# Neurometrics Development for non-neuroscientist social researchers; neuroscientists will benefit too

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## Abstract

Development of neurometrics such as attention, excitement, and interest would allow social scientists to use Neuroscience advancements faster and more easily Neuroscience advancements in their fields. While several private organisations provide such metrics based on raw EEG signals, they often lack academic transparency regarding the methodology specifications and the performance of the computed metrics, leading to reluctance among researchers. Clearly stated metrics performance in predicting the intended cognitive state and an increased transparency with regard to the methodology of their development should diminish this reluctance.

We found that basic neural networks do a very good job in linking the raw EEG values with market leader metrics scores. Nevertheless, we did not link the raw values with direct scores of the cognitive and emotional states in this stage; as the amount of necessary data to train and test neural networks is quite large, we used data sets of EEG readings and their corresponding vendor's metrics from other academic and commercial projects.

Both methodologies to elicit and modulate cognitive states and mean scores for various stimuli, such as images, music plays, and movies excerpts are available, and they would be used in the next stage of our attempt.

**Keywords:** Neurometrics, Neuroscience, Social sciences, Consumer neuroscience, Neural networks

## Introduction

Over the last twenty years, Neuroscience has experienced faster and more significant developments not only than any other social science, but also than the ones achieved by most of the other sciences in general. Publicly financed programs such as Blue Brain Project, Obama Project, and Human Brain Project encouraged universities and research institutes not only to undertake ambitious individual projects but also to cooperate at unprecedented intensity. Private initiatives added to that, with main contributions coming from the leading IT companies, Marketing agencies, and producers of a wide array of instruments meant to facilitate a more in-depth understanding of human emotional and cognitive states – such as research-grade EEG headsets, eye-tracking devices, PET and fMRI apparatus and related software.

Medical applications such as transcranial stimulation put aside, other major achievements have been made, including a completely functional model of a cubic millimetre of a mammalian brain – about 500000 neurons – functional brain-computer-brain interfaces, identifying neural populations and circuits engaged in specific cognitive and emotional states. On the other side, many other social sciences are still dominated by theoretical models of a rather normative than positive essence, while most of them adopt the so-called brainless explanatory models, trying to link human actions and behaviours to various stimuli disregarding the way these stimuli are processed by the brain before turning into decisions to act. It comes at no surprise that many studies published over the last decade found that accuracy rates of the attempts to predict consumer preferences using available Neuromarketing instruments (e.g., EEG readings processed with artificial neural networks) went, on average, between 59% and 89% according to Byrne et all., (2022), depending on the neural network involved, much higher than the ones typically reached via traditional approaches. Predicting and modulating behaviours of interest for many other social sciences are essentially no different, no such science has so far come close to making full use of the Neuroscience developments, although large differences in the adoption speed do exist.

The reasons for the reluctance of researchers from other social sciences to incorporate highly valuable knowledge, methods and instruments of Neuroscience into their work are numerous and beyond the scope of this article. We shall present just one of them, which inspired the research project this paper is based on; namely, in most instances, one needs years of Neuroscience study and training before being able to use the raw readings of an EEG headset, for instance, let aside more complex devices. Even with such a training, direct use of EEG readings in other than medical instances is actually impossible (we focus on EEG as by far the most effective and convenient to use Neuroscience instrument outside the medical domain, single responsible for most of the earlier mentioned major improvement in predictive power. Looking to the electrical activity recorded by various EEG sensors would say nothing to most social science researchers; nevertheless, those recordings are transformed into metrics making a lot of sense to virtually all social scientists, such as attention, engagement, excitement, valence, and cognitive load. Not with perfect accuracy, but tree-four times higher than what we can get by traditional means. The fact that they are still not widely used comes at least partly from the lack of transparency of the private vendors that develops these metrics with regard to their effectiveness and construction methods, and, probably, to a lesser extent, from the costs involved. In the current paper, we bring evidence that reliable metrics may be developed with full transparency and reasonable costs.

## Method

### Research objective, context, and constraints

Our project objective is to construct reliable neurometrics for several cognitive and emotional states based on raw

EEG recordings. The development process should be transparent and model accuracy in measuring the respective states must be revealed and documented. The first part of the project investigated how effective standard artificial neural networks are in computing the desired metrics.

Two types of processes are currently involved in constructing neurometrics: analytically developed and artificial neural networks based. They both use elicited and modulated cognitive and emotional states as the sought for dependent variable and use, in the construction process, various techniques to assess these states, including self-responses, observations, and fMRI images. Nevertheless, they differ in the way they attempt to link these states to EEG readings.

The first type is based on neuroscientists' discoveries with respect to what neural populations are activated when a specific cognitive or emotional state is present. Then, the metric is explicitly constructed as a function of activation of the specific brain areas as measured by the EEG headset. By far the most documented metric of this type is the frontal asymmetry index, computed as log ((L/R) /(L+ R)), where L and R are the levels of activation in the left and right frontal or prefrontal cortices, respectively. Almost all the studies, regardless the frequency waves involved, specific statistical transformations, and frontal or prefrontal cortices activity measured, found significant correlation coefficients between the metric's value and the approaching propensity, liking, and buying intention, respectively: Herman-Jones et all. (2010) found that higher left frontal cortex activation is indicative for the person approaching a situation vs, avoiding it; Knutson et all. (2007) and Ramsøy et all. (2018) brought evidence of a strong correlation of prefrontal cortex asymmetry (more left activation than right) and the willingness to pay for the considered item; Avinash et all. (2018) put into the picture the frontal asymmetry as a strong indicator of liking the music the subjects were exposed to. Although almost always significant, the reported correlation intensity is far from constant and in some cases went into the not statistically significant zone. Even if these indexes have a long history as compared to other metrics, their validity is still not clearly understood by researchers, given that frontal and prefrontal cortices are activated by many other processes. Moreover, most other emotional and cognitive states and responses triggered by various stimuli (engagement, attention, excitement) do not benefit from such straightforward metrics. Please have in mind that generating asymmetry in the activation of left and right frontal and prefrontal cortices are in no way the only brain processes found to be related to approachability, liking or wanting, so there is no way to speculate a causal effect. A few other area were found to be systematically activated when the mentioned states are present, such as the nucleus accumbens or the entire ventral striatum when the presented stimulus elicits an approaching type state or the insula when it elicits an avoidance one. However, some of these deeper brain structures activity is much more difficult to be captured by an EEG headset, so their incorporation in an algorithm using EEG data as inputs is meaningless. They are present though in fMRI based studies, such as Erk et. all (2002), Bechara (2005), and Grosenick et. all (2008) as well as in projects focused exactly on recording their activity via EEG sets with brain implanted sensors, such as Citherlet et. all (2019).

A few EEG metrics developed by private companies with the help of artificial networks have been around for more than 10 years now, and claim high accuracy (e.g. Emotiv, www.emotiv.com). They relate the EEG reading to the metric value via artificial networks. There is no need to perfectly understand the brain structures and circuits activated when a specific state is present – as neuroscience does not perfectly know as of today – but to observe robust correlations across thousands of recordings; of course, neuroscientists may guide further research based on such correlations. Moreover, for algorithms aimed at visual attention prediction, several companies (e.g., Neurons, www.neurosinc.com) provide the performance of the neural network, the sizes of training and testing samples and even by how much their products performance increased when going from analytical compounded functions, considering the documented attention triggers, such as contrast, colour, brightness or texture, to artificial networks based algorithms, obtained by comparing images with the heat maps derived from actual eye-tracking records. For the available EEG neurometrics, there is no model specification (type of network, number of layers, number of neurons), size of the training sample and test sample, performance on the test sample or parameters.

Eliciting and modelling specific cognitive states have been a subject of studies for several decades now. Many methodologies have been put forward over the years, involving techniques from hypnosis to movies and music, observing the induced states and asking the respondents about these states, or, more recently, using fMRI to link the stimuli, elicited states and specific neural activity. Gross et all. (1995) provide a table with the mean value of eight emotions prompted by various movies excerpts (23 seconds to eight minutes) according to self-reported scores, while Kenneth et all. (2008) proposed an improved fMRI technique to track the neural activity associated to each emotional response. Pecheco et all. (2018) and Mashail et all. (2024) provide comprehensive literature reviews, classifying and analyzing over 100 published articles which presented methodologies to elicit and evaluate emotions. While some of these methodologies (for instance the ones involving fMRI) will be ruled out for our research, there are many others from which to choose in the stage two, with this specific purpose collected data. For the first stage, we used a leading vendor's metrics values as proxies for the researched states and their corresponding EEG data collected for other projects as we present in the next section.

**Research design**

Previous recordings gave us enough data sets of independent variables – the readings from a 14 channels Emotiv Epoc X EEG headset - and dependent ones - the corresponding six metrics values computed by one of the leading companies in the market. We used over 8000 data sets in the training stage of three neural networks of six layers and less than 100 neurons developed with the help of PyTorch. Then we used some additional 4000 data sets for the testing part (one should keep in mind that these numbers are not as impressive as they may sound, as one minute of EEG recording may provide up to 120 data sets; this is rarely the case, though, due to noise and various channels malfunctioning). These data sets were extracted from best quality recordings in three different projects. Notice that the projects were both academic and commercial, and the stimuli the respondents were exposed to were quite diverse, as well as the respondents themselves; this would make a consistent relationship even more reassuring.

We used the vendor's metric scores as a proxy for the real values of the cognitive and emotional states in this first stage for three reasons:

1. Although methods to elicit and assess cognitive and emotional states are available, their implementation is quite time consuming;

2. The commercially available metrics claim to be developed exactly in the same manner – linking EEG readings to cognitive and emotional states elicited and assessed by published methods via machine-learning mechanisms (as mentioned, they fail to disclose the methods, algorithms specifications and metrics' effectiveness, though);
3. The first part of our project aimed specifically at testing if simple artificial neural networks may supply reasonable and stable levels of input-output correlations in this instance.

Although we are sure that the results presented in the next section could have been further improved, we considered them enough to go to step two, replacing the metric values with values obtained by specific means for each case.

## Results

In the training stage, all three neural networks we developed produced, for each of the six metrics, results correlated with the original metrics values in the range of 0.85, with slight but not systematic differences between the various metrics – see Table 1.

Table 1. Correlation coefficients in the training stage

| (N=4000) | Metric 1 | Metric 2 | Metric 3 | Metric 4 | Metric 5 | Metric 6 |
|---|---|---|---|---|---|---|
| Model A | 0.87 | 0.81 | 0.80 | 0.82 | 0.91 | 0.84 |
| Model B | 0.82 | 0.83 | 0.84 | 0.81 | 0.85 | 0.86 |
| Model C | 0.88 | 0.85 | 0.86 | 0.84 | 0.89 | 0.87 |

We moved along with our best performing model into the test stage, where its results correlated with the original metrics scores at a minimum of 0.82 level – see Table 2.

Table 2. Model performance in the test stage

| (N=2000) | Metric 1 | Metric 2 | Metric 3 | Metric 4 | Metric 5 | Metric 6 |
|---|---|---|---|---|---|---|
| Model C | 0.84 | 0.83 | 0.82 | 0.82 | 0.85 | 0.83 |

## Discussion

We consider this stage of our project was completed successfully, as the results presented in Table 1 and Table 2 show the ability of standard neural networks to consistently link EEG readings to several neurometrics scores. Although all the models predicted the various metrics with slightly different precision, not knowing how effective each metric is in measuring what it should measure we cannot say that a higher correlation obtained by our model necessarily means it is better at predicting that particular state; we do expect thereby that the algorithms that will emerge when actual cognitive scores (as opposed to the current metrics) are used will slightly differ from the current ones; that was the reason why we did not devoted further efforts to improving the current models.

None of the authors of this article is an expert in artificial neural networks; moreover, the 14 channels headset we used for collecting the EEG data produced a rather large number of recordings that had to be excluded from the analysis while accurate readings from more sensors may have led to even better fit algorithms. That's highly important as a non-invasive EEG based metric cannot use valuable inputs from deeper brain structures.

We are aware that various organizations can produce more effective metrics than ours. Our attempt is aimed at encouraging them to develop the best they can and to be the most transparent they can, given the fact that satisfactory results, such as ours, can be obtained with rather modest time, technical and financial resources. Such developments cannot, in our opinion, but help many more social researchers to incorporate these techniques in their work.

## Conclusion

The first part of our project proved that metrics aimed at measuring cognitive and emotional states of interest for a wide array of researchers in social sciences may be developed with the help of deep neural networks with reasonable efforts. While we used more established algorithms output values as proxies for the envisaged states, we have no reason to believe that the results will differ to a great extent when directly calculated scores for these states are used.

## Recommendations

Three critical areas are to be addressed for the best results in the second part of our project:

1. Choosing the best methodology to elicit and modulate the sought-after states, given their reliability, results so far and our time and technical constraints. While databases such as Open Affective Standardised Image Set (OASIS) provide valence and intensity scores for images evaluated by hundreds of respondents, providing valuable benchmarks, for other states, the benchmarks come from far fewer respondents, requiring additional care and effort to correctly evaluate the values to be linked by the EEG readings.
2. A higher reliability and more channels – probably 32 EEG headset would be used. While more sensor readings may translate into more effective algorithms, they also have the potential to produce an increased number of unusable datasets.
3. Acquiring expertise in neural networks may help design structures with higher potential than the ones we chose in the first part of the project.

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## References


Avinash, T., Dikshant, L., Seema, S. (2018). Methods of Neuromarketing and Implication of the Frontal Theta Asymmetry induced due to musical stimulus as choice modeling. *Procedia Computer Science* 132 (2018), pp. 55-67.

Bechara, A. (2005). Decision making impulse control and loss of willpower to resist drugs: A neurocognitive perspective. *Nature Neuroscience*, *8*(11), 1458-1463.

Byrne, A., Bonfiglio, E., Rigby, C., & Edelstyn, N. (2022). A systematic review of the prediction of consumer preference using EEG measures and machine-learning in neuromarketing research. *National Library of Medicine*. Pubmed ncbi.nlm.nih.gov/pmc/articles/PMC9663791.

Citherlet, D., Boucher, O., Trembley, J., Manon, R., Gallagher, A., Bouthillier, A., Lepore, F., Dhang, K.N. (2019). Role of the insula in top-down processing: an intracranial EEG study using a visual oddball detection paradigm. *National Library of Medicine*. Pubmed.ncbi.nlm.nih.gov/31129871/.

Erk, S., Spitzer, M., Wunderlich, A.P., Galley, L., & Walther, H. (2002). Cultural objects modulate reward circuitry. *Neuroreport, 13*(18), 2499-2503.

Grosenick, L., Greer, S., & Knutson, B. (2008). Interpretable classifiers for FMRI improve prediction of purchases. *IEEE Transactions on Neural Systems and Rehabilitation Engineering, 16*(6), 539-548.

Gross, J. J., Levenson, R.W. (1995). Emotion Elicitation Using Films. *Bpl.studentorg.berkeley.edu, 1995, 9*(1), 87-108

Herman-Jones, E, Gable, P. A., & Peterson, C. K. (2010). The role of asymmetric frontal cortical activity in emotion-related phenomena: A review and update. *BiolPsychol. 84*(3), 451-63.

Kenneth A., N., Quamme, J., R. & Newman, L., E. (2008). Multivariate methods for tracking cognitive states. *Princeton Computational Memory Lab*

Knutson, B., Rick, S., Wimmer, G. E. Prelec, D,. & Loewenstein, G. (2007). Neural predictors of purchases. *Neuron, 53*(1), 147-56.

Mashail, N. A., Malak, B., Mohammad, A. (2024). Eliciting and modelling emotional requirements: a systematic mapping review. *National Center for Biotechnology Information*, doi 10.7717/peerj-cs/1782

Pacheco, C., Garcia, I., Reyes, M. (2018). Requirements elicitation techniques: a systematic literature review based on the maturity of the techniques. *IET Software* 2018; 12(4), 365-378.

Ramsøy, T. Z., Skov, M., Christensen, M., K., Stahlhut, C. (2018). Frontal Brain Asymmetry and Willingness to Pay. *Front. Neurosci., 13 March 2018 Sec. Neural Technology, Volume* 12 – 2018.


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