not receive a normal night's sleep, although this would likely work against our current results rather than account for them. One other drawback was the lack of randomization of participants to Sleepless and Control groups. Although different amounts of sleep are possible, West Point cadets lead a regimented lifestyle, and there is likely to be very similar sleep patterns among them.

CONCLUSIONS

Taken together, these findings suggest that sleep deprivation does lead to a performance deficit in the group as a whole. However, the locus of this deficit seems to reside with participants who utilize explicit, consciousness-demanding, rule-based strategies at the end of Day 1 or at the beginning of Day 2. Sleep-deprived participants who were able to utilize the implicit (essentially automatic) procedural system at the end of Day 1 and continued to utilize this system during Day 2 showed no performance drop from Day 1 to Day 2, much like control participants who were not sleep deprived.

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APPENDIX

Four rule-based decision bound models (2 one-dimensional models and 2 Conjunctive models) and 1 information-integration model (General Linear Classifier) were fit to each participant's data. For more details, see Ashby[34] or Maddox and Ashby.[32]

Rule-Based Models

The One-Dimensional Classifier

This model assumes that participants set a decision criterion on a single stimulus dimension. For example, a participant might base his or her categorization decision on the following rule: "Respond A, if the bar width is small; otherwise respond B." Two versions of the model were fit to the data. One assumed a decision based on bar width, and the other assumed a decision based on orientation. These models have 2 parameters: a decision criterion along the relevant perceptual dimension and a perceptual noise variance.

The General Conjunctive Classifier

One version of this model assumes that the rule used by participants is a conjunction of the type "Respond A, if the bar width is small AND the orientation is < 45°; otherwise, respond B." A second version of this model assumes that the rule used by participants is a conjunction of the type "Respond B, if the bar width is large AND the orientation is > 45°; otherwise, respond A." This model has 3 parameters: 1 for the single decision criterion placed along each stimulus dimension (1 for orientation and 1 for bar width) and a perceptual noise variance.

Information-Integration Models

The General Linear Classifier

The general linear classifier assumes that participants divide the stimulus space using a linear decision bound. Categorization decisions are then based upon which region each stimulus is perceived to fall in. These decision bounds require linear integration of both stimulus dimensions, thereby producing an information-integration decision strategy. The general linear classifier has 3 parameters: the slope and intercept of the linear decision bound and a perceptual noise variance. The optimal model is a special case of the general linear classifier for which the slope and intercept of the decision bound are optimal. The optimal model has 1 free parameter.

Goodness-of-Fit Measure

Model parameters were estimated using the method of maximum likelihood, and the statistic used for model selection was the Akaike Information Criterion (AIC),[37] which is defined as

$$AIC = 2r - 2 \ln L,$$

where r is the number of free parameters and L is the likelihood of the model given the data. The AIC statistic penalizes models for extra free parameters. To determine the best fitting model within a group of competing models, the AIC statistic is computed for each model, and the model with the smallest AIC value is chosen.

FOOTNOTES

[a]A model that assumed that the participant responded randomly (essentially flipping a biased coin) on each trial to determine

the response was also applied to the data. This model never provided the best account of the data and is not discussed further.

[b]A strategy in which the participant gives 1 response to short, shallow-angle stimuli and another response to all other stimuli would be an example of a conjunctive rule-based strategy. A strategy in which the participant gives 1 response to short stimuli and another to long stimuli, ignoring orientation, would be an example of a unidimensional rule-based strategy.