N3 sleep ameliorates anxiety-induced amplified reward learning in dynamically changing environments

Rakshita Deshmukh (rakshitad21@iitk.ac.in)
Department of Cognitive Science, IIT Kanpur
Kanpur, Uttar Pradesh, India

Arjun Ramakrishnan (arjunr@iitk.ac.in)
Department of Biological Sciences & Bioengineering, IIT Kanpur
Kanpur, Uttar Pradesh, India

Abstract:

Coping with dynamic environments has become a modern-day necessity. To do so, one needs to continually adjust their learning rates based on environmental uncertainties due to volatility and stochasticity. Uncertainty assessments are also known to depend on one's internal states such as anxiety and sleep levels. Anxiety incurs misestimation of volatility and leads to over-learning from negative feedback. Whether this is mediated by stochasticity is not well understood. Anxiety is also related to sleep wherein absence of sleep worsens it, while presence of N3 sleep reduces morning levels of it. Whether this benefit translates to learning rate deficits is also currently unknown. To this end, we used a novel probabilistic reversal learning task in which we simultaneously manipulated stochasticity and volatility. Using computational models, we found that high trait anxious (HTA) individuals misestimate stochasticity for volatility by suboptimally increasing their reward learning rates in stable but highly stochastic environments. In the second experiment, using EEG, we show that N3 sleep alleviates these impairments by downregulating and optimizing reward learning rates. In summary, we observed amplified reward learning among anxious individuals and then we show that N3 sleep helps in regulating it. This highlights N3 sleep's potential as a non-pharmacological and non-invasive approach for alleviating anxiety-related learning impairments.

Keywords: flexibility; reversal learning; NREM sleep; trait anxiety; drift-diffusion model

Introduction

While navigating uncertain situations, learning rates increase with environmental volatility (genuine changes) and decrease with stochasticity (random variations) (Piray & Daw, 2021). Trait anxiety, a major vulnerability factor for developing anxiety-related disorders, misestimates volatility by failing to adjust learning rates based on environmental structure, often learning faster from negative feedback, having higher punishment learning rates (Aylward et al., 2019). Although extensively studied by incorporating volatility in paradigms, the precise mechanism behind misestimation of volatility remains unclear. Recent studies propose that it may result from misestimation of stochasticity for volatility and have identified subgroups having increased learning rates with stochasticity, contrary to expected behavior (Piray & Daw, 2023). Thus, a comprehensive understanding of how anxiety causes the confusion between these factors necessitates a joint manipulation of both volatility and stochasticity. Sleep disturbances also co-occur with anxiety, worsening mental health (Ramsawh et al., 2009). However, the presence of sleep, especially the N3 sleep stage confers restorative benefits: reducing morning state anxiety levels and reengaging brain networks implicated with anxiety and sleep loss (Simon et al., 2020). Yet, it's unclear whether N3 sleep can also enhance learning impairments among trait anxious individuals by reducing morning state anxiety levels and optimizing learning rates under uncertain environments. Thus, this study aims to investigate the interplay between anxiety and sleep on learning under uncertainty when volatility and stochasticity are nested within each other, through two experiments. The first experiment examines if high trait anxious individuals (HTA) overestimate volatility by misestimating stochasticity for volatility; the second experiment examines whether N3 sleep stage reduces morning state anxiety and assists in adaptive learning among HTA.

Methodology

90 young adults participated. Anxiety was measured via the STAI-Y. Task included a novel three-option probabilistic reversal learning task, simultaneously manipulating stochasticity (probability of obtaining rewards) and volatility (frequency of most rewarding patch changing). In the first experiment (N=50), 2 participants were excluded for low alertness. Using a 3x2 repeated-measures design, participants made decisions on rewarding patches in 6 environments (counterbalanced) varying in stochasticity (low, medium, high) & volatility (fast, slow). In the second experiment (N=40), participants were recruited based on standard exclusion criteria for overnight sleep studies. Sleep was measured using a wearable EEG device. Using a 2x2x2 repeated measures design, participants played the task pre and post-sleep (session), with stochasticity (high, low), and volatility (fast, slow) manipulation. Anxiety measures were also taken pre and post-sleep. Model based analysis was performed using hierarchical bayesian estimation of reinforcement learning and drift-diffusion models using 'hBayesDM' and 'HDDM' packages in R and Python (Ahn et al., 2017; Wiecki et al., 2013). Group and individual parameter estimates were examined after selecting the best model through prior comparison, posterior predictive and parameter recovery checks.

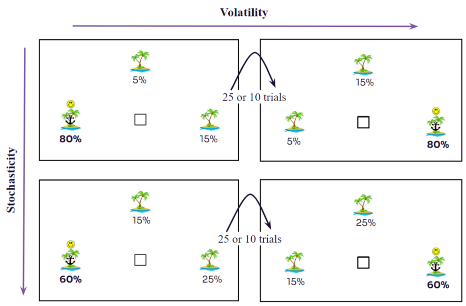

Figure 1 Task Design: In a block in each trial (N=50), 3 patches probabilistically provide rewards (smiley emoji else sad emoji) with volatility being the most rewarding patch changing, and stochasticity being the probability of providing rewards, unknown to the participants.

Results

Model-free analysis using ANOVA and mixed regression found that as stochasticity and volatility increased, rewards earned decreased ($p<.05$), due to lower identification of the most rewarding patch ($p<.05$). In the first experiment, HTA (categorical ≥ 45, and continuous) had lower rewards due to lower cumulative trialwise identification of the most rewarding patch especially in slow volatility-high stochasticity environments ($p<.05$). Model-based analysis revealed that, contrary to expectations, it was higher reward learning rate and not punishment learning rate that was the main culprit. In slow volatility-high stochasticity environments, HTA had higher reward learning rates than LTA (95% HDI [0.03, 0.39]). Simulating agents to get near-optimal values to maximize rewards in these environments from model parameters found that HTA significantly deviated from these optimal values (95% CI [0.18, 0.35]) than LTA, due to suboptimally higher reward learning rates than required. Subsequently, during the decision making phase, HTA also had higher drift-rates but lower boundary values, indicating uncertainty in differentiating between the most rewarding patch and other patches in this environment.

Next we turned to sleep effects: In the second experiment, spending more time in N3 sleep stage benefitted HTA the most in reducing their post-sleep state anxiety levels compared to pre-sleep ($p<.05$). Post-sleep task performance was better than pre-sleep ($p<.05$). Interestingly, N3's benefit also extended in improving HTA's task performance ($p<.05$), especially in reducing their reward learning rates post-sleep wherein HTA did not significantly deviate from optimal reward learning rates post-sleep (95% CI [-0.06, 0.07]). Subsequently, N3 increased drift-rates of HTA making them faster at evidence accumulation, i.e., better at differentiating between most rewarding and other patches. Thus, HTA impairments with slow volatility-high stochasticity were improved with N3.

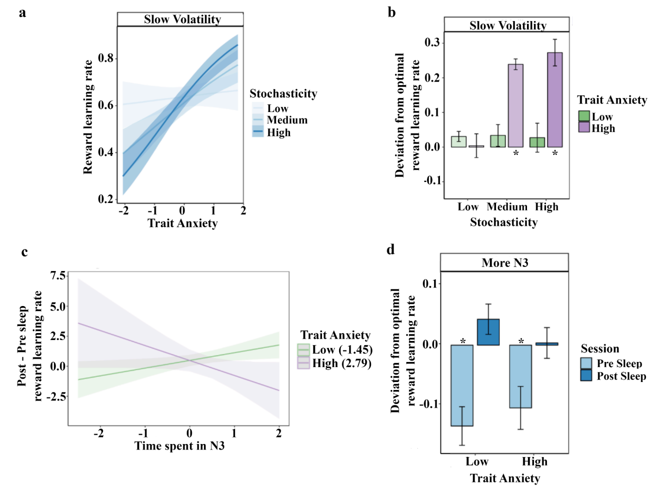

Figure 2 Results: a) Trait anxiety (normalized) increases reward learning rates with higher stochasticity and slow volatility. b) Categorizing into high and low trait anxiety: HTA deviated from near-optimal values in these environments. c) N3 decreased post-sleep reward learning rates for HTA. d) N3 optimized suboptimal pre-sleep reward learning rates post-sleep.

Discussion

The study highlights a previously under-recognised trend of amplified reward learning among anxious individuals. Anxiety led to misestimation of stochasticity for volatility attributable to the task structure that relies on reward based monetary compensation. This could be due to disproportionate salience towards rewards i.e., incentive salience which is usually high in uncertain situations and among anxious individuals (Hellberg et al., 2019). However, N3 sleep reduced reward learning rate, aiding HTA in maximizing rewards. Effectively HTA adapted well to uncertain environments especially in slow volatility environments post N3 sleep. This suggests that targeting N3 sleep holds promise as a non-invasive and non-pharmacological approach to alleviate anxiety-induced impairments especially with respect to navigating dynamically changing environments.

Acknowledgments

This research was funded by SERB start-up research grant to AR.

References

Ahn, W. Y., Haines, N., & Zhang, L. (2017). Revealing Neurocomputational Mechanisms of Reinforcement Learning and Decision-Making With the hBayesDM Package. Computational psychiatry (Cambridge, Mass.), 1, 24–57. https://doi.org/10.1162/CPSY_a_00002

Aylward, J., Valton, V., Ahn, W. Y., Bond, R. L., Dayan, P., Roiser, J. P., & Robinson, O. J. (2019). Altered learning under uncertainty in unmedicated mood and anxiety disorders. Nature human behaviour, 3(10), 1116–1123. https://doi.org/10.1038/s41562-019-0628-0

Hellberg, S. N., Russell, T. I., & Robinson, M. J. F. (2019). Cued for risk: Evidence for an incentive sensitization framework to explain the interplay between stress and anxiety, substance abuse, and reward uncertainty in disordered gambling behavior. Cognitive, affective & behavioral neuroscience, 19(3), 737–758. https://doi.org/10.3758/s13415-018-00662-3

Piray, P. &, Daw, N.D. (2021). A model for learning based on the joint estimation of stochasticity and volatility. Nat Commun 12, 6587. https://doi.org/10.1038/s41467-021-26731-9.

Piray, P., & Daw, N. (2023, July 13). Computational processes of simultaneous learning of stochasticity and volatility in humans. https://doi.org/10.31234/osf.io/kz5ua

Ramsawh, H. J., Stein, M. B., Belik, S. L., Jacobi, F., & Sareen, J. (2009). Relationship of anxiety disorders, sleep quality, and functional impairment in a community sample. Journal of psychiatric research, 43(10), 926–933. https://doi.org/10.1016/j.jpsychires.2009.01.009

Simon, E. B, Rossi, A., Harvey, A. G., & Walker, M. P. (2020). Overanxious and underslept. Nature human behaviour, 4(1), 100–110. https://doi.org/10.1038/s41562-019-0754-8

Wiecki, T. V., Sofer, I., & Frank, M. J. (2013). HDDM: Hierarchical Bayesian estimation of the Drift-Diffusion Model in Python. Frontiers in neuroinformatics, 7, 14. https://doi.org/10.3389/fninf.2013.00014