Human Computer Interaction Meets Psychophysiology: A Critical Perspective

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Abstract. Human computer interaction (HCI) groups are more and more often exploring the utility of new, lower cost electroencephalography (EEG) interfaces for assessing user engagement and experience as well as for directly controlling computers. While the potential benefits of using EEG are considerable, we argue that research is easily driven by what we term naïve neurorealism. That is, data obtained with psychophysiological devices have poor reliability and uncertain validity, making inferences on mental states difficult. This means that unless sufficient care is taken to address the inherent shortcomings, the contributions of psychophysiological human computer interaction are limited to their novelty value rather than bringing scientific advance. Here, we outline the nature and severity of the reliability and validity problems and give practical suggestions for HCI researchers and reviewers on the way forward, and which obstacles to avoid. We hope that this critical perspective helps to promote good practice in the emerging field of psychophysiology in HCI.

Keywords: HCI, EEG, Psychophysiology, Reliability, Validity, Naïve Neurorealism

1 Outline

In the following subsections, we will first briefly summarise the history of EEG and describe the rise in use of psychophysiology in HCI. Following, we will discuss that the reduced costs of equipment as well as the increased popular appeal of neuroscience are likely reasons behind the explosive growth of interest. However, we argue that what we term naïve *neurorealism* can lead to unsubstantiated optimism. In short, this concerns the idea that use of psychophysiological measurements necessarily enables objective knowledge of the mind, and thereby must lead to a high degree of insight and user-control. We explain this and illustrate the point and improve discussion by first outlining a hypothetical example of an application scenarios: the BrainGuitar. The device is, to our knowledge, purely fictional and merely serves here to illustrate some of the more serious caveats that occur in the field. We explain how the known methodological aspects of reliability and validity as pertaining to psychophysiological measurements undermine the credibility of inference of mental states. In particular, the weak signal to noise ratio of EEG is discussed, and how strongly this is affected by artifacts. Finally, we provide guidelines for scientists who consider the utility of psychophysiological measurements as well as reviewers who assess the contributions of others.

2 EEG in HCI

In 1929, Hans Berger [1] dramatically showed how EEG can enable us to non-invasively measure human brain activity at a high temporal accuracy. Berger was also the first to discover alpha waves, one of the most prominent features of the EEG. Alpha waves are easily observed as a stereotypical oscillation in the range of 8 Hz–12 Hz that can be observed over much of the scalp (for a history of Berger's work, see [2]). As they appear in the absence of prominent stimuli, they are often used as an index of relaxation, or brain inactivity (however, observation of alpha waves alone is not a sufficient condition to conclude that a reduction of brain activity took place [3]. We will come back to the issue of performing reverse inferences in Sec. 4.6).

Another important discovery in the field was the P300, a brain signal initially observed in concomitance with the presentation of an unexpected stimulus. Discovered in 1965 [4], it manifests itself as a large positive potential starting at approximately 300 ms post stimulus. The P300 is currently believed to indicate saliency (due to an interaction between attention and memory, under one hypothesis [5]). Due to its characteristics (relatively high amplitude and reliability), the P3 allowed researchers to develop the P3 speller, the first working instance of a Brain-Computer Interface (BCI) [6]. This is particularly useful for patients with serious disabilities, such as the locked-in syndrome, for whom a BCI may be the most efficient way to communicate.

As computer technology increased in quality and availability, EEG became more and more available across domains. The relative ease in which raw brain-related signals can be obtained and analysed led to rapid developments. Researchers and practitioners are now able to develop tools based on EEG and other physiological measurements with common electronic devices. It is now, for example, possible to implement a Brain-Controlled address book based on the P3 speller concept even on mobile phones [7].

2.1 The Rise of Brain Informed Human Computer Interaction

In HCI, EEG is used for various purposes. Affective computing [8] and physiological computing [9] are two intertwined branches of this field: in both, cognitive

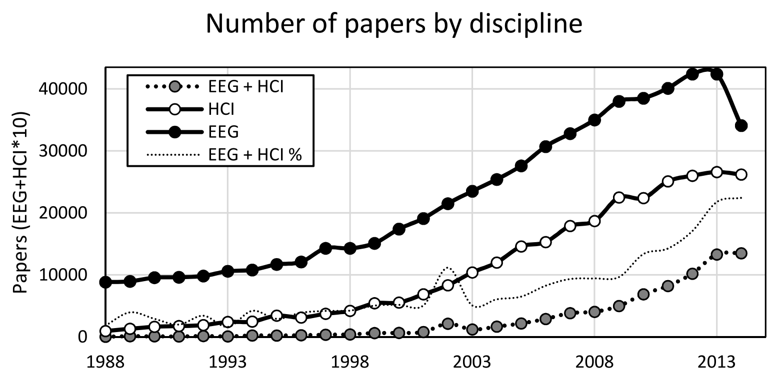

Fig. 1. Growing use of EEG in HCI. The graph displays the growth of published papers in EEG, HCI and the combination thereof, showing greater growth of EEG in HCI (EEG + HCI) than either of its constituent parts, as shown by the growing proportion of EEG in HCI as a function of EEG papers (EEG + HCI %).

and emotional states are predicted or classified based on their physiology (in affective computing, the emotional state is of particular interest). Both investigate how systems should adapt to detected changes in users' own states. For example, it has been attempted to measure task engagement by using EEG alpha asymmetry, i.e. the difference in alpha power between the two hemispheres [10]. In this kind of research, two simultaneous assumptions are made: firstly, alpha power correlates to reduced neural activity and, secondly, greater left than right activity corresponds to positive emotions, and / or high motivation. Another area worth of note is neurofeedback: this area investigates the possibility of building systems that take advantage of "tight feedback loops", so that users' (or patients', for medical applications) cognitive states in a predefined direction. For example, to remain in the domain of alpha oscillations, elderly patients have been trained to increase their peak alpha (10 Hz–11 Hz) power, which was found to be associated with increases in their processing speed and executive function [11]. However, it remains a debated issue that claims regarding the success of neurofeedback may be overblown for marketing purposes, and as many of these systems are commercial, a conflict of interest could be present [12].

The interest of human computer interaction research in psychophysiological data grew exponentially over the last few years. This can be easily seen in Fig. 1, which maps the number of papers (as indexed by Google Scholar) per year from 1988 (the first EEG brain computer interface [6]) to 2014. Of course, scientific production in general continues to grow [13], but it is fair to say that up until 1993, EEG was a fairly uncommon interest for HCI, with ca. 0.6% of publications. However, it seems that the combination of HCI and EEG took off in the subsequent years, roughly doubling in successively 1.5 (1994-1995: 24), 4

(1998-1999: 56), 3.5 (2001-2003: 138), 3 (2005-2007: 297), 3 (2009: 499) and 3 (2012: 1020) years. The same years to double from 1993 numbers for the related disciplines separately would be for 6, 4 and 6 years for HCI and 9 and 10 years for EEG. In other words, the number of published studies using EEG in HCI grows about twice as fast as HCI and three times faster than EEG in general. Whereas use of EEG was extremely rare for HCI in 1993, (at 0.6%), it is now merely uncommon (at 5.2%).

3 Naïve neurorealism

The degree that neuroscience has captured the imagination of the popular press and interest of companies and academic institutions alike is thus understandable, but should be treated with a healthy dose of scientific scepticism. We coin the term *naïve neurorealism* to describe the idea that "the brain cannot lie" and that somehow, a subjective measure immediately becomes objective, accessible and trustworthy because the brain is "directly" involved. The naïvity might stem from the Cartesian assumption that because the brain "causes thought", the measurement of the brain necessarily brings one closer to "the truth".

In HCI, this can for example lead to the idea that one simply plugs in a brain signal and thereby improve an existing user-interface. To illustrate, let us imagine the following, hypothethical scenario in which EEG in HCI could, but should not, be applied:

> *The BrainGuitar.* The guitar remains an extremely popular musical interface. However, its bi-manual multi-touch design is characterised by a steep learning slope that can be an obstacle to many a beginner. We imagine a future in which, rather than relying on our hands, we can directly control the guitar through the use of our brain. The BrainGuitar relies on spectral analysis of EEG signals to determine whether ongoing music is enjoyable or not. If the music produced by the BrainGuitar is not liked, we realign the style to suit the musician's objective taste. A user study was carried out in which 20 practitioners, none of whom had prior experience playing guitar, played 5-10 minutes either with BrainGuitar or normal, classical guitar. We prove with surveys that satisfaction and usability are significantly better with Brain- than normal guitars. Self-reports indicated that BrainGuitar users were surprised to discover their subjective and objective musical taste did not always correspond, showcasing the exploration value of the interface. Finally, we discuss the neurofuture in which everyone can enjoy playing guitar.

In our hypothetical scenario, naïve neurorealism is demonstrated by the invalid assumption that because we use a neural source (possibly), the BrainGuitar is better able to determine whether the user likes a song or not. Combined with the intrinsic appeal of the human mind, this can easily lead to big claims of "mind reading", "mind controling" or "thought identification". However, already in the first BCI-related publication, the authors clarify [6]: "*[...], there is no* *more 'mind reading' in the procedures we describe than there is when a person is handed a pencil and asked to record impressions.*" Mind reading is made vastly more difficult due to concerns regarding reliability and validity.

4 Reliability and validity concerns

Reliability concerns the degree to which measurements are consistent. For example, a measuring tape, properly handled, can reliably indicate a user's height in feet, meters, inches and/or centimetres. It is unlikely to give a very different metric if the measuring is taken on a different day of the week, or by a different person. The validity of a measurement tool concerns the degree to which it measures what it is supposed to measure. A measuring tape can be used to measure one's height, but not weight.

4.1 Source localization

EEG, by contrast, is a very indirect measure: since the electrodes are placed on the skin, rather than in the brain directly, it can only measure the electric potential of the scalp. Electrical potentials with neuronal sources, therefore, are picked up only after having passed other cortical areas, as well as the cerebrospinal fluid, skull and skin, resulting in the well known problem of spatial blurring, and poor spatial resolution of EEG [14]. Indeed, given the already weak signals of individual sources, the only reason we can measure EEG in the first place is because large groups of neurons fire synchronously in the same direction. Accordingly, the topography of an EEG potential gives a poor approximation of its neuronal source, which has given rise to various proposed solutions for predicting scalp activity as a function of a known source (the forward problem, c.f. [15]) and localising sources as a function of measured scalp activity (the inverse problem, [16]).

4.2 Signal to noise ratio

However, as debate regarding localisation problems continues, it is still true that human brain-related EEG has been reliably measured for more than 85 years now [1], and related to specific cognitive functions for over half a century [17]. One of the reasons of this gap again has to do with reliability: although Berger's [1] alpha activity can be easily discerned by the eyes (see Fig. 2, C), being in the range of ca. 30 µV, EEG related to specific sensory or response related events are relatively much smaller. For instance, in the top-right panel, Fig. 2 shows what raw EEG looks like and how much it is affected by visual events (here: focally presented pictures of people).

It is impossible to discern any EEG related to the stimulus due to the amount of background noise relative to the signal (i.e. the low signal to noise ratio). However, as the background noise is presumably unrelated to the event, it can be steadily reduced by repeating the exact same conditions over and over again, and averaging across measurements. Sutton et al. [4] thus used between 30 and

360 repetitions to create the average event related potentials used to discover the P300 (previously mentioned in Sec. 2). Clearly, the number of data points involved in computation over subjects, conditions, channels, timepoints and repetitions was considerable and advancements in EEG benefited accordingly from the availability of computers in university campuses. Much has changed since 1965, but the problem of low SNR in EEG remains. Indeed, both the number of suggested repetitions and emphasis on strong experimental control remains similar in modern EEG [18]. Of particular concern, in this regard, are artifacts in EEG.

4.3 Artifacts

One of the reasons that we require so many repetitions is because EEG is commonly contaminated with artifacts. In particular, EEG is extremely sensitive to eye-blinks and movements, as is portrayed in Fig. 2. In the top left panel, EEG is shown during episodes of eye movements (A) and blinks (B), resulting in activity levels of $>100\,\mu V$. The traditional way to deal with such artifacts is commonly referred to as "artifact rejection by visual inspection", which means that an expert looks at visualisations of the entirety of the data during or after collection, and selects all data that is suspected of being contaminated with artifacts related to eye-movements and blinks, as well as head movements, muscle activity, and so on. The top left panel, in this regard, contains problematic data while the top right seems more normal. These days, EEG studies tend to rely on automatic or semi-automatic classification to distinguish contaminated from clean data, but as the latter tend to account for more variance than the former, artifact rejection is still commonly employed. As this leads to the removal of significant amounts of data, more repetitions are required to sustain the reliability.

Another family of methods commonly employed to enhance SNR are artifact-correction methods. Rather than removing time-points from the data if artifacts are suspected, these methods aim to subtract their contribution from the signal. The classic method for doing this is via linear regression removing the correlation with the electro-oculogram (EOG, [19]), which is normally collected with electrodes placed at sites near the eyes. However, there are drawbacks to this method – it will, for example, also remove the EEG that is collected with EOG electrodes. For this reason, methods that decompose the EEG into components that can be related to artifacts or uncontaminated EEG are becoming more popular [20]. An example is provided in the central top panel of Fig. 2, showing the top left panel as it appeared after removing EOG related components using independent component analysis [21]. Again, the degree of activity after artifact correction is much lower (here ca. 2 times), although it is still clearly higher than during the "clean" interval. For this reason, we have added specific guidelines here regarding artifacts.

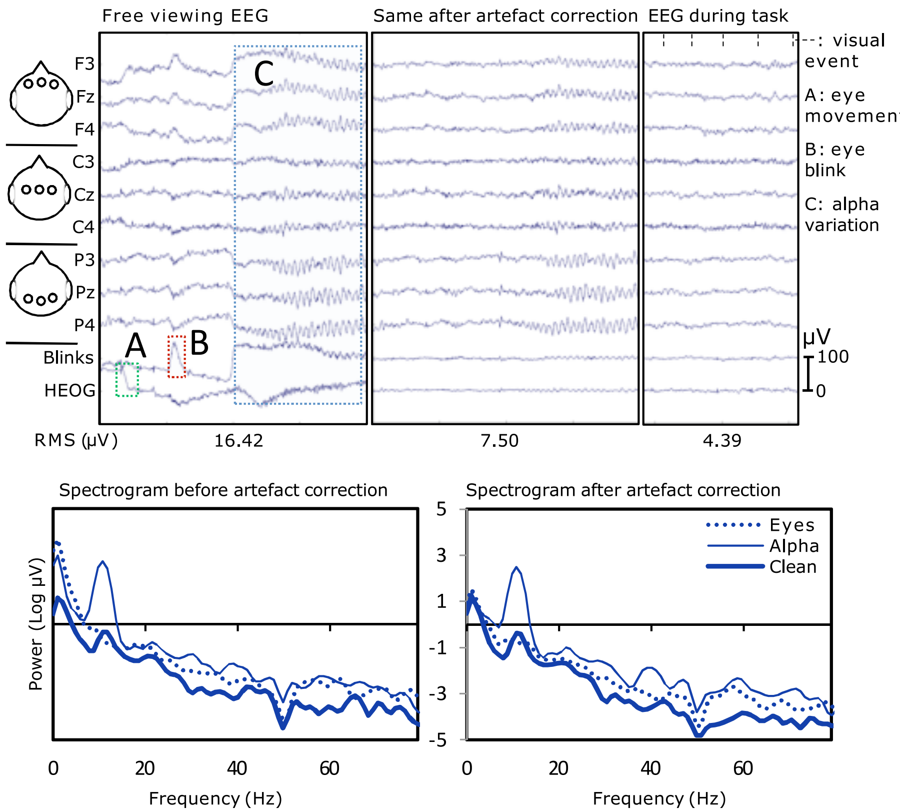

Fig. 2. Effects of artifacts on EEG measurements in time (upper panels) and frequency (lower panels) domains. A, B, and C indicate three common types of contaminating sources related to eye movements, eye blinks and alpha activity. The central top panel shows how artifact correction affects the strongly contaminated top left panel. The top right panel displays typical EEG activity during a task. The lower left panel show the spectral power of the first ("eyes": artifacts A and B), and second ("alpha": C) half of the top left panel, as well as the top-right panel ("clean" data). Finally, The lower right panel shows the spectral power after artifact correction. Data available from `www.hiit.fi/manuel.eugster/aomm2015/`.

4.4 Measuring mental states or systematic artifacts

A common misconception is that artifacts only reduce reliability. However, artifacts may also be disastrous to the validity of a study. For example, the eye movements shown in Fig. 2 strongly affect activity, but not necessarily consistently across spectral frequencies. That is to say, eye movements cause extreme power in the lowest ($<8\,\mathrm{Hz}$) frequencies but do not affect alpha ($8\,\mathrm{Hz}$–$12\,\mathrm{Hz}$) and beta ($13\,\mathrm{Hz}$–$29\,\mathrm{Hz}$) frequencies as much (a common finding, cf. [22]). The higher frequencies ($30\,\mathrm{Hz}$—$200\,\mathrm{Hz}$), meanwhile, are of considerable interest for people interested in consciousness [23], meditation [24] and neurofeedback [25] but as illustrated in Fig. 2, and investigated closer elsewhere [26], [27], it is also possible that eye and muscle movements cause activity within these frequency bands. Consequently, when neuroscientists study how a cognitive function causes differential spectral activity, they aim to control extraneous effects as much as possible to avoid confounds – that is unrelated effects that explain the observed findings. As a result, there is little consensus regarding the relationship between specific frequency bands and cognitive functions.

4.5 Data analysis

Typically, the use of EEG in HCI starts with a simple application idea (here, the BrainGuitar). The first obstacle, as discussed so far, is to map such an idea to a sound neurophysiological paradigm. The second obstacle then, after recording the data, is to rigorously perform the data analysis. Unfortunately, decoding brain states is a difficult data analytic endeavour: major issues are often very specific experimental designs, the unfavourable signal to noise ratio, the vast dimensionality of the data, and the high trial-to-trial variability [28]. Fortunately, recent literature provides comprehensive frameworks for rigorous statistical analysis and predictive modelling: see [29] for a tutorial on single-trial analysis, and [30] for a general approach on evaluating prediction algorithms.

From an application point of view, the final goal of the data analysis is to develop a predictive model which discriminates the different brain states with the highest accuracy. In our hypothetical scenario, this is for example a classifier predicting one of the two classes "I like the song" versus "I don't like the song". Estimating the predictive power and the generalisation error of such a classifier on the measured data is a easy source of mistakes (see [28] for a list of typical pitfalls). Here, we want to underscore one. Neurophysiological paradigms often rely on an imbalance of the brain states under investigation. Consequently, the prediction problem is imbalanced and the used cross-validation scheme as well as the performance measures have to take this into account (see [28], Section 5.6). In the BrainGuitar example, no user had prior experience playing guitar. Therefore, most of the observations are probably "dislikes" and only a few "likes" will be available. A default "I don't like this song" classifier will have a high accuracy but no validity.

4.6 The seductive allure of neurorealism

Neuroscience has brought many advances to our understanding of the brain and mind, to the point that the expectations of its capabilities are clearly exaggerated. Thus, people are known to find even bad explanations more convincing if they come wrapped in neuroscience talk [31]. One of the problems inherent in neuroscience is that the same cognitive (or artefactual) function can map onto various spectral frequencies (see Sec. 4.4) or brain areas, and conversely, that different functions may affect the same frequencies or brain areas. As a result, it is often possible to predict activity in various brain areas (IF mental function X, THEN brain activity Y), but the reverse inference (IF activity Y then mental function X) is fallacious [32], and not necessarily true. Similarly, localising cognitive functions to specific areas can be challenging: for example, hemispheric activity has been linked to both emotional valence (positive / negative emotions) and motivation. Simply observing greater left than right activity would not be informative enough to conclude whether someone is highly motivated, or in a positive mood [3]. Moreover, mappings between brain areas and functions within the same person might not be stable over time, since specialisations in brain areas can adapt to changes in its environment [33]. While it is debatable (c.f. [34]) that the reverse inference can sometimes lead to valuable information, this is not necessarily true.

In the BrainGuitar, one can argue that a correlate for "liking" a song might be found in frontal asymmetry (but see [35]). The fallacy of reverse inference and the naive of the researchers is demonstrated by the surprise of the user: While this should suggest the measurement of liking was invalid, instead they feel the BrainGuitar revealed something beyond the knowledge of the users. Are they sure, we should ask, if they do not pick up correlates that in themselves may be caused by the brain, but are not equivalent to brain signals? For example, eye movements and muscle activity are, of course, caused by brain activity, and contaminate EEG activity, but are not brain activity themselves.

In other words, reverse inferences should be treated with great caution, and overly positive statements such as “enjoyment was determined using EEG” should be avoided. We urge the field (see also [36]) to tread cautiously, particularly when making strong claims in academic work and when talking to the popular media.

5 Other psychophysiological measurements

In this article, we tend to use EEG and psychophysiology interchangeably. This is, on the one hand, because concerns over reliability and validity are not as striking for other physiological measurements such as electrodermal activity (EDA, or galvanic skin response), heart rate (electrocardiogram), respiration rates, and so on. In some cases, combining signals from these sources into a single predictor can provide a better assessment of the users’ state than EEG alone (see [37] for a review).

The source of these measures is rather well localised (the hand, the heart), and the number of associated psychological constructs is limited (usually arousal). However, even for these measures, the relationship is not as simple as it first appears: emotionally exciting stimuli tend to show increased EDA but slowing of heart rate, arousal (as an emotional state) tends to have increased EDA and increased heart rate [38].

Functional near-infrared spectroscopy is another brain imaging technique which measures the blood oxygenation level dependent (BOLD) response, similar to fMRI [39]. This is done by making use of the different light absorption properties of oxygenated and de-oxygenated haemoglobin. It has been successfully employed to image the human brain (see for a review [40]). Although the field remains relatively young, it is generally held that the spatial localisation of superficial frontal sources in particular is good. Given that it is also relatively cheap, at least compared to MRI, and easier to prepare than EEG, it is possible that the technique will be very popular with interdisciplinary disciplines such as HCI. However, it should be stressed that knowing that, for example, the right Brodmann Area 10 is active, does not relieve one from naïve neurorealism: the area has been mapped onto functions of recollection of episodes [41] and odours [42], non-speech sounds [43], risk and reward [44]. Is the BrainGuitar familiar, sound-making, challenging or does it simply smell familiar?

6 Consumer devices

Consumer grade EEG devices are relatively very cheap, usually wireless and are often easier to set up. These two qualities have created a popular sense that the future is mind controlled in mainstream media [45–47]. This future, however, for now largely remains science fiction. In particular, consumer grade devices (e.g. Epoc Emotiv, Neurosky) focus on low cost materials and ease of setting up, which will adversely affect SNR and validity. Science or clinical grade electrodes use highly conducive materials such as silver-chloride (AgCl) and gold in order to capture as much signal from the scalp as possible – materials of which the cost can be prohibitive for single consumers. Furthermore, anything (e.g. air, skin flakes) between the electrodes and scalp will adversely affect SNR, for which reason researchers often prepare the skin (by scraping, use of cleaning materials) and use materials like conducive gel to fill in the space between electrode and scalp. Of course, such procedures are not particularly comfortable and generally require assistance from an extra person.

Finally, while psychophysiology experts prefer the use of many electrodes placed at standardised, equidistant locations on the scalp both in order to increase SNR and to enhance external validity with other research groups, this naturally increases cost and effort. Accordingly, many consumer grade devices use few ($<$16) electrodes. The Emotiv EPOC is a common, noteworthy exception at 14 channels (and two references), although the extra electrodes have a focus on eye and facial muscle activity rather than EEG (but see [48] for a way around). Consumer grade devices provide ready made quantified emotional and cognitive state analysis, but the validity of these classifications cannot easily be assessed as they tend to rest on trade-secrets and subjective reports. This, in fact, leads to exactly the circular problem the present paper is aiming to address: the SNR is poor and it is unclear what is measured. In sum, consumer grade devices may well provide good fun for consumers, but for science these benefits are likely offset by the extra costs and efforts involved if a submission is rejected.

7 Conclusion

The use of psychophysiology in HCI has been remarkable. We have seen many instances in which the fusion of neuroscience and HCI can create new insights and applications. However, the popularity and naïve neurorealism can lead to an overly optimistic idea of making psychophysiology a simple plugin of the human-computer interaction. More importantly, we discussed issues of reliability and validity that make claims regarding direct mind-control tenuous.

To help this exciting new field, we would like to conclude with a few questions. From our experience, it is useful to keep these questions in mind while developing and presenting EEG-in-HCI applications. We hope they may prove beneficial to other researchers and reviewers.

1. How much does the quality of the apparatus involved reflect the study's aims?
2. How much does the conclusion reflect the known limitations of the measurements?
3. Which method was used to correct and/or reject data? How many repetitions were used in the analysis (BCI: training)?
4. Which electrode sites were used as channels and which reference(s) were employed?
5. Do the psychophysiological markers correspond to what the authors aim/claim to measure or could differences have been caused by correlated variables? Is the paradigm sound?
6. Does the control condition provide a valid comparison?
7. Has the work been communicated to the press with an unbiased, factual report, and were all communications with the press reviewed by the involved researchers?

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