NIH T32 Research Statement

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Abstract

In this proposal, we briefly describe a cross-validation study between neuroimaging methods, psychological assessments, and clinical outcomes. In the first part, we presented the background of the research topic, outlined the materials, methods, and expected results. We discussed the significance of the study, including future research directions, publications expectations, etc. In the second part,we listed the authors' related papers and projects that may contribute to the proposal.

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Chapter 1

Research Statement

1.1 Introduction

In the field of psychiatric mental health, clinical decision-making relies on multiple diagnostic methods, including physician choice, neuroimaging results, and psychological behavioral assessments.

Neuroimaging data play an increasingly important role in clinical research. However, despite their rich physiological details, this information is difficult to interpret in a behavioral sense. The gap between neuroimaging and behavioral assessments limits the prevention, diagnosis, and treatment of mental illness.

In a recent research article Smith et al., 2015, a neural connectivity pattern was found that predicts a range of positive-negative behaviors, including clinical behaviors such as drug use. Using an independent sample, Goyal et al., 2022 replicated this result. Although this finding is of great value, it is still difficult to explain this connection pattern in behavioral language. Assuming that the neural connectivity pattern can be explained in psychological behavioral language, these findings will guide clinical intervention, prevention, education, etc.

Previous studies have attempted to address the link between neuroimaging and psychological behavioral traits, such as Beaty et al., 2016, Simon et al., 2020, Van Schuerbeek et al., 2016, and Toschi et al., 2018. However, most of these studies investigated the relationship between neuroimaging and individual personality traits, rather than a personality mode. Although valuable knowledge, these results are limited in interpreting neural imaging results into behavioral languages.

1.2 Proposed Research

In this study, we expect to identify a set of stable psychological features that are strongly associated with the brain connectivity related to clinical outcomes of interest.

These set of psychological features will appear in the form of "behavioral patterns", that is, combinations of psychological traits and interactions between them.

Specifically, when applied to PTSD samples, we would define a subset of functional connectives for neuroimaging, i.e., the "PTSD brain connectives", that are relevant to the PTSD outcomes.

Meanwhile, a set of psychological features will be selected, that are closely associated to the "PTSD brain connectives". We will further conduct hypotheses testing regarding the associations between the personality features and PTSD outcomes, including symptom severity, diagnosis, prognosis, etc.

If these association tests achieved statistical meaningfulness, we may claim that we discover a set of "PTSD psychological-behavior patterns", which are related to both brain connectives and the clinical outcome.

1.2.1 Methods, Materials, and Expected Results

We need a clinical sample that each participant completes

- Neuroimaging data (e.g., fMRI, fNIRs), from both treatment and control groups, either resting states or with clinical-related tasks.
- Psychological trait surveys, such as personality, cognition, behavior, etc.,
- Clinical assessments related to the outcome of interest.

The Statistical methods include high-dimensional functional variable selection methods, canonical correlation analysis, independent components analysis, regression analysis, mediated regression analysis, etc.

1.2.2 Discussion and Limitations

If successful, this research may shed light on the behavioral interpretation of neuroimaging results. This may be important because it will make neuroimaging results more meaningful, interpretable, and understandable to the general audience. This will help in the treatment process of mental illness and will benefit the general audience in terms of prevention, education, and pre-screening.

This research proposal could potentially lead to both clinical outcome research articles, and methodology articles focusing on a), high dimensional variable selection for clinical neuroimaging data, and b) computational feature reconstruction for clinical neuroimaging data.

Both the "brain connectivity mode", and the "personality mode", have the potential to be extended to other clinical or nonclinical (e.g., behavioral) outcomes. These may further lead to future journal publications, future funding opportunities, as well as transnational research opportunities.

References

Beaty, R. E., Kaufman, S. B., Benedek, M., Jung, R. E., Kenett, Y. N., Jauk, E., Neubauer, A. C., & Silvia, P. J. (2016). Personality and complex brain networks: The role of openness to experience in default network efficiency. *Human brain mapping*, *37*(2), 773–779.

Goyal, N., Moraczewski, D., Bandettini, P. A., Finn, E. S., & Thomas, A. G. (2022). The positive–negative mode link between brain connectivity, demographics and behaviour: A pre-registered replication of smith et al.(2015). *Royal Society Open Science*, *9*(2), 201090.

Simon, S. S., Varangis, E., & Stern, Y. (2020). Associations between personality and whole-brain functional connectivity at rest: Evidence across the adult lifespan. *Brain and behavior*, *10*(2), e01515.

Smith, S. M., Nichols, T. E., Vidaurre, D., Winkler, A. M., Behrens, T. E., Glasser, M. F., Ugurbil, K., Barch, D. M., Van Essen, D. C., & Miller, K. L. (2015). A positive-negative mode of population covariation links brain connectivity, demographics and behavior. *Nature neuroscience*, *18*(11), 1565–1567.

Toschi, N., Riccelli, R., Indovina, I., Terracciano, A., & Passamonti, L. (2018). Functional connectome of the five-factor model of personality. *Personality Neuroscience*, *1*, e2.

Van Schuerbeek, P., Baeken, C., & De Mey, J. (2016). The heterogeneity in retrieved relations between the personality trait 'harm avoidance'and gray matter volumes due to variations in the vbm and roi labeling processing settings. *PloS one*, *11*(4), e0153865.

Chapter 2

Author's relevant works

2.1 Publication

Yuan, Y., & Billor, N. (2024). Sure independent screening for functional regression model. Communications in Statistics-Simulation and Computation, 1-20. [full text]

Turkmen, A. S., Yuan, Y., & Billor, N. (2019). Evaluation of methods for adjusting population stratification in genome-wide association studies: Standard versus categorical principal component analysis. Annals of human genetics,83(6), 454-464. [full text]

Yuan. Y., Billor, N., and Turkmen, A. S. (2018, August) Benford's Law Based Outliers Detection for Population Stratification in Genotype Data. Paper presentation at 2018 Joint Statistical Meeting, Vancouver, CA. [full text]

Yuan, Y., Hack, E. M., & Fan, J. (2015, August). Reconsidering Using Bogus-Statement Inventory and Over-Claiming Questionnaire to Detecting Faking. Academy of Management Annual Meeting Proceedings.[full text]

2.2 Projects

We have also included author's relevant projects for your reference, as indicated in Figure 2.1 and Figure 2.2

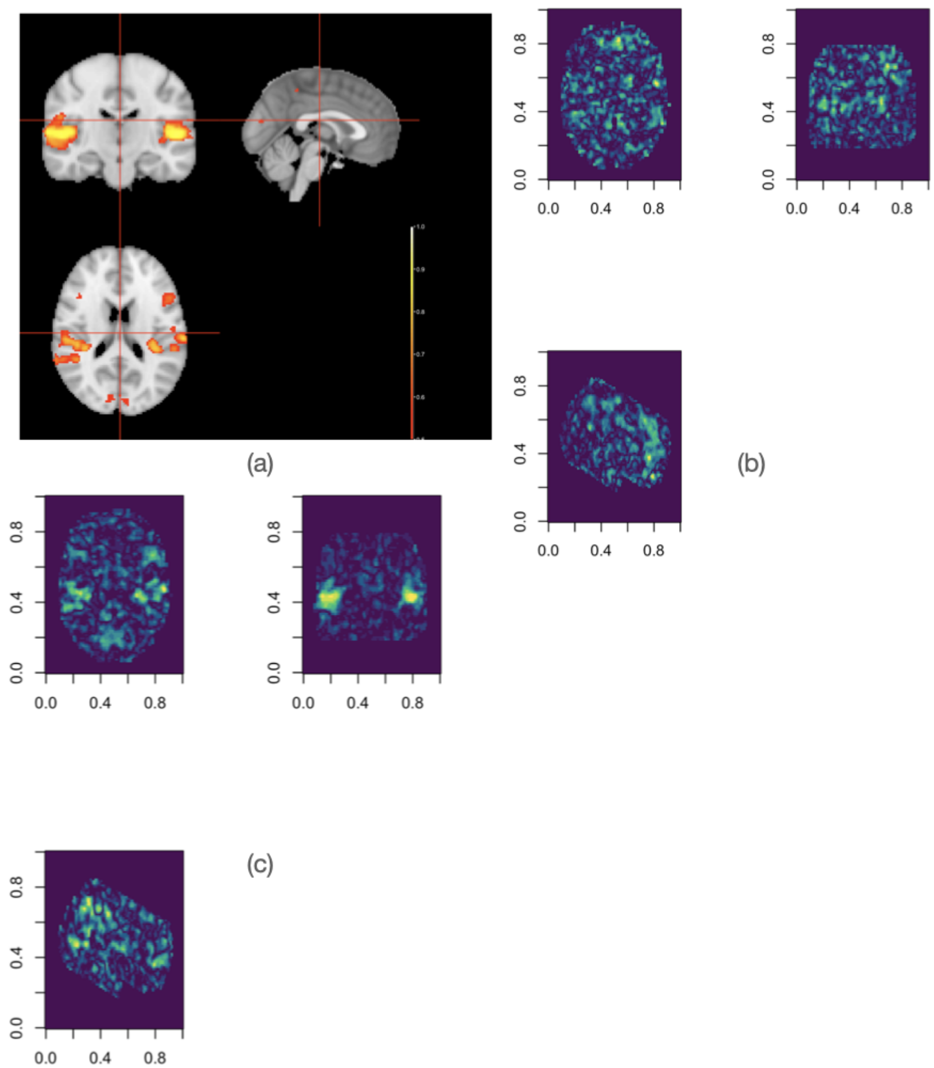

Figure 2.1: fMRI feature reconstruction, using novel feature reconstruction techniques. (a): Regions of activation of vocal vs. voice conditions; (b) feature reconstructions of brain regions of activation for nature voices, and (c) feature reconstructions of brain regions of activation for human vocal. The data of this "voice localizer" scan is freely available on the online platform OpenNEURO(Gorgolewski et al. 2017).

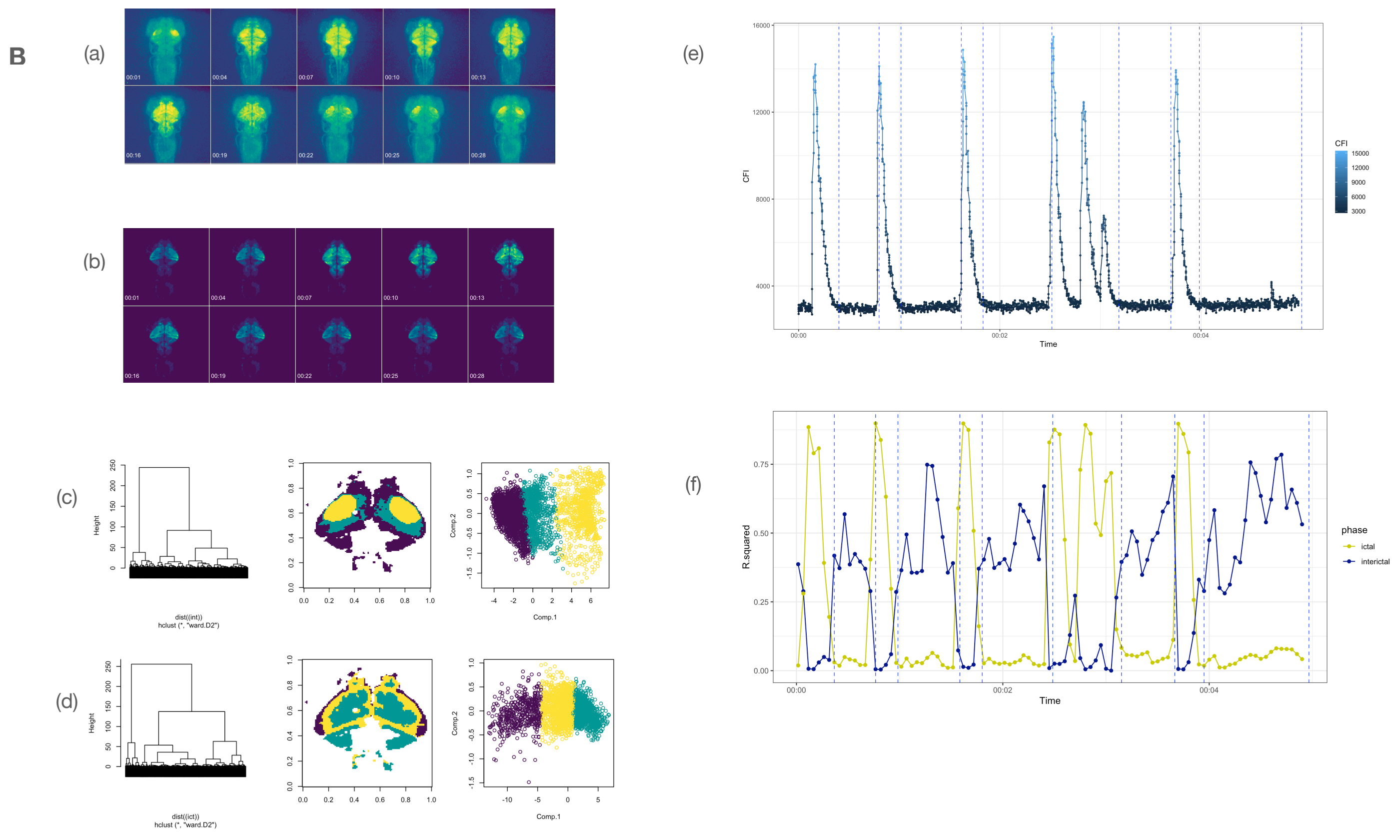

Figure 2.2: B. Project of calcium fluoresces intensity imaging (CFI) reconstruction of zebrafish larvae during of PTZ induced epileptic seizure. (a) reconstructed CFI images of the sample across a complete seizure cycle, sampled at $n = 10$ equally spaced time points; (b) original CFI images for the same sample, at the same time points as (a); (c) extracted patterns from interictal periods; (d) extracted patterns from ictal periods; (e) averaged calcium fluouresces intensity curve form bodypixels, across five epileptic cycles; (f) anti-correlation network from ictal patterns (yellow), and interictal patterns (blue), across five epileptic cycles, measured with the model R^2 of reconstructed image features at each sampled time point against discovered patterns. Data came from collaborator as in Zheng et al., (2020).