Using Interpersonal Similarity in Complex Networks from Physiological Data to Assess Attentional Focus: A Cautionary Tale

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Teaming and Shared Attention

- Military teams are moving into increasingly dynamic environments and organizational structures that rely on distributed teaming
- Team SA is essential for proper and efficient handling of team tasks
- However, Team SA is difficult to measure and manage in distributed teaming settings
- It is critical to be able to evaluate joint attention and similarity of task investment so that targeted and timely interventions aimed to improve team functioning can be intelligently designed

Image source: https://en.wikipedia.org/wiki/Air_Battle_Manager#/media/File:961st_AACS_Cope_North_2019.jpg
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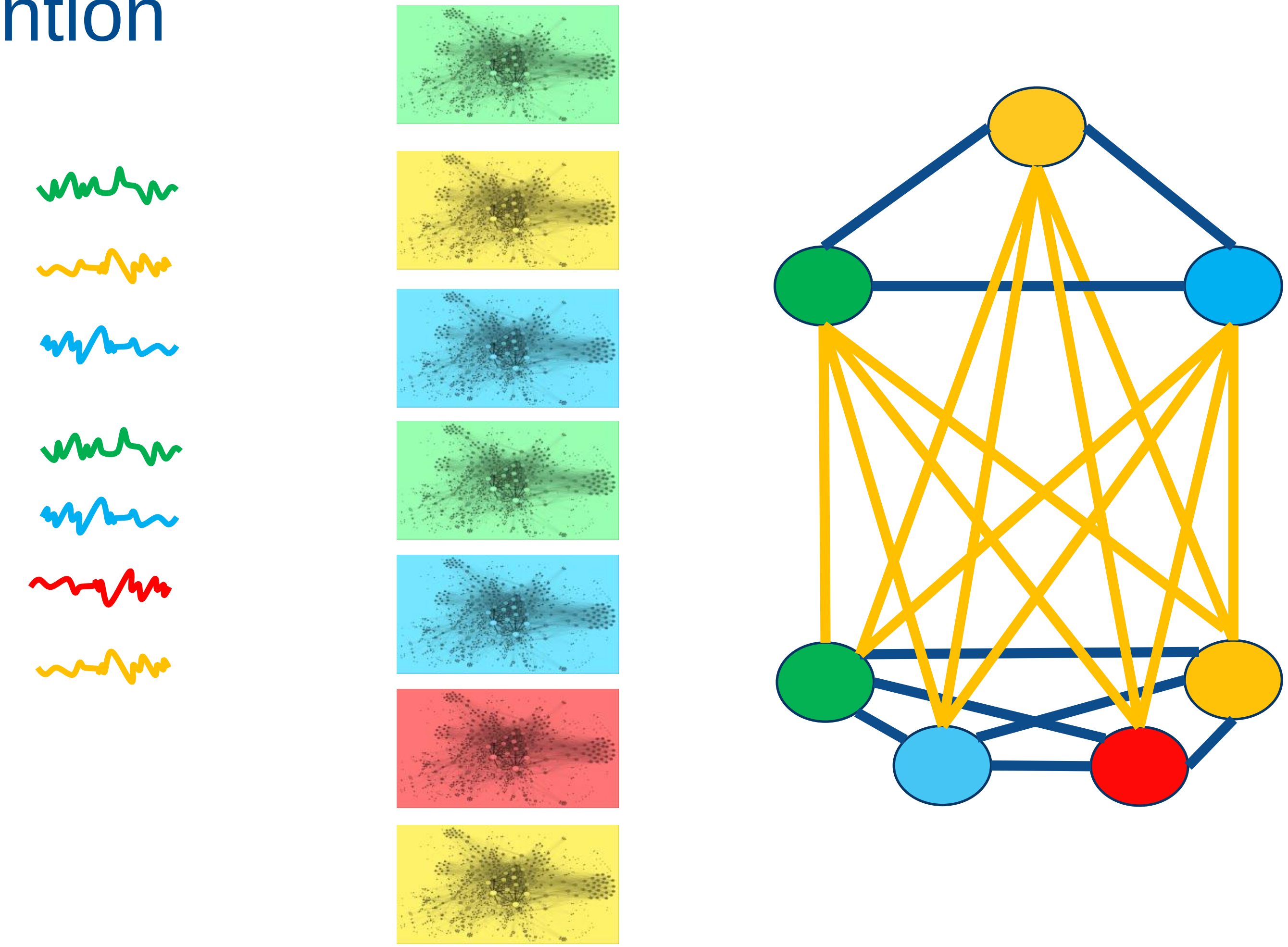
Measuring Shared Attention

- Measuring shared attentional constraints in environments with multiple sources of disturbance is quite difficult (Stanton, Salmon, Walker, Salas, & Hancock, 2017).
  - Using techniques that can objectively evaluate similarity in complex and potentially multivariate data sources can help with this problem
- Hyperscanning: Simultaneously measuring multiple individuals for similarity or synchrony in physiological and behavioral data
  - Often relies on correlation
  - Correlation assumes stationarity and linearity, often violated in real world teaming situations

Measuring Shared Attention

- Multiplex recurrence network analysis can evlaute the dynamical similarity of complex multivariate data
- Average mutual information, conceptually similar to a nonlinear correlation, of degree distribution measures the topological similarity of networks



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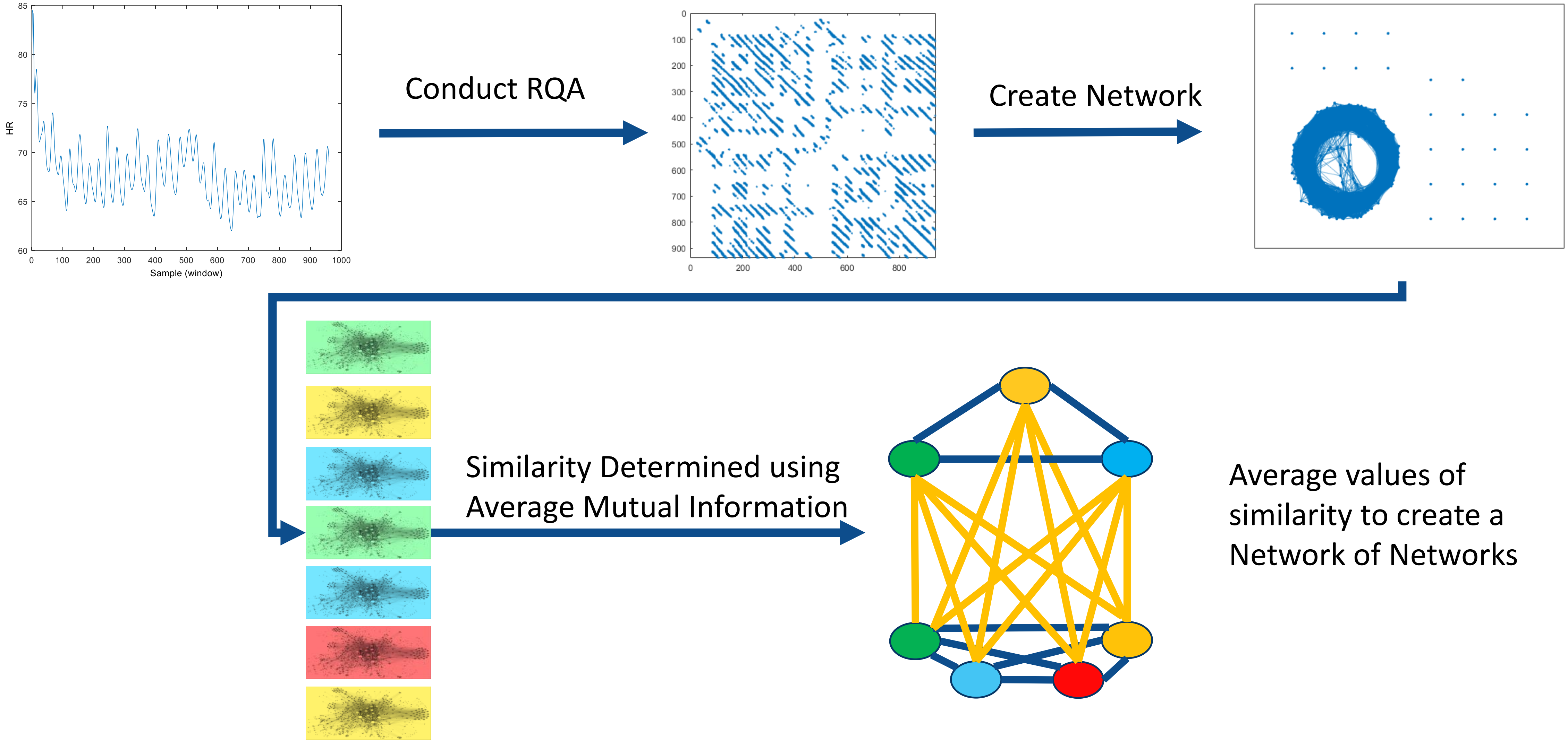
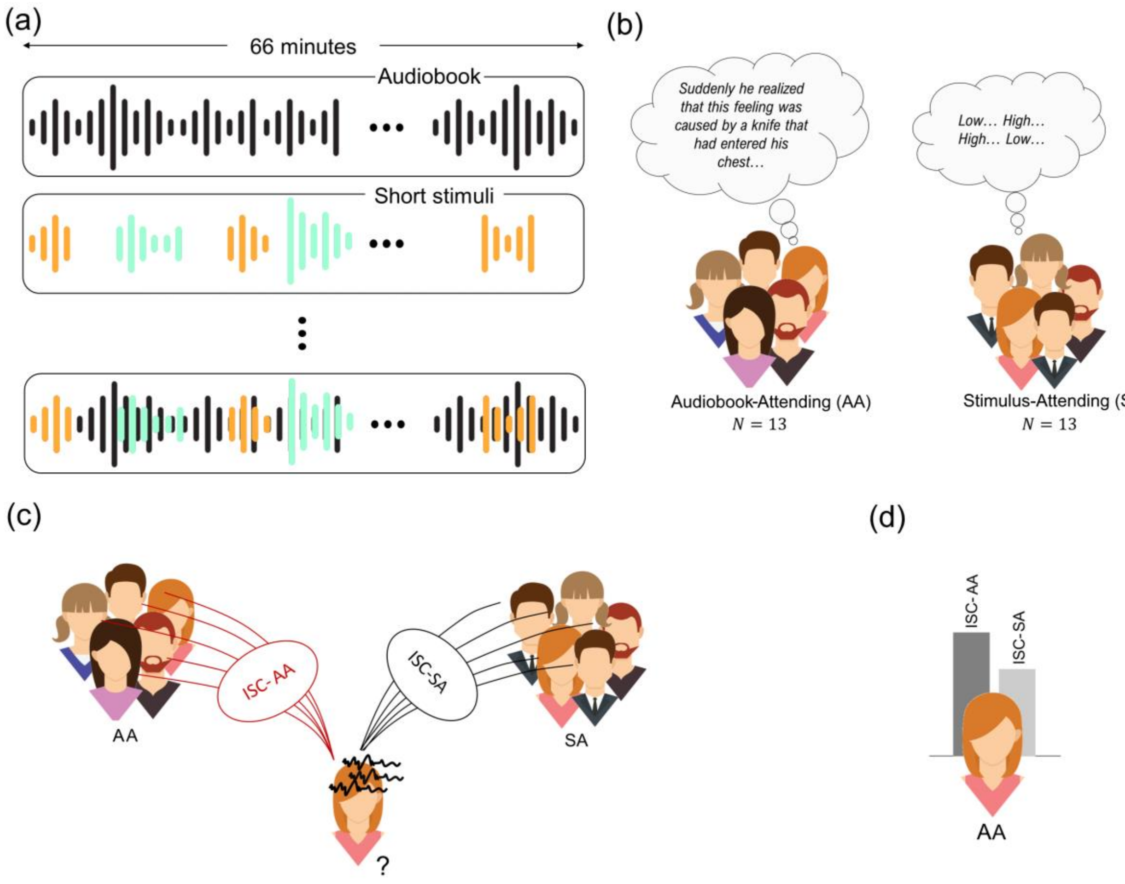
Multiplex Recurrence Network Analysis



Present Work

- We used the multiplex recurrence network approach to re-evaluate existing data (Stuldreher, Thammasan, van Erp, & Brouwer, 2020)
- Individuals listened to an audiobook while also occasionally being presented with affectively salient or cognitively demanding stimuli
  - Instructed to attend audio book or stimuli
  - Researchers found that intra-group synchrony was a predictor of attentional instruction



Present Work

- Purpose: Evaluate the similarity in physiological responses between individuals as a function of whether individuals were instructed to attend to the stimuli or to attend to the audiobook.
  - Try to improve classification outcomes obtained from previous study by moving to a multivariate approach
  - First step: univariate between subjects analysis for dynamical similarity (more general than synchrony)
    - What we are presenting in this work
  - Second step: multivariate analysis
- Expectations:
  - Expect within-group similarity to be higher than between group similarity
  - E.g., Participants in the audiobook attending group will be more similar to other participants in the audiobook attending group than to participants in the stimulus attending group and vice versa (main effect of similarity type)

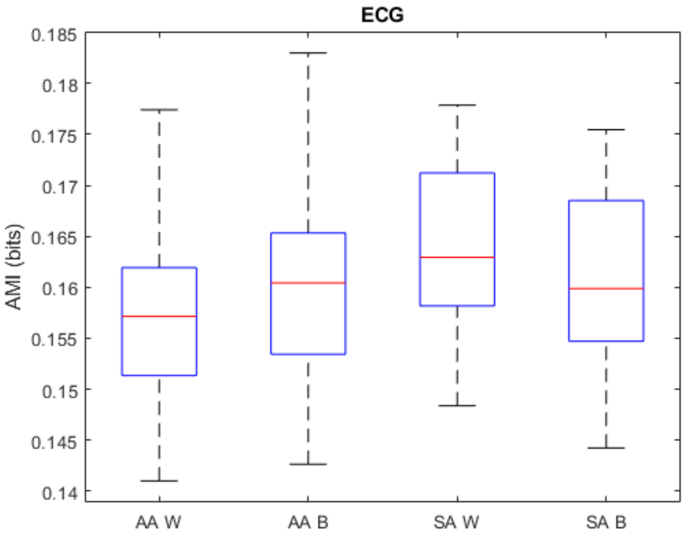
Method

- Data were collected while participants listened to a 66 minute long audiobook.
  - During the presentation of the audiobook, distracting sounds were played at certain times throughout the audiobook (fixed to the same time for all participants).
  - Participants were either instructed to attend the audiobook (audiobook attending group) or the distracting sounds (stimulus attending group).
- Physiological data (EEG, EDA, and ECG) were collected from participants using an ActiveTwo MK II system (BioSemi, Amsterdam, Netherlands) sampling at 1024 Hz.
- For ECG and EDA, data were downsampled and split into 120 s epochs with 87.5% overlap.
- For EEG, theta power was estimated from .5 s of data with a 75% overlap.
  - These summary data were then split into 120 s epochs with 87.5% overlap.

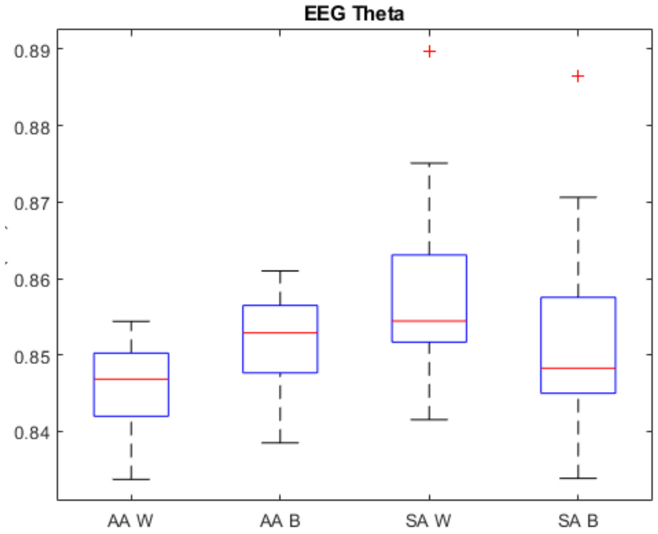
Method

- In each 120s window, recurrence quantification analysis was conducted to create a complex network representation of the system dynamics.
  - Recurrence networks were used to assess similarity between time series using average mutual information (Eroglu et al., 2018).
- **Average values of similarity between an individual's time series and the time-series of all other individuals in the same condition (intra-group similarity) and the time-series of all individuals in the other condition (inter-group similarity) were calculated.**
  - These values of intra- and inter-group similarity were entered into a mixed ANOVA, with similarity type (intra, inter) as the within-subject's variable and stimulus attending condition as the between-subject variable.
- To verify findings, surrogate data analyses were conducted

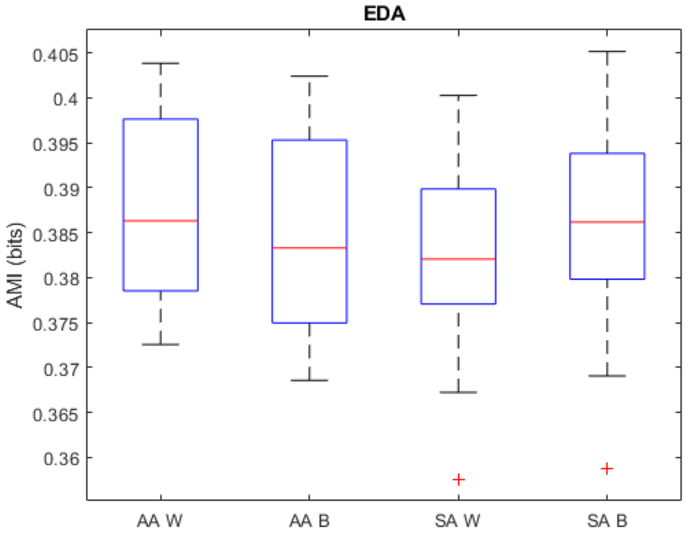
Findings: Interactions!



$F(1,24) = 164.50$, $p < .001$

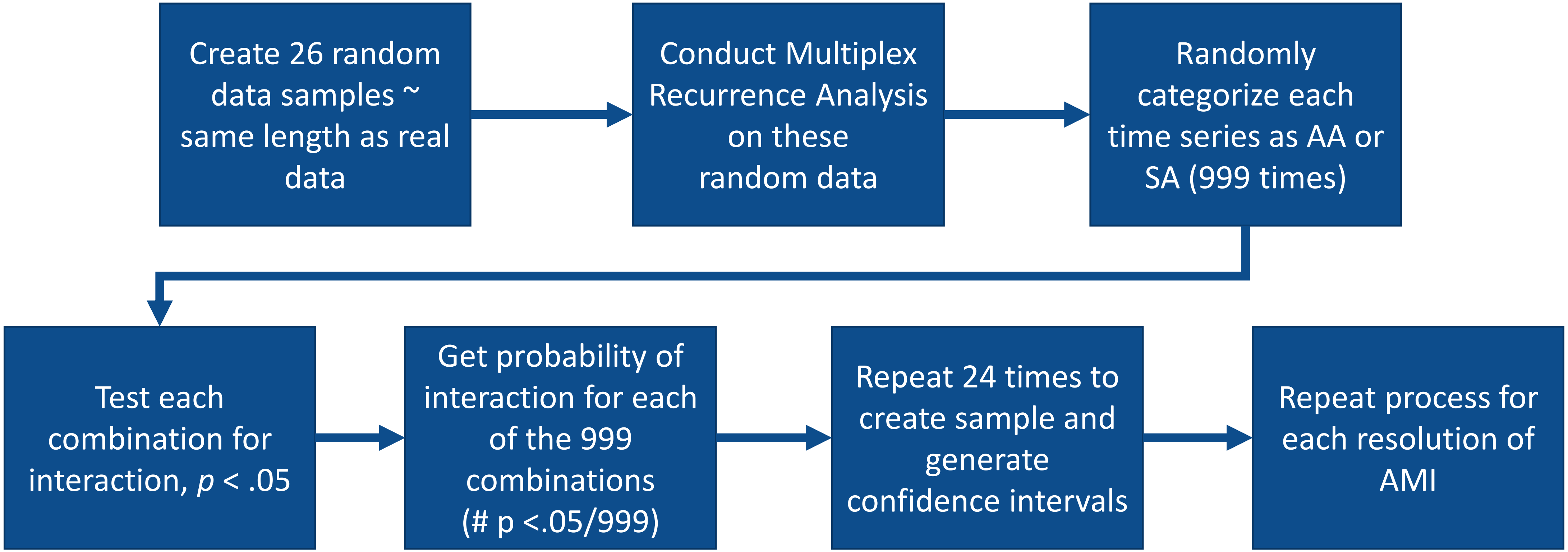


$F(1,24) = 1078.78$, $p < .001$.

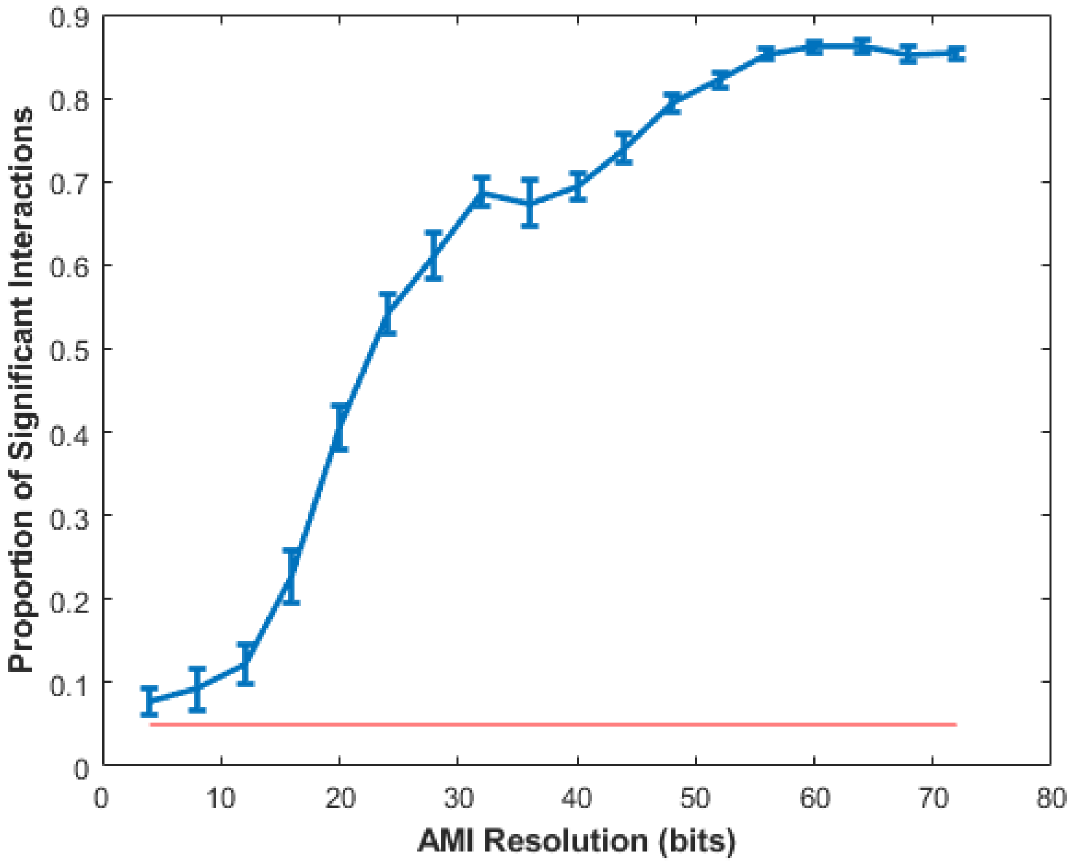


$F(1,24) = 268.624$, $p < .001$

Surrogate Analysis: Test the Probability of an Interaction



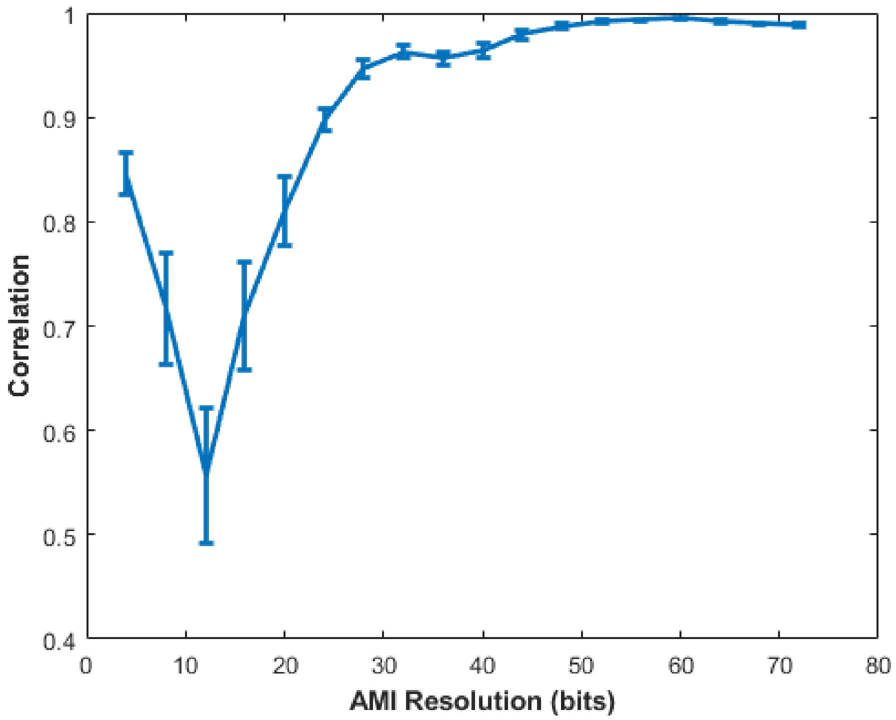
Surrogate Analyses



The average value of the proportion of significant interactions as a function of bin size

Surrogate Analyses

- To evaluate what may be driving the disparity of information content, we evaluated the relationship between the **entropy of each random time series and the average AMI between that time series and all others**:



The average Pearson correlation between the entropy (randomness) of each time series and the average AMI between that time series and all others for each of the 24 sets of randomly generated data

Conclusions

- Analyses showed strong differences in the repeated measure of inter-group similarity as a function of stimulus attending condition.
- However, the strength of these interactions, with extreme *F* statistics, was concerning and the disparity in patterning is confusing: EEG and ECG were consistent, though EDA was the opposite.
- When we conducted surrogate analyses using **randomized data** similar patterning resulted: One group was shown to consistently have more canonical dynamics, on average, than the other group.
- It was found that patterning in the data were dependent upon the resolution of the AMI algorithm (i.e., the number of bins used in discretizing the data), with high resolutions generating patterning in random data that were similar to that found in actual participant data.

Conclusions

- Due to the method of averaging pairwise similarity between all individuals, a very small subset of the data can have a disproportionate effect on group averages.
- In the case of random data, due to the limitations of sample size, some randomly generated number sequences resulted in networks with higher entropy of degree distribution, causing increased similarity with other random networks.
- The pairwise averaging of similarity with these files appears to disproportionally inflate their influence and cause higher average similarity in the condition to which they are assigned.
  - Many more additional outstanding questions remain, including those regarding the limitations of this method of pairwise comparison for intra- and inter-group similarity generally, and how the resolution of partitioning algorithms affect outcomes from network similarity metrics from networks that are generated with different types of structure.
- Hyperscanning and evaluating similarity of peoples' signals is an informative tool for group processes
  - However, these analyses are not straightforward and results should be critically viewed and always checked against surrogate analyses.

References

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