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Implicit learning is better at subjectively defined non-optimal time of day

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Abstract
Individual preferences in morningness-eveningness rhythms modulate temporal fluctuations of cognitive performance over a normal day. Besides enhanced cognitive performance at individual’s peak time as derived from morningness-eveningness questionnaires, a few studies have shown increased implicit memory abilities at a non-optimal time of day. Various subjective factors might also determine the clock time for high or low cognitive efficiency. Using an artificial grammar learning task, we show enhanced implicit learning of high-order information at non-optimal (versus optimal) time of day as subjectively defined by participants, irrespective of morningness-eveningness scores. Our results suggest that subjectively defined efficiency periods are a modulating factor in the testing of cognitive functions.

Key words: Artificial Grammar Learning, Subjective Vigilance, Objective Vigilance, Synchrony Effects, Chronotype.
1. INTRODUCTION

Circadian and homeostatic processes regulate the timing and structure of sleep and neurobehavioral performance (Borbely, 1982; Wyatt, Ritz-De Cecco, Czeiler et al., 1999) over the 24-hour cycle. Individual chronotype that reflects interindividual differences in circadian preference additionally modulates the sleep-wake schedule and temporal fluctuations of cognitive performance over a normal working day (Roenneberg, Wirz-Justice & Merrow, 2003; Schmidt et al. 2007). Enhanced cognitive efficiency at peak time of day (i.e. synchrony effects) – as derived from morningness-eveningness questionnaires – has been reported in various cognitive domains including executive and alerting components of attention (Matchock & Mordkoff, 2009), inhibitory control (May & Hasher, 1998), visuospatial working memory (Rowe, Hasher & Turcotte, 2009) and long-term declarative memory (May, Hasher & Foong, 2005). However, May et al. (2005) found better performance on perceptual and conceptual priming tasks at off-peak than at peak times of day. Similarly, Rowe, Valderrama, Hasher et al. (2006) showed, by superimposing irrelevant distractors on target items in a judgment task, that irrelevant elements are better implicitly memorized during non-optimal periods. Hence, these reports suggest that high-demanding attentional tasks are better performed at peak times of day whereas performance on more automatic tasks would improve at off-peak times. At non-optimal time of day indeed, attentional control decreases and may less efficiently oppose automatic processes (May et al., 2005). In all of these prior studies, the optimal/non-optimal clock time for testing was defined according to morningness-eveningness scores, which may actually not fully match optimal/non-optimal moments for performance as subjectively experienced by some participants. Indeed, a wide variety of factors (from biological to social) may determine the best and worst moments for a particular type of cognitive performance in an individual. It is therefore of interest to explore cognitive performance based on the individual's subjective feeling about its peak/off-peak time for cognitive performance, rather than derived from a chronotype compound score built considering a variety of different domains (e.g. appetite, physical and cognitive performance, time for sleep and wakefulness periods, easiness to wake up, ...). In the present study, participants learned abstract high-order information using an artificial grammar learning (AGL) task (Meulemans & Van der Linden, 1997), an implicit learning paradigm relying on automatic processes. Participants were tested at their subjectively self-defined peak vs. off-peak time of day irrespective of morningness-eveningness scores.
2. METHODS

2.1. Population and context of testing
Thirty-six university students (10 males; mean age=25.08, range=20-30 years) participated in this study approved by the local Ethics Committee. Sleep quality for the month prior to the experiment was assessed using the Pittsburgh Sleep Quality Index (PSQI; Buysse, Reynolds, Monk et al., 1989). Use of sleeping pills and bad sleep quality (PSQI global score > 6) were exclusion criteria. Sleep quality during the night preceding the experiment was assessed using an adapted version of the St. Mary’s Hospital Sleep Questionnaire (Ellis, Johns, Lancaster et al., 1981). Participants had neutral to moderate chronotypes (range 30-70 on the Morningness-Eveningness Questionnaire [MEQ]; Horne & Ostberg, 1976). At the recruitment phase, subjects had to indicate at what time of day they usually felt at their best (or their worst) to perform on cognitive tasks. The experimental session was then defined at the participant’s self-defined optimal (OP) or non-optimal (NOP) moment. Participants were randomly allocated to the NOP or the OP condition.

2.2. Experimental material and procedure

2.2.1. Artificial grammar learning task
The artificial grammar learning (AGL) task is described elsewhere (Peigneux, Meulemans, Van der Linden et al., 1999). The material consisted of 63 letter strings (length 4-7 consonants) generated using the transitional rules of a finite-state grammar. The grammar comprised six different consonants (F, V, M, T, R, X) distributed across fourteen positions between nine nodes, in such a way that it does not produce meaningful strings or acronyms, for instance "TV". Fifty-one grammatical (G) strings were used for the incidental learning phase, the 12 other G strings for the testing phase. Additionally, 12 nongrammatical (NG) strings were constructed for the testing phase (see below). In NG strings, the transitional rules of the grammar were violated at one or two positions within the letter string (except in the first or in the last position). Grammatical (G) and NG strings were also constructed in such a way that grammaticality judgments could not be based on a simple knowledge of pairs or triplets (chunks) of letters. Amongst others, chunk strength and novelty parameters were controlled, and G and NG strings were matched for the frequency of the possible triplets in the initial position (for a complete presentation of controlled parameters, see Meulemans & Van der Linden, 1997). For instance, whereas "TXRMXV" was a grammatical string, "TXFRMXV" was a NG item because "TXFR" could not be followed by "M" in the finite-state grammar.
During the *incidental learning* phase, participants were informed that they would be administered an immediate memory test. Each grammatical string was presented on a computer screen for 3 seconds; afterward, the participant had to repeat the letters of the G strings in the same order as presented. If the recall was correct, the following item was presented; if not, the item was shown again. A learning score was computed as the total number of presentations needed to correctly repeat the 51 sequences.

During the *classification* (testing) phase, participants were informed that the previously presented letter strings were constructed according to a complex system of rules, so difficult that it was impossible to unravel them. They were then asked to classify the 24 G and NG test items as being grammatical or not based on their intuition. No feedback was given as to the correctness of the judgements. At the end of the session, participants were asked to verbally report whether they detected regularities within the grammatical material, and if yes to explain what were these regularities.

### 2.2.2. Additional measurements

A digit span task and a 10-minute version of the Psychomotor Vigilance Task (PVT; Dinges & Powell, 1985) were administered before the AGL task. Participants' sleepiness was also self-rated using the Karolinska Sleepiness Scale (KSS; Akerstedt & Gillberg, 1990) before study, between the learning and testing phases, and immediately after testing.

### 3. RESULTS

#### 3.1. Characteristics of the participants and vigilance scores

As shown in Table 1, OP and NOP groups did not differ significantly according to chronotype (MEQ score), sleep quality and sleep latency during the previous night (St. Mary questionnaire). Although sleep duration for the previous night was marginally longer in the OP (8.6±1.2 hours) than in the NOP group (7.7±1.5 hours; p = .07), means were normal and above 7 hours in both conditions. Conversely, sleep quality during the previous month (PSQI) was better in NOP than OP participants (p = .02), but global scores were below the cut-off score for sleep problems in both groups. As expected, mean KSS scores were higher in the NOP than in the OP group (Mann-Whitney test: U=17; Z=4.58; p < .0001), reflecting higher subjective sleepiness. Within-individual KSS scores were similar at the three assessment points (Friedman ANOVA: χ²(36,2)=1.49; p=.48). Mean reaction times in the PVT (n=34, 2 missing data) were also longer in NOP than OP participants (t(32)=3.08; p = .004), indicating lower objective and subjective vigilance in participants who were tested at their self-defined
non-optimal time. Clock time for testing was on average later in NOP than OP participants ($t(32)=2.47; p=.02$), but also widely distributed (range OP: 9 hours 11 minutes-18h18m; NOP: 8h22m-20h37m). Additionally, nonparametric Spearman tests revealed a negative correlation between peak clock times and MEQ chronotype scores ($r = -0.5; p= .05$), but no correlation between off-peak clock times and chronotype scores ($r = -0.08; p= .78$). Finally, short-term memory (digit) span was similar between OP and NOP groups ($t(34)=0.04; p=.97$; mean span=7.9, range=6-10).

--- Insert Table 1 here ---

### 3.2. Implicit learning

During the AGL task, learning scores were similar in the OP (56.06±2.08; N=16) and the NOP (56.55±3.43; N=20) groups ($t(34)=0.50; p=.62$). During the classification phase, a two-way ANOVA with between-participants factor Group (OP vs. NOP) and within-participants factor Grammaticality (G vs. NG) revealed a main effect of grammaticality ($F(1,34)=34.04; p<.0001$). As expected, the grammatical strings were more often classified as grammatical than the nongrammatical ones. One-sample t-tests conducted against the 50% classification chance level were significant in both groups for grammatical items (both $ps<.0001$; OP: Cohen’s $d=1.39$ and NOP: $d=2.49$), but not for non-grammatical items (both $ps>.18$; OP: $d=.35$ and NOP: $d=.08$). The Grammaticality by Group interaction was also significant ($F(1,34)=4.63; p=0.04$). Note that introducing the prior night's sleep duration as covariate reduced to a trend, but did not abolished the interaction effect ($F(1,33)=2.64; p<.1$), suggesting that part of the observed differences might be ascribed to the marginal differences in sleep duration reported above. Post-hoc Tukey tests revealed a significantly higher acceptance rate for G items (80.4±12.2%) than NG items (51.7±20%) in the NOP group ($p<.001$), and only a trend for higher acceptance of G than NG items in the OP group (G items: 68±12.9%; NG items: 54.7±13.3%; $p=.08$). Classification scores for G items tended to be higher in NOP than OP participants ($p=.07$). We also computed delta scores, i.e. the difference between G and NG acceptance rate (G minus NG) within each experimental group (see Figure 1). T-tests against the 0 value revealed a significant delta score both in NOP (28.7±21.4.5%; $t(19)=6.01, p<.0001$; Cohen’s $d=1.34$) and OP (13.3±21.6%; $t(15)=2.46, p=.027; d=.61$) participants. Additionally, a t-test for independent samples revealed that the difference between G and NG acceptance rate was significantly higher in the NOP than in the OP group ($t(34)=2.15, p=.039; d=.72$). All participants verbally reported either incomplete,
absent or incorrect explicit knowledge of the grammar rules, in line with prior studies which evidenced the genuinely implicit nature of AGL when using carefully controlled material (e.g. Meulemans & Van der Linden, 1997).

3.3. Link between implicit learning performance and vigilance
Spearman analyses revealed a significant correlation between mean KSS scores and endorsement rate of G items ($r(36)=0.33; p=.05$), but not NG items ($r(36)=-0.07; p=.69$). The correlation between endorsement rates and mean RTs in the PVT was not significant (G: $r(34)=0.15$; NG: $r(34)=-0.01$; all $ps>.05$). These results suggest that the more the participants subjectively felt sleepy, the better they classified G items.

4. DISCUSSION AND CONCLUSIONS
Our results revealed enhanced implicit learning at subjectively defined non-optimal (or off-peak) versus peak time of day, as shown by a larger difference between G and NG acceptance rates in the NOP than in the OP conditions. Classification of the NG strings remained at chance level for both groups, and verbal reports indicated that participants did not gain explicit knowledge about the material. We further observed that subjective sleepiness ratings (KSS scores) were positively correlated with classification accuracy for grammatical strings. Hence implicit performance was improved when subjective sleepiness ratings increased. This pattern of results suggests a benefit of the fall-off in subjective alertness (as experienced at off-peak time of day) on implicit memory performance, in line with prior studies in which off-peak time was defined on the basis of chronotype scores (May et al., 2005; Rowe et al., 2006). Conversely, implicit performance was not correlated with objective measures of vigilance (PVT). However, an additional analysis using self-reported sleep duration as confounding covariate reduced, but did not abolished the interaction effect between clock time and grammaticality judgements. This result suggests that at least part of the observed effects might be ascribed to differences in prior sleep quantity. Notwithstanding, sleep duration was sufficient and above 7 hours in both experimental conditions; furthermore, sleep duration was longer in the OP condition, preventing the hypothesis that results are attributable to partial sleep deprivation. From a methodological point of view, prior studies tested performance at optimal (OP) vs. non-optimal (NOP) time of day in repeated measure designs, whereas we compared performance between participants either in the OP or in the NOP condition.
Although more optimal, the use of a within-participant design was not possible in the present study due to the incidental nature of learning in the AGL task. Indeed, the first testing would have modified the participants' awareness for the second testing, thereby altering the implicit learning component of the task (see e.g. Dienes et al., 1995).

Despite similar, neutral to moderate chronotypes between groups, self-defined peak and off-peak time widely differed from one individual to the other (see clock testing time range Table 1). Notwithstanding, objective and subjective sleepiness scores were higher at self-defined off-peak than peak time, showing that individuals can accurately predict their periods of higher versus lower efficiency within a day. Although clock time for testing took place on average later in NOP than OP participants, the wide range and overlap (from 9:00 to 18:00) in testing time indicates that subjectively defined cognitive efficiency periods are not entirely captured by chronotype questionnaires. Additionally, we found a relationship between MEQ scores and subjectively defined peak time, but not with off-peak times. This dissociated result might be explained considering that mostly questions about performance peak periods are asked in the MEQ, not about off-peaks, making it less sensitive to the determination of non-optimal moments. On the other hand, PVT performance and KSS scores were lower at off-peak than peak time, in line with our participants' prediction about their non-optimal period.

Our results are in line with the hypothesis that a beneficial impact of off-peak time on automatic processes (such as for instance implicit learning in the AGL) is subtended by a decrease in the efficiency of executive functions (May et al., 2005; for a review see Schmidt, Collette, Cajochen et al., 2007). Specifically, Yoon, May & Hasher (1999) proposed that such a beneficial effect could be subtended by a decrease in the efficiency of inhibition processes. Accordingly, performance on the AGL task was found to be better in children exhibiting attentional deficits (Rosas, Francisco, Tenorio et al., 2010). In this respect, our findings indicate that subjectively defined non-optimal time-of-day should be taken into account when testing for implicit memory performance, in addition to chronotype, sleepiness and vigilance parameters. Indeed, chronotype-based measures might be suboptimal to determine the off-peak time for testing, at which implicit memory performance appears to be enhanced. Future studies should probe whether these subjective synchrony effects also apply for explicit memory or other tasks in which executive and controlled processes are at play. Indeed, investigating executive and controlled processes at individually subjectively defined optimal vs. non-optimal time of day will help to better understand how cognitive performance in different domains are impacted by diverse determinants, including diurnal variations, chronotype and sleepiness.
ACKNOWLEDGEMENTS
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REFERENCES


FIGURE LEGEND

Figure 1. Left panel. AGL task. Endorsement rate (%) for Grammatical (G) and Non Grammatical (NG) strings in Optimal vs. Non-Optimal conditions. Right panel. G minus NG (%) endorsement rates in Optimal vs. Non-Optimal conditions. T-tests against chance (50%) level at $p<.001$ (+++) or $p<.05$ (+). Error bars represent standard deviations.
Table 1. Sleep, vigilance, chronotype parameters and time of testing

<table>
<thead>
<tr>
<th></th>
<th>Optimal group</th>
<th>Non-optimal group</th>
<th>p-value</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>MEQ (global score)</strong></td>
<td>49.1 ± 6.1</td>
<td>50.4 ± 6.3</td>
<td>0.52</td>
</tr>
<tr>
<td><strong>PSQI (global score)</strong></td>
<td>4.8 ± 1.4</td>
<td>3.6 ± 1.5</td>
<td>0.02</td>
</tr>
<tr>
<td><em>St Mary’s Questionnaire</em></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Sleep duration (hours)</td>
<td>8.6 ± 1.2</td>
<td>7.7 ± 1.5</td>
<td>0.07</td>
</tr>
<tr>
<td>Sleep latency (minutes)</td>
<td>18.2 ± 17.2</td>
<td>14.1 ± 10.8</td>
<td>0.40</td>
</tr>
<tr>
<td>Global score</td>
<td>497.9 ± 97</td>
<td>516.4 ± 50.6</td>
<td>0.46</td>
</tr>
<tr>
<td><strong>PVT</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Mean RTs (ms)</td>
<td>315.6 ± 22.9</td>
<td>349.6 ± 38.5</td>
<td>0.004</td>
</tr>
<tr>
<td><strong>KSS scores</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Before learning</td>
<td>2.9 ± 1.3</td>
<td>5.2 ± 1.8</td>
<td>&lt; 0.001</td>
</tr>
<tr>
<td>Between learning and testing</td>
<td>2.9 ± 1.1</td>
<td>5.8 ± 1.2</td>
<td>&lt; 0.001</td>
</tr>
<tr>
<td>After testing</td>
<td>2.9 ± 1.3</td>
<td>5.6 ± 1.8</td>
<td>&lt; 0.001</td>
</tr>
<tr>
<td>Total mean</td>
<td>2.9 ± 1.1</td>
<td>5.5 ± 1.3</td>
<td>&lt; 0.001</td>
</tr>
<tr>
<td>Clock testing time (hours)</td>
<td>12.8 ± 2.9</td>
<td>15.7 ± 3.6</td>
<td>0.02</td>
</tr>
</tbody>
</table>

Notes. MEQ: Morningness-Eveningness Questionnaire; PSQI: Pittsburgh Sleep Quality Index; PVT: Psychomotor Vigilance Task; KSS: Karolinska Sleepiness Scale.