

**Multi-timepoint pattern analysis (MTPA):
Improving classification with neural timeseries data**

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Abstract

Long, naturalistic stimuli are effective in evoking meaningfully differential neural response patterns between groups. However, the resulting timeseries data often have a high number of features compared to a limited sample size, increasing the likelihood of overfitting and reducing predictive power. This paper introduces multi-timepoint pattern analysis (MTPA) as a temporal dimension reduction approach for improving prediction accuracy when building models with long neural timeseries data. Using feature selection with elastic net regression, MTPA identifies predictive neural patterns while preserving the temporal structure and interpretability of the data. Across two experiments with distinct populations and objectives, MTPA demonstrated consistent advantages over approaches using principal component analysis (PCA), windowed averaging, and no dimension reduction. Experiment 1 predicted persistent work-related psychological states in business professionals, achieving accuracies up to 79.1%. Experiment 2 predicted cognitive load and narrative context during video viewing in undergraduates, with accuracies up to 66.5%. These findings suggest that MTPA may be a useful tool for analyzing neural data from extended naturalistic designs, enabling researchers to improve prediction accuracy across diverse outcomes and obtain new insights into the temporal dynamics of neural responses.

Keywords: Feature selection, machine learning, neural synchrony, fNIRS

Word count: 4,997

It is widely believed that a 10:1 sample-to-feature ratio is optimal for machine learning classification (Concato et al., 1995; Peduzzi et al., 1996; c.f., Vittinghoff & McCulloch, 2007). This poses a challenge for neuroscientists, as the cost, time, and resource-intensive nature of neuroimaging typically constrain experimental sample size. At the same time, naturalistic stimuli, such as movie clips, are becoming more common in brain-as-predictor approaches (e.g., Dieffenbach et al., 2021; Li et al., 2022; Parkinson et al., 2018; Yeshurun et al., 2017). While these stimuli are beneficial for evoking distinguishable neural response patterns between groups that extend to real-world processes (Jääskeläinen et al., 2021; Nastase et al., 2020; Finn et al., 2020), they necessarily generate a high number of features. A typical study might include 30 participants (samples) but hundreds of timepoints (features), creating a sample-to-feature ratio closer to 1:10 instead of 10:1. This can increase the risk of overfitting and decrease the model's ability to predict out-of-sample cases (Guyon & Elisseeff, 2003; Hua et al., 2009; Kohavi & John, 1997). To retain the richness of extended stimuli while still enabling robust predictive modeling, we propose reducing the temporal dimensionality of neural timeseries data prior to classification.

Neuroscientists currently address the problem of high dimensionality in a spatial context when performing multivoxel pattern analysis (MVPA). In some cases, fMRI may record 100,000 voxels per volume but only a few hundred or so trials (Mwangi et al., 2014), so MVPA applies dimension reduction to remove uninformative voxels prior to training the classifier (Weaverdyck et al., 2020). No such systematic approach exists for social neuroscientists aiming to reduce the dimensionality of a long neural timeseries following a naturalistic stimulus, so we introduce *multi-timepoint pattern analysis* (MTPA) as a temporal analog to MVPA. While MVPA

performs a spatial searchlight to select for the most predictive voxels, channels, or regions, MTPA exercises feature selection over a timeseries, effectively serving as a temporal searchlight to determine the most predictive timepoints.

A promising approach within MTPA is feature selection through elastic net regression, which combines penalties from lasso and ridge regression to reduce dimensionality while retaining the most predictive features (Zou & Hastie, 2005). By selecting for individual features without transforming or aggregating the data, elastic net preserves interpretability between the features, cognitive processes, and timepoints in the stimulus. Elastic net-based MTPA was first developed for another study (Goldstein et al., 2025) to predict psychological outcomes in business professionals. While this initial work demonstrated the method's utility, it focused exclusively on elastic net and did not compare it to other dimension reduction approaches, including feature extraction techniques like principal component analysis (PCA; Jolliffe & Cadima, 2016) or down-sampling techniques like windowed-averaging.

Present study

The purpose of this study is to introduce and validate the MTPA approach, offering a new tool for building predictive models with long neural timeseries. To show how this method can be applied generally and affect prediction accuracy for a range of outcomes, we apply MTPA to two separate datasets, each with different scientific objectives, populations, and outcome measures.

Experiment 1 aims to predict whether real-world businesspeople feel overwhelmed, burned out, or in need of a new or different challenge in their career. Experiment 2 aims to predict a) whether people are experiencing cognitive load while they watch a video and b)

whether people are given context for the protagonist's behavior prior to watching the video. Together, these experiments allow us to explore how different approaches perform when predicting persistent yet malleable mental states (Experiment 1), cognitive processes (Experiment 2), and experimentally-induced narrative perspectives (Experiment 2). Across both experiments, participants' brain responses were measured with functional near infrared spectroscopy (fNIRS), which serves as an especially useful tool for predicting with extended naturalistic stimuli given its superior portability, tolerance for movement, and participant comfort compared to fMRI and EEG (Burns & Lieberman, 2019; Scholkmann et al., 2014).

While MTPA uses feature selection to reduce dimensionality, we also compare its performance to other dimension reduction techniques, including a feature extraction-based MTPA using PCA, down-sampling with windowed averages, and models with no temporal dimension reduction. We focus our analyses on neural activity in the dorsal mPFC (dmPFC), anterior mPFC (amPFC), and TPJ – fNIRS-accessible default mode network hubs respectively implicated in mentalizing and social cognition, affective and self-referential processing, and the construction of subjective construals (Lieberman, 2022; Lieberman et al., 2019; Roy et al., 2012).

Across both studies, we expect that MTPA will outperform the other approaches in prediction accuracy. Although we expect feature extraction-based MTPA to predict outcomes more accurately than models that use down-sampling and no dimension reduction, we expect feature selection-based MTPA to be most generally effective, ultimately making the case for an interpretable and predictive approach tailored to the temporal structure of extended naturalistic stimuli.

While the main scope of this project is to compare MTPA to more conventional analytic approaches, we also have hypotheses surrounding the predictive capability of each ROI. For predicting people's psychological lenses surrounding their careers in Experiment 1 and whether people were given narrative context in Experiment 2, we expect that all ROIs will be predictive in some capacity given their roles in high-level meaning making and socio-cognitive processing broadly. For Experiment 2, we expect that cognitive load will affect activity in medial prefrontal areas while TPJ processing will remain unchanged (see the CEEING Model of Pre-Reflective Subjective Construal; Lieberman, 2022), so only activity in the amPFC and dmPFC should reliably predict whether people are experiencing cognitive load.

Experiment 1: Methods

The data for Experiment 1 were reported in a separate study using a single analytical approach and focusing on the psychological implications of the findings (Goldstein et al., 2025). That paper provides a comprehensive description of the experimental design, data collection, and primary results. The current study focuses specifically on comparing different dimension reduction techniques for neural timeseries data.

Participants

Participants ($N = 68$) were business executives who attended "Summit LA," which is an organizational festival that invites successful founders, CEOs, and other executives to build community and discuss ideas for a weekend in Los Angeles. Of the 68 participants, 47 identified as male and 21 identified as female. One participant did not fill out the post-study survey necessary for analysis, leaving a final sample of $N = 67$ (mean age = 41.5 years old, $SD = 9.87$).

Procedure

Participants who provided consent were invited into a pop-up neuroimaging lab in an office suite near the festival and fitted with an fNIRS cap. The experimental session consisted of two parts. First, participants engaged in a group interaction task where they took turns pitching each other ideas. The current study uses data from the second half of the session, unrelated to the group interaction task. In this phase of the experiment, participants' brains were scanned with fNIRS while they watched a video compilation of other executives talking about their attitudes toward work (Figure 1). After watching the videos, participants completed a post-study survey with a battery of questions probing their thoughts and feelings toward their career.

Outcome measures

After watching the videos, participants responded to four outcome measures that probed negative social-emotional sentiments toward their career: "I need a new or different challenge," "I feel overwhelmed," "I feel underappreciated," and "I feel burned out." Participants were instructed to respond to the measures as if they were thinking about their career in general. We used a 7-point Likert scale from "strongly disagree" to "strongly agree." We selected these specific outcomes because we believed them to be generally representative of aversive work-related experiences yet distinct enough from one another to capture different elements of the phenomenon.

To prepare data for machine learning, responses were binarized into "high" and "low" groups. Midpoints of response distributions were chosen to ensure near-balanced group distributions. Due to skewness, the underappreciated measure was excluded from further

analysis. Minority groups were upsampled via randomized repetition to address class imbalance.

fNIRS data acquisition and preprocessing

We used NIRx NIRScout machines with a sampling rate of 3.906 Hz at wavelengths of 760 and 850 nm. Optodes on the fNIRS caps were arranged at 3-cm average source-detector separation distance over the prefrontal cortex (PFC), the temporal parietal junction (TPJ) and superior parietal lobule (Figure 2). 10-10 UI external positioning system was used to standardize the layout of our probes.

fNIRS data was sent through a customized preprocessing pipeline (Binnquist & Burns, 2021). Several steps were then employed to reduce dimensionality and smooth the data during preprocessing. First, we selected specific brain ROIs. Given neural synchrony research implicating the default mode network in semantic and socio-cognitive processing (Lieberman, 2022), we focused our search to channels over the bilateral TPJ, the amPFC, and the dmPFC. Once the channels were averaged into their respective ROIs, we resampled the timeseries for each ROI from 3.906 Hz to one sample per second to further smooth our signal.

Model training and prediction

This research compared analytic approaches for neural timeseries-based machine learning models. For each model, our analysis process can be broken down into two parts – dimension reduction and classification. Analyses primarily differed in how they reduced dimensionality.

Dimension reduction. We applied three approaches: MTPA with elastic net feature selection, MTPA with PCA feature extraction, and a down-sampling method using windowed

averages. These approaches are also compared to a model which used the entire neural timeseries without dimension reduction.

MTPA with elastic net feature selection. The feature selection-based MTPA was developed for Goldstein et al. (2025) to predict whether people feel overwhelmed, burned out, or in need of a new or different challenge with this same dataset. In this case, the temporal searchlight was performed with elastic net regression – a regularized regression technique that combines penalties from lasso (L1) and ridge (L2) to determine the best features. Lasso alone tends to delete features too easily if they are highly correlated, as in a timeseries (Zou & Hastie, 2005). On the other hand, ridge regression handles multicollinearity well, but it does not eliminate features. Elastic net combines the strengths of both methods – robust shrinkage and retention of useful correlated variables, making it particularly well-suited for high-dimensional datasets like those encountered in neuroimaging. By nature of being a feature selection approach, elastic net also allows us to map exact features back onto timepoints in the stimulus, offering added benefit of exploring what is occurring in the stimulus when neural responses diverge between groups.

For these analyses, we used MATLAB's *lassoglm* to execute the elastic net feature selection. *lassoglm* determines the variables that are most representative of between group differences by selecting the lambda, or shrinkage parameter representing the strength to which coefficients are penalized and reduced to 0, automatically through 10-fold cross-validation. Elastic net is also adjusted by a penalty parameter, alpha, which determines the relative contribution of the lasso and ridge penalties. For our purposes, the alpha parameter was manually set at 0.9 – closer to lasso to encourage as much sparsity as possible while still

accounting for potential correlations among predictors. The combination of alpha and lambda parameters on the training set determined which features were retained. We then reduced the features of the training and testing timeseries to the selected features from the elastic net. All other features in the training and testing timeseries were discarded.

MTPA with PCA feature extraction. The feature extraction-based MTPA used principal component analysis (PCA) to reduce the dimensionality of the neural timeseries. PCA transforms high-dimensional data into a smaller set of orthogonal components while retaining as much variance as possible. The first component captures the direction of maximum variance in the data, the second component captures the maximum variance orthogonal to the first, and so on. While PCA does not retain individual timepoints in the way feature selection methods do, it allows for a compact representation of the neural data, which can be particularly advantageous for high-dimensional datasets with limited sample sizes.

We used MATLAB's *pca* function to perform PCA feature extraction. To ensure that we optimized the number of components while avoiding overfitting, we applied 10-fold cross-validation within the training set to test the performance of models with different numbers of components. The number of components that achieved the highest cross-validated accuracy in the training data was then retained. Once the optimal components were identified, the training and testing timeseries were both projected onto this reduced set of components, and all other features were discarded.

Down sampling with windowed averages. For the down-sampling approach, we averaged over sets of features rather than selecting or transforming individual variables. By averaging adjacent timepoints within a window, this method helps to suppress noise and

variability while retaining meaningful trends in the data. This can be especially useful for cognitive processes when fine-grained temporal fluctuations may not provide much predictive value, as may be the case for high-level cognitive and social processes.

To optimize the performance of this approach, we used 10-fold cross-validation within the training set to test a range of possible window sizes from 2 seconds to 1-minute. The window that yielded the best cross-validated accuracy was then applied to both the training and test datasets.

Classification via neural reference groups approach. The classification process was identical for all analyses compared here. We followed a neural reference groups approach (Dieffenbach et al., 2021) that trained models to recognize patterns of neural activity for people in two distinct groups and then classify new people based on the group with which they show more neural similarity. Considering that the main goal of this paper is to evaluate how dimension reduction affects prediction with neural timeseries, we chose a logistic regression classifier over other models because of its linear framework and simplicity, though different methods may also be employed with the same dimension reduction approaches.

We used leave-one-out cross validation to train and test our model. Our analyses were performed independently for each question and each ROI. The predictive performance of the model was evaluated on the held-out test samples' timeseries. This entire process, including the dimensionality reduction was repeated for every sample in our data, and we completed 50 iterations of this process to reduce sampling bias in our prediction. Cross-validated predictive performance was averaged across folds and iterations.

Significance testing and comparison

Permutation testing was used to assess how our actual predictive performance compared to what we would anticipate by chance. We conducted each approach described above 1000 times with shuffled labels. The outcome was a random chance-level distribution of cross-validated prediction accuracies representing the null hypothesis. Statistical significance was calculated by finding the number of permuted samples that are equal to or exceed the observed prediction accuracy, divided by the total number of iterations.

To evaluate the performance of the four methods across ROI-measure combinations, we conducted one-way ANOVA tests comparing prediction accuracies for each combination. The accuracies from the 50 iterations were used as the distributions for each group in the ANOVA. Significant differences were followed by post hoc Tukey's HSD tests to identify pairwise differences between methods (e.g., elastic net vs. no dimension reduction).

Experiment 1 Results and Discussion

Feature selection-based MTPA successfully predicted participants' psychological outcomes in four out of nine tests, spanning two of three measures (feeling overwhelmed and needing a new or different challenge) and all three ROIs (Figure 3). Using neural activity from the TPJ, the MTPA accurately predicted whether participants felt overwhelmed with 72.84% accuracy ($p = 0.004$). Neural activity from the dmPFC also predicted whether people felt overwhelmed with 64.51% accuracy ($p = 0.034$). The strongest predictive performance overall occurred when neural activity in the dmPFC was used to predict whether participants felt in need of a new or different challenge in their careers (79.13%, $p < 0.0001$). The amPFC also

showed predictive power approaching significance for this outcome, with accuracy reaching 63.29% ($p = 0.058$). These data were reported in Goldstein et al. (2025).

To evaluate how feature selection-based MTPA performed relative to other approaches, we tested the prediction accuracy of a feature extraction-based MTPA using PCA, down sampling with windowed averages, and a model using the full timeseries without dimensionality reduction. Across these approaches, PCA, windowed averaging, and the no dimension reduction model each showed moderate accuracy only for predicting whether people were burned out using the dmPFC. Prediction accuracies were 66.60% ($p = 0.011$), 63.43% ($p = 0.037$), and 65.79% ($p = 0.014$) for PCA, windowed averaging, and the full timeseries models without feature selection, respectively. These approaches did not predict any other outcomes or brain measures.

To evaluate how feature selection-based MTPA performed relative to other approaches, we conducted ANOVA comparisons across analytical approaches for the ROI-measure combinations that demonstrated at least modest prediction accuracy. The results showed significant differences in prediction performance for all comparisons ($p < 0.0001$). Post hoc Tukey's HSD tests revealed that elastic net statistically outperformed all other approaches for four out of five tests, while PCA performed best on the remaining test, followed closely by no dimension reduction (Figure 4). Specifically, when predicting whether someone felt overwhelmed using the TPJ, elastic net achieved significantly higher accuracy than PCA, windowed averaging, and no dimension reduction (mean differences: +27.58%, +24.18%, and +22.15%, respectively, all $p < 0.0001$). When predicting whether someone felt overwhelmed using the dmPFC, elastic net again outperformed PCA, windowed averaging, and no dimension

reduction (mean differences: +15.52%, +15.28%, and +15.05%, all $p < 0.0001$). Elastic net exhibited the highest performance when predicting whether someone needed a new or different challenge with the dmPFC, exceeding PCA, windowed averaging, and no dimension reduction (mean differences: +28.07%, +26.07%, and +19.16%, all $p < 0.0001$). Elastic net also demonstrated significantly higher accuracy than PCA, windowed averaging, and no dimension reduction when predicting whether someone needed a new or different challenge with the amPFC (mean differences: +7.00%, +5.97%, and +4.03%, all $p < 0.0001$). Conversely, elastic net achieved significantly lower accuracy compared to PCA, windowed averaging, and no dimension reduction when predicting whether someone was burned out with the dmPFC (mean differences: -18.72%, -15.55%, and -17.91%, respectively, all $p < 0.0001$).

Results from this experiment demonstrate the advantages of MTPA models using elastic net feature selection. While feature extraction, down-sampling, and using the full timeseries each predicted one out of nine possible ROI-measure combinations, feature selection-based MTPA successfully predicted four combinations spanning two out of three outcome measures and all target ROIs. These findings confirmed our hypotheses, offering preliminary evidence for MTPA's use as a tool for predicting complex psychological states with neural timeseries data.

Experiment 2 Methods

Experiment 2 aimed to predict two distinct outcomes: whether participants were experiencing experimentally-induced cognitive load while watching a video and whether participants were given prior contextual information about the protagonist's behavior prior to the video. Although the type of outcome measures and participant population differ from

Experiment 1, the model training, prediction, significance testing, and comparison procedures remain identical to ensure consistency and support the generalizability of the previous findings.

Participants

Participants ($N = 92$) were undergraduate students recruited through the Psychology student subject pool. 20 identified as male, 71 as female, and 1 as non-binary. The mean age was 23.16 years ($SD = 6.00$). We aimed to recruit 30 participants per condition, with a slight oversampling to account for potential data loss. Due to equipment failure, data from one participant were excluded, resulting in 91 participants included in the final analysis. Participants were required to be fluent English speakers, have normal or corrected-to-normal vision, and be naïve to the movie clip used as a stimulus.

Procedure

All participants were scanned with fNIRS while they watched a three-minute scene from the movie “Brothers.” The video depicted a character behaving aggressively while other characters become upset and try to restrain him. The protagonist’s behavior could be interpreted through either situational or dispositional factors, and the video was displayed without sound to create more variability in interpretation. Participants viewed the clips under the following conditions: no-context, context, and context/dual-task (Figure 5). In the no-context condition, participants were simply instructed to watch the video closely. In the context condition, participants were told “This man has just learned that his wife has been cheating on him with his best friend.” Participants in the context/dual-task condition were given the same prompt, but they were also instructed to memorize a series of eight random digits prior to the

video, repeat these numbers in their head during the video, and recall the numbers in the correct order after the video. This simple dual-task design was used to induce cognitive load.

Outcome measures

We aimed to predict central aspects of participants' condition assignment – whether they were experiencing cognitive load and whether people received context for the protagonist's behavior. To ensure a balanced sample and reduce confounds, each outcome only utilized two out of the three conditions. When predicting whether people were experiencing cognitive load, we used the context and the context/dual-task conditions as our two classes. As a result, both classes were consistent in that they received context, differing only in whether they experienced cognitive load. When predicting whether people received context, the context and no context conditions were used. In this case, neither class performed the dual-task, so they differed only in whether they received context.

fNIRS data acquisition and preprocessing

We used NIRx NIRSport2 machines with a sampling rate of 3.8147 Hz at wavelengths of 760 and 850 nm. The probe layout was comprised of 32 light sources and 32 detectors with a 3-cm average source-detector separation distance over the entire head (Figure 6). 10-10 UI external positioning system was used to standardize the layout of our probes.

fNIRS data was sent through the same preprocessing pipeline described in Experiment 1. Though we had full-head coverage with this montage, we selected the same ROIs as in the previous experiment to limit comparisons and remain consistent. We resampled the timeseries for each ROI to one sample per second to further smooth our signal.

Experiment 2 Results and Discussion

Feature selection-based MTPA using elastic net regression successfully predicted both outcomes – whether someone was experiencing cognitive load while they watched a video and whether someone was given context for a character’s behavior prior to the video (Figure 7). First, neural activity in the amPFC predicted whether participants were experiencing cognitive load with 66.53% accuracy ($p = 0.026$). Models using neural activity from the TPJ predicted whether people had received contextual information about the protagonist prior to the video with 65.93% accuracy ($p = 0.024$).

Beyond the elastic net approach, models using feature extraction-based MTPA with PCA were able to predict whether participants received narrative context with neural activity from the amPFC (64.75%, $p = 0.031$). The windowed averaging approach produced the next highest prediction accuracy for the same ROI-measure combination (62.30%, $p = 0.049$). The full timeseries did not achieve significant predictive performance for any of the measures or ROIs.

To evaluate how feature selection-based MTPA performed relative to other approaches, we conducted ANOVA comparisons across analytical approaches for the ROI-measure combinations that demonstrated significant prediction accuracy. The results showed differences in prediction performance for all comparisons ($p < 0.0001$). Post hoc Tukey's HSD tests revealed that elastic net statistically outperformed all other approaches for two out of three tests, while PCA performed most effectively for the remaining test (Figure 8). Specifically, when predicting whether someone was experiencing cognitive load with the amPFC, elastic net achieved significantly higher accuracy than PCA, windowed averaging, and no dimension reduction (mean differences: +20.40%, +13.07%, and +15.23%, all $p < 0.0001$). When using the

TPJ to predict whether someone was given context prior to watching the video, elastic net also outperformed PCA, windowed averaging, and no dimension reduction (mean differences: +9.69%, +6.72%, and +8.76%, all $p < 0.0001$). However, when using the amPFC to predict whether someone was given context prior to watching the video, PCA outperformed all other methods (elastic net: +4.23%, $p < 0.0001$; windowed averaging: +2.16%, $p = 0.003$; no dimension reduction: +2.98%, $p > 0.0001$).

Overall, these findings replicate and extend the findings from Experiment 1. PCA, and to a lesser extent windowed averaging, was effective in predicting one measure with one ROI, but the elastic net approach was able to predict both outcome measures using two out of three ROIs. By successfully predicting both cognitive load and prior narrative context from neural data, MTPA proves to be an effective method for identifying predictive neural patterns in naturalistic settings above and beyond alternative methods or no temporal dimension reduction. These findings also support MTPA's general effectiveness across different types of measures and participant populations.

Additionally, by demonstrating that the amPFC predicts whether someone is experiencing cognitive load or not while the TPJ predicts narrative context, the elastic net MTPA revealed patterns that align with emerging theories differentiating sub-areas of the default mode network (Lieberman, 2022). Specifically, the CEEing model hypothesizes that TPJ will be more sensitive to narrative framing than cognitive load due to its role in integrating sensory and non-sensory information into pre-reflective construals, whereas mPFC regions will be more sensitive to cognitive load given their role in more effortful reflective processes. To illustrate these functional differences, a two-way ANOVA between ROI (amPFC and TPJ) and outcome

measure (whether someone was under cognitive load and whether someone received narrative context prior to the video) revealed a significant interaction: $F(1, 196) = 316.95, p < 0.0001$ (Figure 9). This interaction indicates that the effect of the specific ROI depends on the measure being predicted. There were also simple effects for ROI within each measure (load: $F(1, 98) = 177.98, p < 0.0001$; narrative context: $F(1, 98) = 140.99, p < 0.0001$) and for the measure within each ROI (amPFC: $F(1, 98) = 155.31, p < 0.0001$; TPJ: $F(1, 98) = 163.85, p < 0.0001$). Together, these results suggest functional differentiation across the TPJ and amPFC align with theoretical frameworks like the CEEing model – the TPJ demonstrates a significant role in how context framing shapes how we see and understand a narrative while the amPFC demonstrates a greater sensitivity to cognitive load. Notably, these patterns were only apparent when using the MTPA approach with elastic net, further underscoring the advantage of applying feature selection-based dimension reduction techniques when working with neural timeseries data.

Discussion

This study introduces and validates MTPA as an effective method for reducing the temporal dimensionality of neural timeseries data into a sparse and interpretable set of features for machine learning. Across two experiments, feature selection-based MTPA using elastic net regression consistently outperformed than alternative and more conventional methods, predicting six out of twelve possible tests. PCA and windowed averaging performed effectively on two occasions. Using the full timeseries without feature selection was successful only once. These findings demonstrate the broad efficacy and applicability of using MTPA prior to classification, specifically emphasizing the advantage of feature selection-based MTPA.

Approaches were compared across significant ROI-measure combinations, and elastic net outperformed all other methods in six out of eight tests, often with large and statistically significant mean differences (e.g., elastic net exceeded PCA, windowed averaging, and baseline by 27.6%, 24.2%, and 22.2%, respectively, when predicting whether someone needed a new or different challenge with the dmPFC). In contrast, PCA emerged as the top-performing method in two tests, suggesting that PCA can serve as a viable alternative in some cases although it mostly fell short of elastic net overall. The baseline approach that did not apply dimension reduction and windowed averaging lagged elastic net or PCA in all comparisons.

Notably, feature selection-based MTPA generalized well across both experiments despite their differences in methods and objective. Experiment 1 was conducted in the field with a real-world population of business professionals and successfully predicted persistent, oft-hidden social-emotional states such as feeling overwhelmed and needing a new or different challenge in one's career. Experiment 2 was conducted in a controlled laboratory setting with an undergraduate participant population and focused on cognitive load and narrative context during video viewing. MTPA with elastic net successfully predicted outcome measures in all three tests. Feature selection-based MTPA's ability to generalize across distinct populations (real-world and lab-based) and outcome types (persistent psychological states, cognitive processes, and contextual understanding) highlights its strength and versatility.

Interpretability and practical applications

Beyond its higher predictive power compared to other methods explored here, MTPA offers a second critical advantage – interpretability. By selecting specific timepoints that contribute to group-level differences, elastic net allows researchers to map neural responses

back to precise moments in a stimulus. This temporal specificity allows us to reverse-engineer the specific timepoints in the video stimulus that evoke distinct neural profiles between groups, offering insights into the connection between stimulus content, neural activity, and psychological lenses (for an example, see Goldstein et al., 2025).

In contrast, PCA transforms the data into components that maximize variance but lose direct connection to the original timepoints. While PCA achieved moderate prediction accuracy in some cases, its lack of temporal interpretability limits its utility for understanding the dynamics of neural responses during complex, naturalistic stimuli. Similarly, methods like windowed averaging smooth over meaningful temporal fluctuations and fail to leverage the richness of long neural timeseries. We believe this is another reason why MTPA with elastic net feature selection is the optimal choice for most cases using naturalistic stimuli.

Conclusion

The ability to analyze neural responses from extended naturalistic designs has become a central goal in social neuroscience. However, while these stimuli afford ecologically valid experiences that closely approximate real-world processes, their length and resulting temporal complexity pose major computational challenges due to overfitting and poor generalization. This study demonstrates that MTPA alleviates these challenges by reducing the timeseries into sparse yet interpretable patterns of timepoints that improve predictive power. Consistent findings from the two experiments showed that feature selection-based MTPA predicts a variety of measures above and beyond PCA, windowed averaging, and no temporal dimension reduction – approaches that all either eliminate psychological interpretability, aggregate over important variability, or use overwhelmingly long neural timeseries. As naturalistic stimuli

become increasingly prevalent, methods like MTPA will be essential for leveraging the brain to predict how people think, feel, and behave in dynamic, real-world contexts.

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Disclosure of interest

The authors declare no competing interests.

Data availability

Data for these experiments can be accessed online at <https://osf.io/b84c3/>.

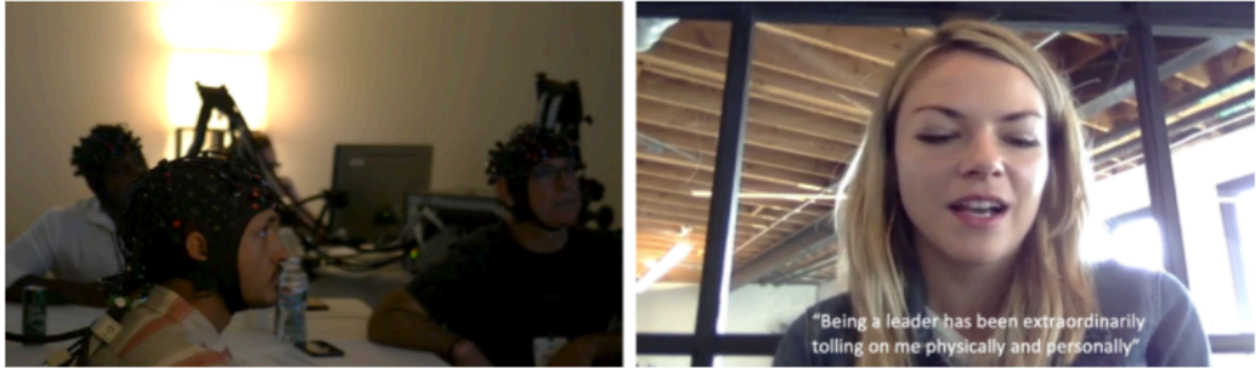


Figure 1. Stills from the experiment and video stimulus. The left image shows participants wearing fNIRS and watching the video together. The right image is a still from the video stimulus, where other business executives were instructed to speak about the positive and negative aspects of their work. Captions were not included in the original stimulus.

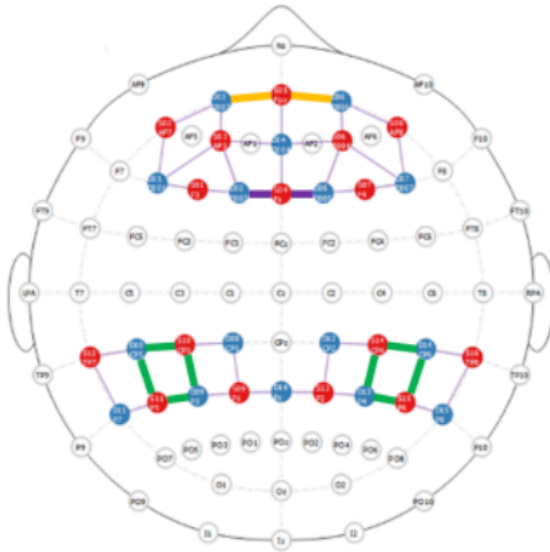


Figure 2. Montage of fNIRS probes across the prefrontal cortex, temporal parietal junction, and superior parietal lobule. The red dots represent source optodes and the blue dots represent detector optodes. ROIs are highlighted in orange (amPFC), purple (dmPFC), and green (TPJ).

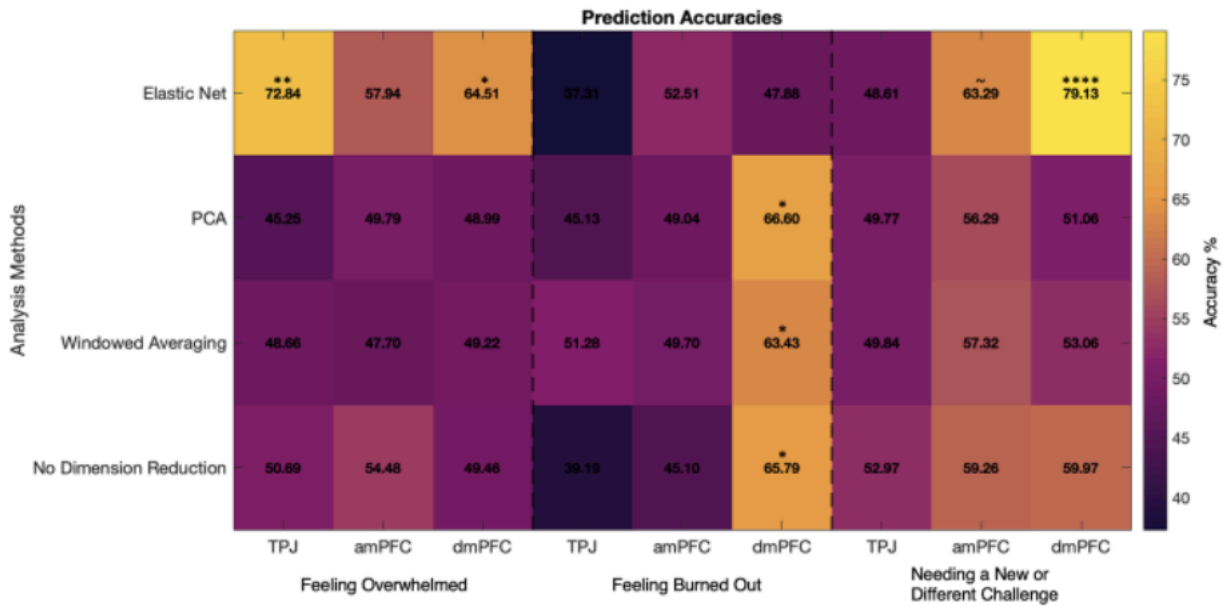


Figure 3. Heatmap of prediction accuracies for each analysis approach, ROI, and outcome measure. Note: **** $p < 0.0001$, *** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$, ~ $p < 0.06$

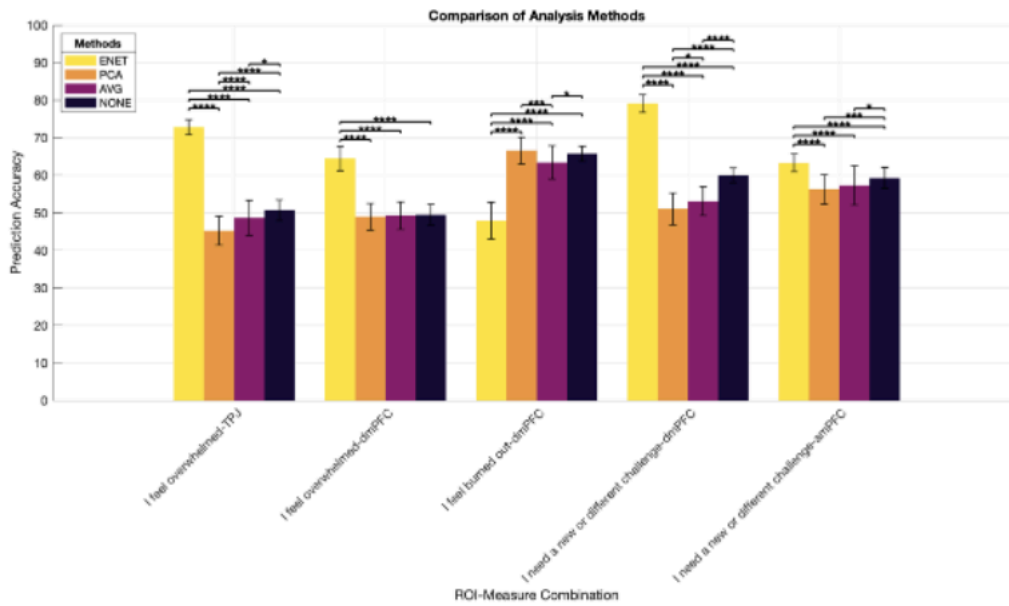


Figure 4. ANOVA comparisons of prediction accuracies across analysis methods for significant

ROI-measure combinations. Bars represent mean prediction accuracies with standard

deviations, and significance brackets indicate pairwise differences from Tukey's HSD tests.

Note: **** $p < 0.0001$, *** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$



Figure 5. Instructions provided to participants in each of the three conditions for Experiment 2.

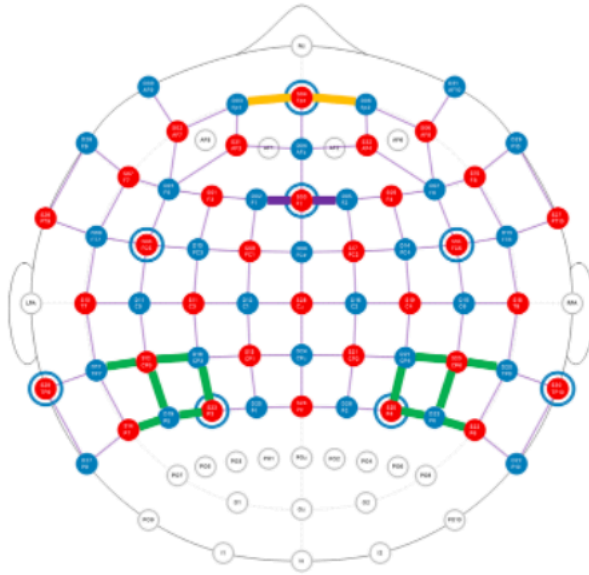


Figure 6. Montage of fNIRS probes for the 108-channel full-head setup. The red dots represent source optodes and the blue dots represent detector optodes. Red dots encircled with blue rings represent short-channel detectors which aid in preprocessing. ROIs are highlighted in orange (amPFC), purple (dmPFC), and green (TPJ).

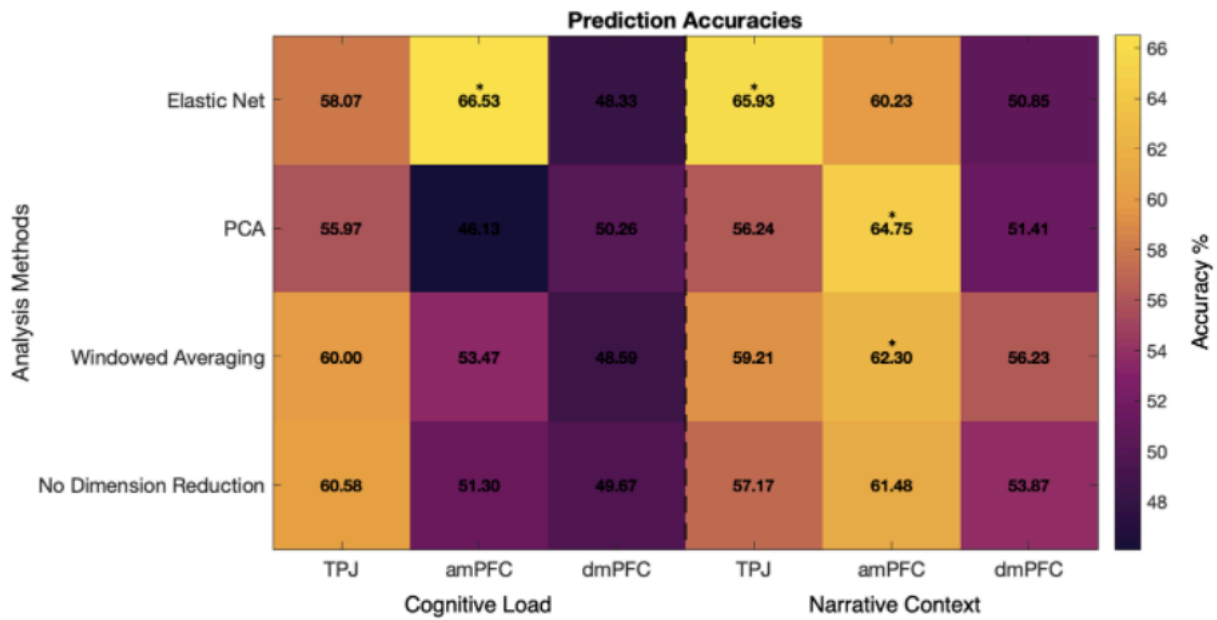


Figure 7. Heatmap of prediction accuracies for each analysis approach, ROI, and outcome measure. Note: * $p < 0.05$, ~ $p < 0.06$

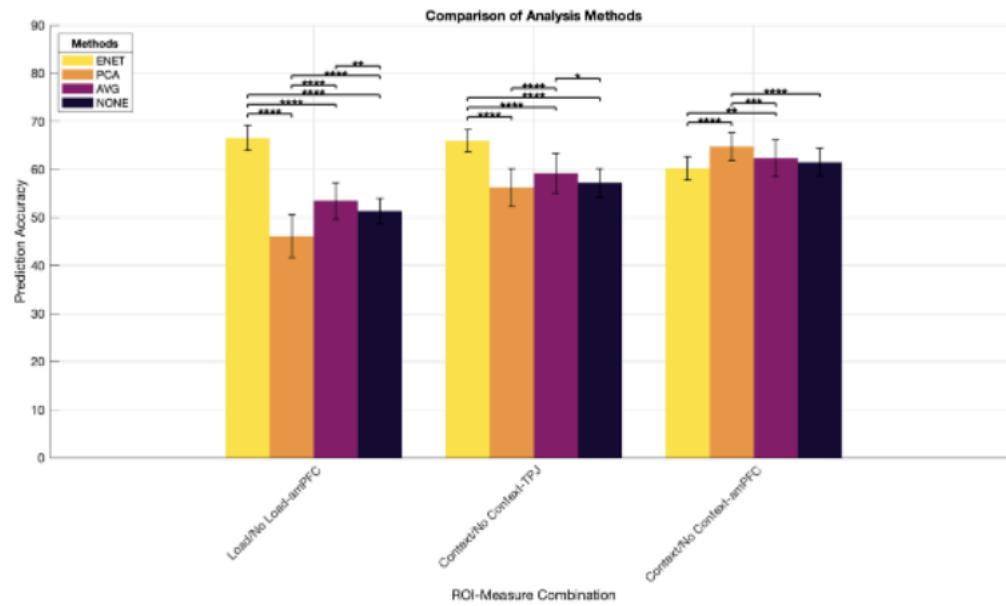


Figure 8. ANOVA comparisons of prediction accuracies across analysis methods for significant

ROI-measure combinations. Bars represent mean prediction accuracies with standard

deviations, and significance brackets indicate pairwise differences from Tukey's HSD tests.

Note: **** $p < 0.0001$, *** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$

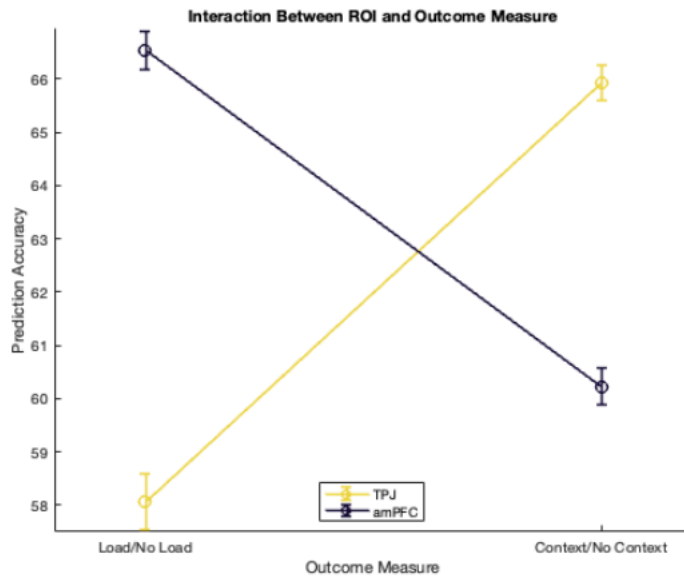


Figure 9. Interaction between brain region and outcome measure. Interaction and all post hoc pairwise comparisons are significant $p < 0.0001$.

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