NAVAL HEALTH RESEARCH CENTER

LOW HAND TEMPERATURE PREDICTS INDIVIDUAL DIFFERENCES IN COGNITIVE ADAPTABILITY DURING COLD WATER IMMERSION

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- Cold water immersion (CWI):
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- Stakes are high when humans must operate in extreme environments such as in extreme cold, requiring better explanation *and* prediction where poor performance holds real-world consequences



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- Ignores critical aspects of data at the individual level
- No ability to account for non-linear patterns potentially present within the intervals of measurement
- Two processes can produce nearly identical means and variances, but have very different underlying dynamics, such as differential temporal dependencies and/or patterns of fluctuations (Van Orden et al., 2003, JEP: General)



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 Our aim for the present investigation was to assess variation in adaptability (stability and flexibility) across individuals during CWI using non-linear dynamical methods and clustering, and to link these behaviors to variations in cold stress responses (i.e., skin and core temperatures) and demographic information.



Time

Oostenveld R, Fries P, Maris E, Schoffelen J-M. FieldTrip: open source software for advanced analysis of MEG, EEG, and invasive electrophysiological data. *Comput Intell Neurosci.* 2011;2011:156869. https://www.fieldtriptoolbox.org/example/entropy_analysis/

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- We employed sample entropy (SampEn) analyses to the time series of individuals' response times (RTs) in two tasks to index stability.
 - Singular value indexing complexity over time and takes into account the *total information* of time series.



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• Entropy provides an ideal metric to make predictions based on patterns of complexity (e.g., the loss of complexity hypothesis; Newell et al., 2006, Handbook of the Psychology of Aging)



 Considered the autocorrelation function (ACF) of the RT time series and errors as indices of flexible responding (i.e., how much future values are dependent on past values)



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- Predict cluster membership: hand, skin, and core temperature, age, height, weight, body fat percentage, body mass index (BMI)



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Methodology

- Sixty-four active duty military personnel volunteered for the study across two winters
- Final *N* of 57 after exclusions ($M_{AGE} = 26$ years, SD = 5.31, $M_{HEIGHT} = 176$ cm, SD= 7.79, $M_{WEIGHT} = 79.5$ kg, SD = 10.52, $M_{BMI} = 25.7$ kg/m², SD = 5.8, and $M_{\% BODYFAT} = 17.9\%$, SD = 6.14)





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- Simple reaction time (SRT) task: respond as fast as possible to stimulus
- Match-to-sample (MTS) task: encode target, choose between target and distractor, or neither



Results: Hierarchical Clustering



 Data-driven clustering algorithm converged on a k = 2 solution using Ward's linkage method (maximize differences between centroids; Panel 1)

Results: Hierarchical Clustering



Points within the plot are individual participants. The larger circle (Cluster 1) and larger triangle (Cluster 2) represent the centroid of each cluster in the left panel.

- Data-driven clustering algorithm converged on a k = 2 solution using Ward's linkage method (maximize differences between centroids; Panel 1)
- Cluster 1 was associated with lower SampEn values for both the SRT and MTS tasks relative to Cluster 2 (Panel 2)

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- Cluster 1 RTs became more destabilized in both tasks relative to Cluster 2



Results: Autocorrelation



ACF = autocorrelation function (k=1); SRT = simple reaction time; MTS = match to sample

- ACF was higher for Cluster 1 for the SRT (Cluster 1, *M* = .38, *SD* = .16; Cluster 2, *M* = .24, *SD* = .12; BF_{ALT} = 39.48)
- ACF was also higher for Cluster 1 for the MTS (Cluster 1, M = .22, SD =.16; Cluster 2, M = .08, SD = .09; $BF_{ALT} = 155.64$)
- Overall, ACF was higher for the SRT (*M* = .29, *SD* = .15) relative to the MTS (*M* = .14, *SD* = .14), BF_{ALT} > 100,000

Results: Omission Errors



 For the SRT, the polynomial (quadratic) GLMM demonstrated a significant interaction term, where Cluster 1 demonstrated a more negative quadratic trend (i.e., more peaked) across trials, Z = -8.19, p
< .001 (Panel 1)

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95% confidence intervals are displayed as the shaded bands. The black vertical line denotes the point within the SRT and MTS trial sequences where participants entered the pond; SRT = simple reaction time; MTS = match to sample.

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- For the MTS, the polynomial GLMM demonstrated a significant interaction effect over the quadratic term, b = 32.2, SE = 12.04, Z = 2.67, p = .008
 - Cluster 1 was more peaked earlier in the trial sequence; Cluster 2 increased over time and began flattening and dropping later



Results



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- Cluster 1 was associated with:
 - Lower response stability (lower SampEn in both tasks)
 - Weaker response flexibility (more autocorrelation and higher peaked omission error functions in both tasks)
- Taken together, we can infer that Cluster 1 individuals (~37% of the sample) were highly affected by CWI relative to individuals in Cluster 2 and demonstrated worse adaptability to the stressor



Results: Prediction

- Predict cluster membership using *stepAIC* algorithm (forward and backward selection w/ penalization)
- Regressors included individuals' age, height, weight, body fat percentage, BMI, and hand, core, and mean skin temperatures pre-immersion



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- Regressors included individuals' age, height, weight, body fat percentage, BMI, and hand, core, and mean skin temperatures pre-immersion
- Pre-immersion hand temperature was the best predictor of cluster classification, with individuals with higher pre-immersion hand temperature being more likely to belong to Cluster 2, OR = 1.2, 95% CI [1.04, 1.39], p = .01, Nagelkerke pseudo-R² = .16
- The x-intercept indicates an input pre-immersion hand temperature value of 14.22 °C, which corresponds to the 50% probability point in the function



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- Both are likely interrupted by intense catecholamine release, including norepinephrine, which can increase substantially within minutes of CWI (Frank et al., 1997, *American Journal of Physiology-Regulatory, Integrative and Comparative Physiology*)
- Norepinephrine is directly implicated in over-arousal and poor performance due to scanning attention (Aston-Jones & Cohen, 2005, Annual Review of Neuroscience)



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- Pre-immersion hand temperature variation may have been due to localized cold habituation from repeated cold exposure (e.g., Makinen, 2010, Medicine and Science in Sports and Exercise)
- Participants were exposed to cold intermittently and organically through participation in other course activities leading up to study participation. It is possible that the degree or frequency of exposure differed between participants



Follow-On Work



- Are attentional effects general or specific to speeded manual responses?
- Winter 2022 Hypothermia Labs (~60 participants)
- Auditory SRT task with vocal responses
- Skin temperatures taken at hands AND feet
- Pain and subjective thermal sensation ratings



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Thank you for your attention