Study Information
Design Plan
Sampling Plan
Variables
Analysis Plan
Other

Study Information

1. Title

Neural correlates of expectations and experiences of pain, perceived pain, and cognitive effort

2. Authors

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3. Description (optional)

Expectations have been shown to modulate our experiences. For example, top-down expectations of pain have been shown to modulate pain experience (Wager et al., 2013; Cormier et al., 2013; Sawamoto et al., 2000; Koyama et al., 2005; Lorenz et al., 2005; Brown et al., 2008; Atlas et al., 2010; Bingel et al., 2011; Wiech et al., 2014b) Similarly, task expectations have shown to influence task performance in cognitive domains (Swanson & Tricomi, 2014). However, studies to date have examined expectations in separate domains, which does not allow for the comparison or contrast of neural representation of expectations across different domains. Neural representation of expectations may be strikingly different across affective and cognitive domains ("domain-specific"), or it may be a common representation that acts upon different experiences ("domain-general"). Therefore, we propose to investigate the neural representation of expectations and examine the domain generality and specificity of expectations, by examining multiple tasks that span affective and cognitive domains.

4. Hypotheses

4.1 Behavioral

- Is there a main effect of cue on expect rating — i.e. do cues modulate expectations?
- Is there a main effect of cue on actual rating — i.e. do cues modulate actual experiences?
- Is there a main effect of stimulus intensity on actual rating? — i.e. Is there a difference in actual ratings across the three levels of stimulus intensity?

4.2. Neuroimaging

4.2.1. Neuroimaging Discovery validation analysis

- Which model (fixed epoch model/variable epoch model/flexible basis function) best explains the BOLD signals of different epoch types?

4.2.2. Neuroimaging Parametric modulation analysis

- During the cue period, is there a univariate activation/multivariate pattern modulated as a function of expectation rating?
- During the stimulus period, is there a difference in univariate activation/multivariate pattern for trials with higher cues?
- During the stimulus period, is there a univariate activation/multivariate pattern modulated as a function of actual ratings?
- During the stimulus period, is there a univariate activation/multivariate pattern that activates as a function of expectation ratings?
- During the stimulus period, is there a univariate activation/multivariate pattern that activates as a function of stimulus intensity?

4.2.3. Neuroimaging Mediation analysis

- Is the stim period mediator significant? — which voxels/patterns significantly mediate the relationship between cue and actual rating?
- Is the cue period mediation significant? — which voxels/patterns mediate the relationship between cue and actual experience voxel/pattern?

4.2.4. Neuroimaging Variance decomposition analysis

- In a given epoch, how much variance is explained by the domain-general vs. domain general maps?

4.2.5. Neuroimaging Bayesian model selection

- Amongst the domain-general and domain-specific mediators, which is the winning model?

4.2.6. Neuroimaging Task difficulty classification

- Do certain biomarkers predict task difficulty?
- Can biomarkers from a particular domain (e.g. pain classifier) predict task difficulty in a different task domain (e.g. trials from cognitive task)?

Design Plan

In this section, you will be asked to describe the overall design of your study. Remember that this research plan is designed to register a single study, so if you have multiple experimental designs, please complete a separate preregistration.

5. Study type (required)

5.1. ✔ **Experiment** - A researcher randomly assigns treatments to study subjects, this includes field or lab experiments. This is also known as an intervention experiment and includes randomized controlled trials.

5.2. Observational Study - Data is collected from study subjects that are not randomly assigned to a treatment. This includes surveys, ñnatural experiments,î and regression discontinuity designs.

5.3. Meta-Analysis - A systematic review of published studies.

5.4. Other

6. Blinding (required)

6.1. ✔ **No blinding** is involved in this study.

6.2. For studies that involve human subjects, they will not know the treatment group to which they have been assigned.

6.3. Personnel who interact directly with the study subjects (either human or non-human subjects) will not be aware of the assigned treatments. (Commonly known as “double blind”)

6.4. Personnel who analyze the data collected from the study are not aware of the treatment applied to any given group.

7. Is there any additional blinding in this study?

No

8. Study design (required)

Describe your study design. Examples include two-group, factorial, randomized block, and repeated measures. Is it a between (unpaired), within-subject (paired), or mixed design? Describe any counterbalancing required. Typical study designs for observation studies include cohort, cross sectional, and case-control studies.

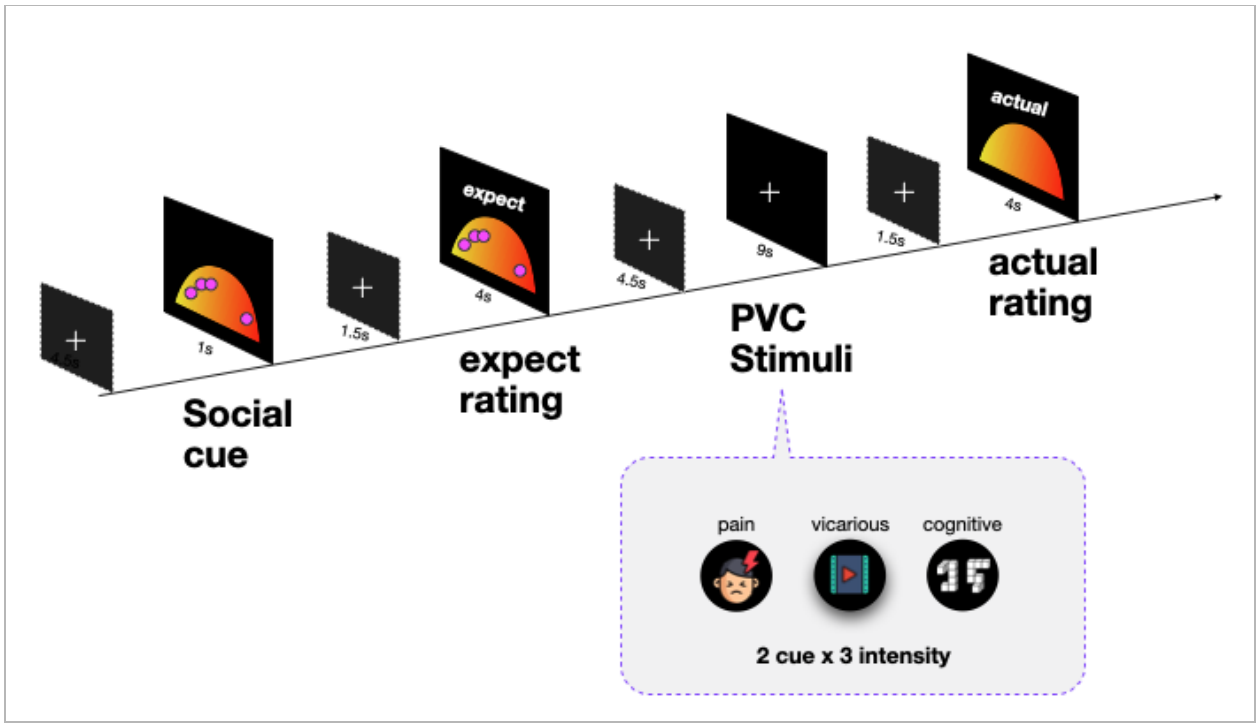


Figure 1. Example of one trial

- Within subject design
- 3 task (cognitive, pain, vicarious pain)
  x 2 cue (high social cue, low social cue)
  x 3 stimulus intensity of task (high, medium, low).
- Randomized repeated measures
- 6 Blocks of each task. 12 trials per block. Participants would experience the 2 cue x 3 stimulus intensity configuration twice
- Counterbalancing:
  1. Trial level: Order of cue and stimulus intensity is counterbalanced; 10 versions of counterbalanced orders were created. Each participant was pseudo-randomly assigned to these counter balanced versions.
  2. Task level: we used a latin square design to counterbalance the order of the three tasks.

Sampling Plan

In this section we'll ask you to describe how you plan to collect samples, as well as the number of samples you plan to collect and your rationale for this decision. Please keep in mind that the

data described in this section should be the actual data used for analysis, so if you are using a subset of a larger dataset, please describe the subset that will actually be used in your study.

9. Existing data (required)

Preregistration is designed to make clear the distinction between confirmatory tests, specified prior to seeing the data, and exploratory analyses conducted after observing the data. Therefore, creating a research plan in which existing data will be used presents unique challenges. Please select the description that best describes your situation. Please do not hesitate to contact us if you have questions about how to answer this question (prereg@cos.io).

9.1. Registration prior to creation of data: As of the date of submission of this research plan for preregistration, the data have not yet been collected, created, or realized.

9.2. Registration prior to any human observation of the data: As of the date of submission, the data exist but have not yet been quantified, constructed, observed, or reported by anyone - including individuals that are not associated with the proposed study. Examples include museum specimens that have not been measured and data that have been collected by non-human collectors and are inaccessible.

9.3. Registration prior to accessing the data: As of the date of submission, the data exist, but have not been accessed by you or your collaborators. Commonly, this includes data that has been collected by another researcher or institution.

9.4. ✔ **Registration prior to analysis of the data:** As of the date of submission, the data exist and you have accessed it, though no analysis has been conducted related to the research plan (including calculation of summary statistics). A common situation for this scenario when a large dataset exists that is used for many different studies over time, or when a data set is randomly split into a sample for exploratory analyses, and the other section of data is reserved for later confirmatory data analysis.

9.5. Registration following analysis of the data: As of the date of submission, you have accessed and analyzed some of the data relevant to the research plan. This includes preliminary analysis of variables, calculation of descriptive statistics, and observation of data distributions. Please see cos.io/prereg for more information.

10. Explanation of existing data (optional)

If you indicate that you will be using some data that already exist in this study, please describe the steps you have taken to assure that you are unaware of any patterns or summary statistics in the data. This may include an explanation of how access to the data has been limited, who has observed the data, or how you have avoided observing any analysis of the specific data you will use in your study.

- As of July 1, 2021 We have collected behavioral and neuroimaging from 24 participants.
- The behavioral data was analyzed for 20 participants, as a manipulation check
    - The two main questions were 1) Is there a main effect of stimulus intensity on actual ratings? 2) Is there a main effect of cue on actual ratings?
    - Both effects were significant.
- the neuroimaging data was not analyzed (raw data, no QA, no analysis at the time of preregistration)

11. Data collection procedures (required)

Please describe the process by which you will collect your data. If you are using human subjects, this should include the population from which you obtain subjects, recruitment efforts, payment for participation, how subjects will be selected for eligibility from the initial pool (e.g. inclusion and exclusion rules), and your study timeline. For studies that donÍt include human subjects, include information about how you will collect samples, duration of data gathering efforts, source or location of samples, or batch numbers you will use.

- Participants will be recruited from the upper valley area in New Hampshire.
- Recruitment efforts: flyers, facebook ads, listservs, sona system
- Payment: $400 at the end of 4 sessions. Hourly rate for participants who dropout without completion
- Eligibility: Exclusion criterion: 1) Self-reported substance abuse within the last 6 months, 2) Study-specific criteria for current or recent chronic pain, 3) Contraindications to fMRI (e.g. ferromagnetic metal in the body, claustrophobia, pregnancy), 4) Younger than 18 years old or older than 55 years old, 5) left-handed (ambidextrous participants are allowed)
- Study timeline: 1-2 year

12. Sample size (required)

Describe the sample size of your study. How many units will be analyzed in the study? This could be the number of people, birds, classrooms, plots, interactions, or countries included. If the units are not individuals, then describe the size requirements for each unit. If you are using a clustered or multilevel design, how many units are you collecting at each level of the analysis?

- Our target sample size is 120 participants. We will attempt to recruit up to 150 participants, expecting drop-out or unusable brain data.

13. Sample size rationale (optional)

This could include a power analysis or an arbitrary constraint such as time, money, or personnel.

The sample size (n = 120) was chosen to power the study at 80% power for voxel-wise analyses with whole-brain family-wise error of Cohen's d = 0.5 or larger. Recent estimates for voxel-wise effects in fMRI studies average around d = 0.5 (Poldrack et al., 2017). Our proposed sample size of n = 120 provides 80% to detect moderate effects of d = 0.5, and over 95% power to detect "large" effects of d = 0.8. We will test for sex differences in exploratory analyses, with 80% power to detect very large effects (d = 1.1). This power calculation is appropriate for making inferences on voxel-wise contributions to multivariate predictive models, i.e., to identify brain regions with stable predictive weights when training models. When testing multivariate predictive models on new individuals, different calculations apply. First, effect sizes can be substantially larger, and second, multiple comparisons correction is not required as information is integrated into a single measure. Estimated effect sizes for the Neurologic Pain Signature response tested on data from the Colorado 3T scanner (n = 23) were d = 2.12 for a 2-degree difference in painful heat. In our other prior work, the effect size when testing the high vs. low negative emotion signature was d = 4.7 (Chang et al., 2015), and testing the vicarious pain signature (also on the Colorado scanner) was d = 3.9 (Krishnan et al., 2016), all in out-of-sample participants. For testing, our proposed sample sizes are powered to detect much smaller effects: With n = 120, we have 80% power to detect small effects (d >= 0.26) at p < .05 two-tailed, and sex differences in predictive accuracy for effects of d >= 0.52. If effect sizes for multivariate models are as large as in our previous work (d = 2.0 and above), we will be able to make accurate inferences about individuals. Thus, our proposed sample sizes are appropriate for identifying regions that contribute consistently to multivariate predictive models across individuals, and testing those predictions with high power.

Variables

In this section you can describe all variables (both manipulated and measured variables) that will later be used in your confirmatory analysis plan. In your analysis plan, you will have the opportunity to describe how each variable will be used. If you have variables which you are measuring for exploratory analyses, you are not required to list them, though you are permitted to do so.

14. Manipulated variables (optional)

Describe all variables you plan to manipulate and the levels or treatment arms of each variable. This is not applicable to any observational study.

3 task (pain/vicarious/cognitive)

- We used three tasks to cover the scope of affective and cognitive domains.
- pain task: thermal heat delivered to the non-dominant arm.

- vicarious pain task: 5 second video clips of shoulder pain patients in pain.
- cognitive task: 3d figures for a mental rotation task.

2 Social cues (high/low)

- We manipulated the social cues by using the mean and standard deviation of a beta distribution.

3 levels of stimulus intensity (low/medium/high)

- Within each task, there are three different levels of stimulus intensity delivered.
- pain task: 48, 49, 50 celsius with a 5 second plateau
- vicarious pain task: videos of low, medium, high pain intensity (Each video was selected from the McMaster shoulder pain database and categorized based on a combination of the PSPI rating and observer rating.)
- cognitive task stimulus intensity levels: 50, 100, 150 degree-rotated 3d figures

15. Measured variables (required)

Describe each variable that you will measure. This will include outcome measures, as well as any predictors or covariates that you will measure. You do not need to include any variables that you plan on collecting if they are not going to be included in the confirmatory analyses of this study.

- fMRI signal
  - T1w (mprage)
  - Diffusion MRI
  - Task fMRI
- Onset time of each event
  - fixation period
  - cue period
  - expectation rating period
  - stimulus period
  - actual rating period
- Self report (angle of rating)
  - expect rating (semicircular scale, angle range 0-180, labels include ‘no sensation’, ‘barely detectable’, ‘weak’, ‘moderate’, ‘strong’, ‘very strong’, ‘strongest sensation of any kind’)
  - actual rating (semicircular scale, angle range 0-180, labels include ‘no sensation’, ‘barely detectable’, ‘weak’, ‘moderate’, ‘strong’, ‘very strong’, ‘strongest sensation of any kind’)
- Reaction time
  - expect rating
  - actual rating
- Mouse trajectory
  - expect rating
  - actual rating

- Physiological data (Biopac)
    - Electrodermal activity (EDA)
    - Photoplethysmography (PPG) response
    - Onset time of each event recorded in digital channels
    - TTL signals for pain trials (onset, offset)
    - TTL signals from scanner

Analysis Plan

You may describe one or more confirmatory analysis in this preregistration. Please remember that all analyses specified below must be reported in the final article, and any additional analyses must be noted as exploratory or hypothesis generating.

A confirmatory analysis plan must state up front which variables are predictors (independent) and which are the outcomes (dependent), otherwise it is an exploratory analysis. You are allowed to describe any exploratory work here, but a clear confirmatory analysis is required.

16. Statistical models (required)

I. Neuroimaging analysis

The steps of our neuroimaging analyses are listed in figure 1. Our main questions are focused on investigating brain mediators that mediate the relationship between cue to actual ratings; in order to address these questions, we first start out by modeling the signals and constructing parametric modulation maps. We plan to implement a less commonly used approach, discovery validation analysis, to model the BOLD signal (i.e., fixed-epoch model/variable-epoch model/flexible basis function model) and identify the best fitting model (**Analysis 1**). Using the identified HRF model, we will conduct a parametric modulation analysis and model the stimuli with parametric modulators, executed in four different versions (univariate/multivariate x domain-general/specific; **Analysis 2**). After constructing the parametric modulation maps, we now are able to investigate our central question of brain mediators that mediate the relationship between cue to actual ratings, where we use the parametric modulation maps as inputs for the two-path mediation analysis. The purpose of this two-path mediation analysis is to search for the two brain mediators that mediate the relationship between cue and actual rating (**Analysis 3.1**) Utilizing these found mediators, we will conduct a multi-path mediation analysis, which will identify the path between cue to expectation to actual stimulus experience to actual ratings (**Analysis 3.2**). Once the mediator brain maps are discovered, we plan to run a variance decomposition analysis, in order to identify how much variance is explained by the

domain-general mediator map versus the domain-specific mediator map. The purpose is to identify the proportion of variance explained by domain-general vs. domain-specific processes (**Analysis 4**). Relatedly, we will also conduct a Bayesian model selection analysis to identify whether the voxels/patterns are better explained by the domain-general model or the domain-specific model (**Analysis 5**). Lastly, separate from the mediation analysis, we plan to analyze the stimulus epoch and classify them with pre-identified biomarkers (**Analysis 6**).

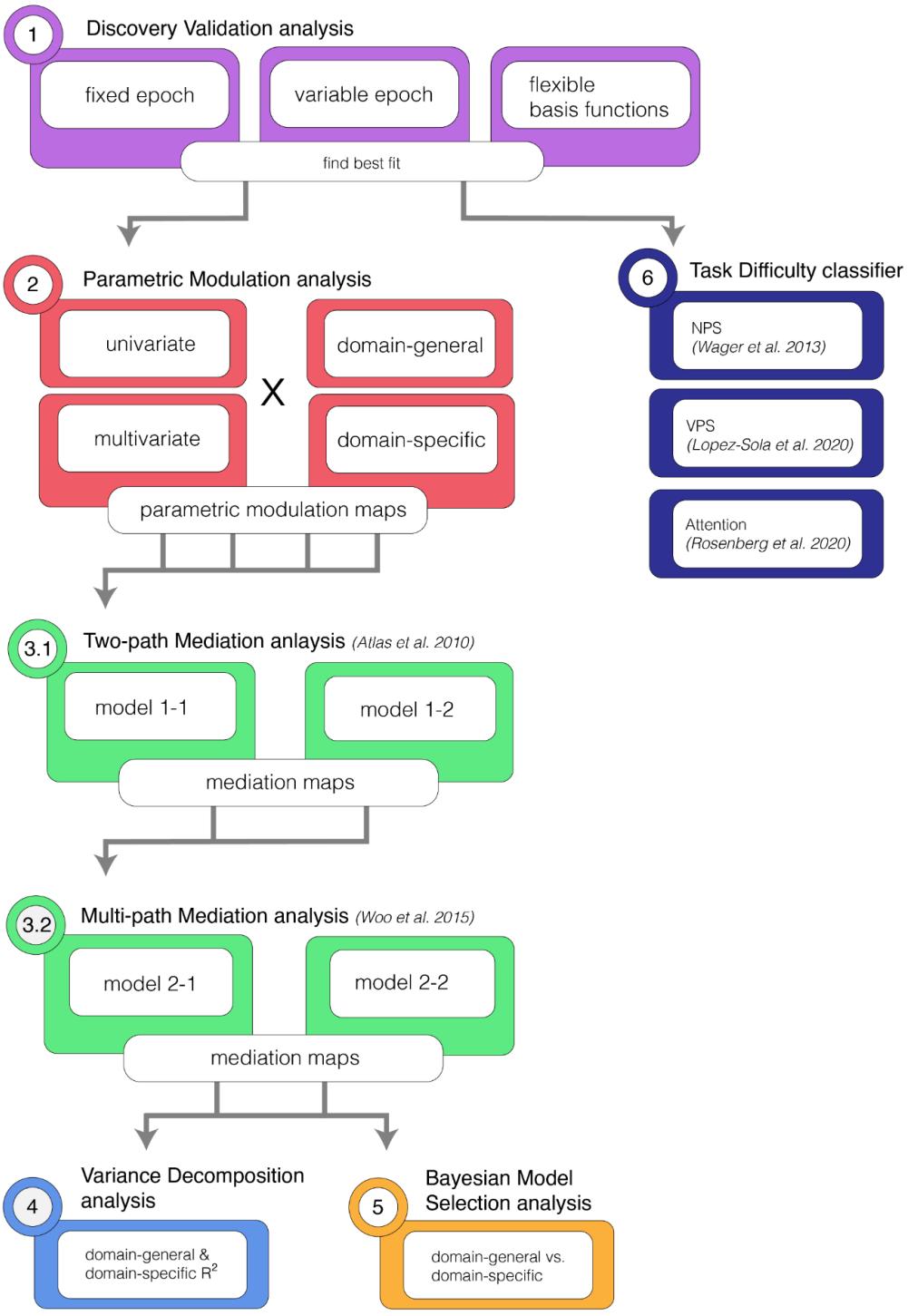


Fig 1. steps of neuroimaging analysis.

† **Regressor Glossary:** combinations of these regressors will be used for each model appropriately.

First-level regressors

- epoch of cue period ("**CUE**")
    - Parametric modulator: cue [high=1; low=-1] ("**CUE_pm-cue"**)
    - Parametric modulator: expect rating ("**CUE_pm-expect"**)
- epoch of expect rating period ("**RATING_EXPECT**")
- epoch of stimulus period ("**STIM**")
    - Parametric modulator: cue [high=1; low=-1] ("**STIM_pm-cue"**)
    - Parametric modulator: actual rating ("**STIM_pm-actual"**)
    - Parametric modulator: expect rating ("**STIM_pm-expect"**)
    - Parametric modulator: stimulus intensity level ("**STIM_pm-taskdiff"**)
    - Parametric modulator: M2 mediator voxel-wise average (**"STIM_pm-M2"**)
- epoch of actual rating period ("**RATING_ACTUAL**")

┼ As for the duration of the actual and expect rating regressor, we will use the reaction time of the rating response.

First level covariates

- Motion nuisance covariates (24 motion covariates)

2nd-level regressors

- mean-centered cue effect on actual ratings from behavioral analysis (19.1)
- mean-centered stimulus intensity effect from behavioral analysis (19.1)
- Revised Self-Monitoring scale
- Gender

1. **Neuroimaging** Discovery validation analysis

a) **Main question**: what is the best model for fitting the BOLD signal during the expectation phase and stimulus experience?
The canonical hemodynamic response function (HRF) makes several assumptions including that the time course of the evoked afferent signal is known and that this signal coincides throughout the brain. However, these are strong assumptions; the HRF can differ depending on different types of stimuli. Therefore, we will conduct three models of BOLD signal fitting and determine the best fit.

b) Method:

- Fixed epoch model
    - description: model the epoch using each onset time and the duration of the epoch. For example, when modeling a fixed CUE epoch, we would use the onset of the cue period and model the duration as the cue onset presentation time (1s).
- Variable epoch model

        - description: model the epoch from the beginning of the cue period until the end of the expect rating. For example, when modeling a variable CUE epoch, we would use the onset of the cue period, but model the duration of the cue AND expect rating phase, as the psychological process of expectations may extend beyond the cue epoch of 1s, up until the stimulus epoch. While the total duration of cue and expect rating differs due to jitters in between, the average duration would amount to 11s.
    - Flexible basis function:
        - description: model the BOLD signal as a weighted combination of simple basis functions.

We plan to determine the winning model using bayes factors.

2. **Neuroimaging** Parametric modulation analysis

a) **main question:**
- Is CUE_pm-expect significant? — during the cue period, is there a univariate activation/multivariate pattern modulated as a function of expectation rating?
- Is STIM_pm-cue significant? — during the stimulus period, is there a difference in univariate activation/multivariate pattern for trials with higher cues?
- Is STIM_pm-actual significant? — during the stimulus period, is there a univariate activation/multivariate pattern modulated as a function of actual ratings?
- Is STIM_pm-expect significant? — during the stimulus period, is there a univariate activation/multivariate pattern that activates as a function of expectation ratings?
- Is STIM_pm-level significant? — during the stimulus period, is there a univariate activation/multivariate pattern that activates as a function of stimulus intensity?

b) **method**: types of parametric modulation analysis

Univariate vs. multivariate (number of dependent variables)
- For the univariate analyses, we estimate the parametric modulation maps via bootstrapping methods.
- For the multivariate analyses, we estimate the parametric modulation maps via stratified 10-fold cross validation.

Domain-general vs. domain-specific (domain)
- For the domain-general model, we include all trials from all three tasks.
- For the domain-specific model, we include task-specific trials from each task.

We will conduct 2 (number of dependent variables) x 2 (domains) parametric modulation analyses for the 5 aforementioned questions.

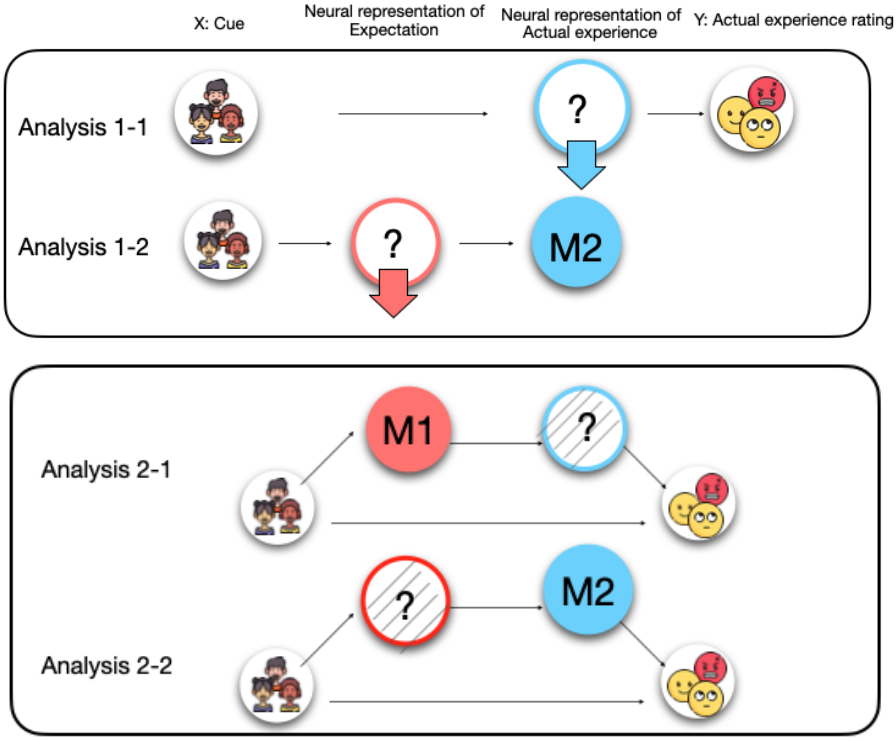
3. **Neuroimaging** Mediation analysis (two-path, then multi-path)

a) **main question:** Do expectations mediate actual experiences? (see 19.3.1)
- Is the stim period mediator significant? — which voxels/patterns significantly mediate the relationship between cue and actual rating?

- Is the cue period mediation significant? — which voxels/patterns mediate the relationship between cue and actual experience voxel/pattern?

b) <u>method:</u> (two-path, then multi-path)

We plan to identify the neural representation of a) expectations and b) experiences of pain, vicarious pain and cognitive effort, which mediate the relationship of cue and actual ratings. “Experience” refers to the stimulus period where participants are delivered pain/vicarious pain/cognitive stimuli; “actual ratings” refers to the subsequent ratings completed after each stimulus period, i.e. self reported “experience”. In order to conduct a multi-path analysis, a two-path mediation analysis is necessary to identify potential mediators. The figure illustrates the two-part analysis.



3.1. Two-path mediation analysis

First, We will conduct a two-path mediation analysis to identify the two neural representations via a whole brain search.

Analysis 1-1.

During the stimulus period, **i**s there a neural representation of actual experience that mediates the relationship between cue and actual ratings? We denote the identified neural representation of actual experience as “M2”.

Analysis 1-2.

Using the identified actual experience representation (M2) from analysis 1-1, we next explore the neural representation of expectancy effects.
Main question: During the cue period, is there a neural representation of expectation that mediates the relationship between cue and actual experience representation? We denote the identified neural representation of expectation as “M1”.

3.2. Multipath mediation analysis

With the identified representation of expectation (M1) and actual experience (M2), we conduct a multi-level multi-path mediation analysis (Woo et al., 2015).

Analysis 2-1.

Using the identified neural representation of expectations (M1) from analysis 1-2, we search for patterns that mediate cue to M1 and actual experience ratings. In other words, we fix cue, M1, and ratings, while searching for the neural representation of actual experiences.

Analysis 2-2.

Using the identified neural representation of actual experience (M2) from analysis 1-1, we search for patterns that mediate cue to M2 and actual experience ratings. In other words, we fix cue, M2, and ratings, while searching for the neural representation of expectations.

c) Types of mediation analysis

Univariate vs. multivariate (number of dependent variables)

- For the univariate analyses, we estimate the mediation maps via bootstrapping methods.
- For the multivariate analyses, we estimate the mediation maps via stratified 10-fold cross validation.

Domain-general vs. domain-specific (domain)

- For the domain-general model, we include all trials from all three tasks.
- For the domain-specific model, we include task-specific trials from each task.

We will conduct **2** (number of dependent variables) x **2** (domains) mediation analyses for model 1-1, 1-2, 2-1, and 2-2.

Appendix 1 for model 1-1. Example of a two-path mediation analysis for a univariate, domain-general analysis

- **Main question**: Which voxels mediate generalizable cue effects on actual experience? (i.e. searching for M2)
- **How is the mediation map defined?**

    - We multiply path a and path b maps, i.e. indirect effect ab (Mackinnon and Dwyer 1993), in order to derive the M2 map.
    - **Definition of path a**: parametric modulation map of stimulus period, modulated with cue (**"STIM_pm-cue")**
        - model regressors includes: 1) CUE, 2) RATING_EXPECT, 3) STIM, 3-1) **STIM_pm-cue**, 4) RATING_ACTUAL
    - **Definition of path b**: parametric modulation map of stimulus period modulated with actual ratings ("**STIM_pm-actual**") controlling for cue (i.e., while turning off the orthogonalization in order to run a multiple regression;
        - model regressors include: 1) CUE, 2) RATING_EXPECT, 3) STIM, 3-1) STIM_pm-cue, 3-2) **STIM_pm-actual**, 4) RATING_ACTUAL
- **Resulting derivatives**: One domain-general M2 map (each M2 map will be averaged across voxels, so that we have one value per trial) These values will later be used as the outcome variable in model 1-2.

Appendix 2. Example of a two-path mediation analysis for a multivariate, domain-specific analysis (model 1-2)

- **Main question**: Which patterns mediate the effect of pain cue on actual pain brain pattern? (i.e. searching for M1)
- **How is the mediation map defined?**
    - We multiply path a and path b maps, i.e. indirect effect ab (Mackinnon and Dwyer 1993), in order to derive the M1 map.
    - **Definition of path a**: parametric modulation map of cue period, modulated with cue ("**CUE_pm-cue**")
        - model regressors include: 1) CUE, **1-1) CUE_pm-cue**, 2) RATING_EXPECT, 3) STIM, 4) RATING_ACTUAL
    - **Definition of path b**: parametric modulation map of cue period, modulated with averaged voxel-wise value of M2 map
        - model regressors include: 1) CUE, 2) RATING_EXPECT, 3) STIM, 3-1) STIM_pm-cue, **3-2) STIM_pm-M2**, 4) RATING_ACTUAL
- **Resulting derivatives**: One pain-specific M1 map

4. **Neuroimaging** Variance decomposition analysis

a) **Main question:** In a given epoch, how much variance is explained by the domain-general vs. domain general maps?
b) **Method:** We plan to conduct a variance decomposition analysis (benchmarking the commonality analysis from Nimon *et al.*, 2008) with the domain-general and domain-specific mediation maps, uncovered from the multi-path mediation analysis (**Analysis 19.2.3.2**). We partition each participants' variance explained on actual ratings,

which results in four components: 1) unique variance from domain-general model, 2) unique variance from domain-specific model, 3) shared variance between domain-general and domain-specific model, 4) unexplained variance.

5. **Neuroimaging** bayesian model selection

a) **Main question:** Amongst the domain-general and domain-specific mediators, which is the winning model?
Using the domain-general and domain-specific mediator maps from the cue and stimulus period, we intend to identify the winning model that best explains expect and actual ratings.
b) **Method**: Bayesian model selection and exceedance probability for identifying the best models, i.e. domain-general vs. domain-specific.

6. **Neuroimaging** task difficulty classification

a) **Main question:** Do certain biomarkers predict task difficulty? Also, can biomarkers from a particular domain (e.g. pain classifier) predict task difficulty in a different task domain (e.g. trials from cognitive task)?
While the scope of the project focuses on expectations and modulations in experiences, we also plan to replicate prior findings on biomarkers on pain, vicarious, and cognitive stimuli. The plan is to use previously identified biomarkers and classify stimulus period trials from the three domains of pain, vicarious, and cognitive.
b) **Method:** Apply the following weight maps from each biomarker test classification accuracy
    - Pain biomarker (NPS; Wager et al. 2013)
    - Vicarious biomarker (VPS; Lopez-Sola et al. 2020)
    - Cognitive biomarker (Rosenberg et al. 2016)

II. Behavioral analysis

Regressor Glossary:

Outcome variable: actual rating and expect rating
Fixed-effect regressors
- Cue [high = 0.5; low = -0.5]
- Stimulus intensity linear: [high = 0.5; med = 0; low = -0.5]
- Stimulus intensity quadratic: [high = -0.33; med = 0.66; low = -0.33]

Random-effect regressors
- subjects

Main question:
- Is there a main effect of cue on expect rating — i.e. do cues modulate expectations?
- Is there a main effect of cue on actual rating — i.e. do cues modulate actual experiences?
- Is there a main effect of stimulus intensity on actual rating? — i.e. Is there a difference in actual ratings across the three levels of stimulus intensity?

Method: Hierarchical linear modeling

17. Transformations (optional)

If you plan on transforming, centering, recoding the data, or will require a coding scheme for categorical variables, please describe that process.

Hyperalignment
- Construct Hyperalignment mappers using naturalistic video stimuli (collected in a separate task but from identical participants in this data collection pool)
- Methods will be identical to Haxby et al., 2011
- The aim is to compare task effect sizes against hyperalignment, anatomical alignment and within-subject alignment.

18. Inference criteria (optional)

What criteria will you use to make inferences? Please describe the information youÍll use (e.g. p-values, bayes factors, specific model fit indices), as well as cut-off criterion, where appropriate. Will you be using one or two tailed tests for each of your analyses? If you are comparing multiple conditions or testing multiple hypotheses, will you account for this?

- For statistical inference, we plan to use $q < 0.05$, false discovery rate (FDR) corrected for statistical inference
- For visualization purposes, we plan to also use liberal thresholds (uncorrected $p<.01$, $p<.005$, $p<.0001$, $q<.01$, $q<.05$ etc)

- We plan to use 1) voxel-wise, 2) pattern-wise analyses for the univariate and multivariate analyses. In addition, we will conduct 3) parcel-wise analyses (using the atlas from Glasser et al. 2016) in order to increase power.

19. Data exclusion (optional)

19.1. How will you determine what data or samples, if any, to exclude from your analyses? How will outliers be handled? Will you use any awareness check?

19.2. **Example**: No checks will be performed to determine eligibility for inclusion besides verification that each subject answered each of the three tastiness indices. Outliers will be included in the analysis.

19.3. **More information**: Any rule for excluding a particular set of data is acceptable. One may describe rules for excluding a participant or for identifying outlier data.

Neuroimaging

- Use mahalanobis distance measure to detect outliers and exclude from neuroimaging analysis (see Geuter et al., 2020)
- Remove images with a framewise displacement greater than 0.9.

Behavioral

- Exclude trials without any ratings from behavioral analysis
- Exclude trials with a rating that is 70% within the radius from behavioral analysis
- Exclude a trial if the stimulus was not delivered, i.e. pain trial that failed to trigger from behavioral analysis

20. Missing data (optional)

Neuroimaging

- Missing runs: some participants may not complete a run due to equipment failure or time limits. Each task (pain, vicarious, cognitive) has 6 runs in total. We will include participants who have completed 3 runs of each task. In other words, those with more than three pain/vicarious/cognitive runs will be included in the analysis.
- Trials without any stimulus delivery: some trials may not have thermal heat delivered due to equipment failure. In these cases, we are able to keep track of stimulus delivery via socket connection and TTL triggers. We plan to exclude a trial from the neuroimaging analysis if the stimulus was not delivered, i.e. pain trial that failed to trigger.
- Trials without any ratings, but successful stimulus delivery: We plan to demean the ratings (within subject, within run) and assign a value of 0 to the trials with no ratings. As for the duration of such trials, we plan to assign mean duration to trials with no ratings.

Behavioral

- Missing trials (i.e., trials without any ratings) will be excluded from analysis.

21. Other (Optional)

If there is any additional information that you feel needs to be included in your preregistration, please enter it here. Literature cited, disclosures of any related work such as replications or work that uses the same data, or other context that will be helpful for future readers would be appropriate here.

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