

On streamlining data reporting and data sharing practises for promoting research reproducibility in screen-based neuromarketing studies

V. Mygdalis^{a*}, Vangelis P. Oikonomou^b, Kostas Georgiadis^b, Fotis P. Kalaganis^b, Spiros Nikolopoulos^b, Ioannis Kompatsiaris^b and N. Dens^a

^aDepartment of Marketing, University of Antwerp, Antwerp, Belgium;

^bCentre for Research & Technology Hellas, Information Technologies Institute (ITI), Thessaloniki, Greece

*Vasileios Mygdalis (Vasileios.Mygdalis@uantwerpen.be) is the corresponding author

On streamlining data reporting and data sharing practises for promoting research reproducibility in screen-based neuromarketing studies

This paper highlights the importance of standardization in data reporting and data sharing principles in screen-based experiments, from a technical perspective. By focusing on EEG and ET studies, we analyse the reasons that may cause cross-study inconsistencies, hinder research reproducibility and thus limit the potential impact of each research study. To address those issues, we propose a set of guidelines that can serve as a baseline for streamlining neuromarketing studies, including practical advice for improving data reporting and providing incentives for full open data sharing. These guidelines include a detailed list of how experimental conditions should be reported, what type of variables should be extracted, what naming conventions should be used and how these data could be shared. These guidelines can serve as a checklist for almost any ET and EEG-related marketing studies.

Keywords: neuromarketing; eye-tracking; Electroencephalogram

Subject classification codes: include these here if the journal requires them

Introduction

Screen-based neuromarketing studies employ advanced and expensive sensors such as eye-trackers (ET) and electroencephalograms (EEG), in order to collect a wealth of consumer-independent spatiotemporal high-dimensional data, including video recordings and electrical signals corresponding to some given input stimuli e.g., a visual advertisement appearing on a computer screen (Pfiffelmann et al., 2020). These studies increasingly depend on trustworthy signal processing techniques for extracting objective and reliable independent variables that are presumably less prone to biases than other self-reported variables (Vraga et al., 2016). This uptrend is accompanied by a surge in the availability of sensors in universities and research institutions and the active involvement of engineering disciplines in the domain. Signal processing techniques are employed for

the simplification of the collected high-dimensional data signals (e.g., gaze data) into interpretable, comprehensible, one-dimensional variables (e.g., attention time). Typically, a statistical analysis is thereby performed to seek correlations with other independent variables collected using different methods (e.g., questionnaires) and/or with dependent variables (De Keyzer et al., 2023) with the goal of answering some specific research question related to the study.

Despite the fact that many studies have already been conducted by employing ET and/or EEG sensors, we argue that we are still very far from having extracted the maximum amount of factual knowledge that could be distilled by analysing such sensor data. The main reason we identify is the lack of standardization of the data reporting and data sharing practises. More precisely, the variables used in the studies are not standardized; different terminology might be used for identical variables or completely different procedures may be followed to extract seemingly identical variables. Another reason is that the data collected in the studies are maybe not saved, maintained and shared in the most optimal way. The outcome of the raw sensor data acquired and analysed to conduct some study after the study is completed, is up to the researchers and depends on whether proprietary software was employed for their analysis or not. The typical case for many research studies is to either not share any data at all, or to share highly post-processed data that can only be used to reproduce the results of the particular study, not to conduct any other study.

The aim of this paper is to highlight the importance of standardization in data reporting and data sharing principles. By focusing on EEG and ET studies, we pinpoint to the reasons that may cause cross-study inconsistencies, hinder research reproducibility and thus limit the potential impact of each research study. To address those issues, we propose a set of variables that should be extracted and reported in every relevant study,

no matter if they are useful in the particular study or not. Furthermore, we discuss the experimental protocol that should be taken into consideration prior to each study, that is a simple additional step that can help the study increase its impact, as have been proven in other disciplines like computer vision. These guidelines can serve as a checklist for almost any ET and EEG-related marketing studies.

The rest of the paper is structured as follows. Sections 2 and 3 overviews the experimental protocols in ET and EEG studies, respectively, discussing the challenges in terms of experimental settings and what and how variables are extracted from the raw signals. In Section 4 we discuss the proposed practices that promote cross-study coherence and research reproducibility in the respective neuromarketing experiments. Finally, conclusions are drawn in Section 5.

2. Eye-tracking

Eye-tracking technology is one of the most important tools for quantifying consumer attention in screen-based marketing experiments (Orquin & Wedel, 2020; Wedel & Pieters, 2008). The application of eye-tracking technology has assisted in the evaluation of different types of visual stimuli, including different ad designs and product placement options (Ronft et al., 2023), namely banner or native advertising (De Keyzer et al., 2023), personalized advertising (Pfiffelmann et al., 2020) and social media advertising (Boerman & Müller, 2022; Kohout et al., 2023) to name a few. The analysis of ET data has also assisted in the quantification of cultural differences, such as in food (Zhang & Seo, 2015) and color (Wu et al., 2020) preferences or even in decision making (Moriuchi & Moriyoshi, 2024). We discuss below what variables are typically used to evaluate such differences.

2.1 The eye-tracking signal and variables

Modern eye-tracking sensors compute a multi-dimensional signal consisting of 4 core geometric variables that span over time (Georgiadis et al., 2023), namely the *estimated relative eye positions* (X,Y coordinates of eye position on the screen normalized to [0,1]) and *pupil size* in mm, for both the left and right eye, captured every specific time intervals (i.e., according to the sensor sampling frequency e.g., 120Hz). In every case, the raw format representation of the signal is of little to no real use to a statistical analysis, so it needs to be processed. Typically, the raw eye-tracking signal is post-processed in conjunction with the visual stimuli in order to extract the core attention variables; *fixation time*, *fixation counts*, *saccade count*, *dwell time*, *scanpaths*, *attention maps* and their variations/aggregations. To this end, researchers are required to define what are the actual visual stimuli on the screen, i.e., the specific *Areas Of Interest* (AOI). Therefore, the outputs of an eye-tracking analysis are the unconstrained raw signal, the “filtered” signal per AOI, and the corresponding signal spatio-temporal aggregations. Depending on the research question, different consumer attention variables (or better aggregations) might be more appropriate than others, e.g., time to first fixation is more appropriate for evaluating bottom-up stimuli, while dwell time and attention maps are more appropriate for evaluating top-down ones (van der Laan et al., 2015).

2.2 Sources of cross-study variance in ET studies

Even when assuming the exact same eye-tracking device employed between experiments, there are still quite a few additional sources of variance that should be taken into account. The positional signal needs to be extrapolated from one specific pixel to a wider area in the screen, according to the sensor *spatial resolution* and therefore the important variables that should always be reported are related to scene geometry, i.e., the *distance of the subject/participant to the screen*, the *screen size* and its *resolution*. Second,

sensor calibration per subject can have a severe impact on the sensor accuracy (Krafka et al., 2016) and appropriate calibration per subject is not always trivial, especially when dealing with non-adults (Zeng et al., 2024). More precisely, the variables used in ET studies are not standardized; variables with different names such as total fixation time and fixation duration might refer to the same procedure, or sometimes, completely different procedures may be followed to extract seemingly identical variables (e.g., total fixation time might be computed by adding up fixations with a minimum duration of 150ms (Ronft et al., 2023), 90ms (Liang et al., 2021), 58ms (van der Laan et al., 2015), or even 300ms (Gheorghe et al., 2023), which understandably lead to completely different numbers). Another source of variance can be introduced by the definition of AOIs by the researchers. Sometimes researchers are advised to define a little wider areas to compensate for sensor inaccuracies (Orquin & Wedel, 2020). According to technical studies (Vehlen et al., 2022), the definition of wider AOIs should be done with extreme care, as increasing the size might increase fixation recall (number of correctly identified fixations to the AOI) but with the cost of decreasing precision (misclassified non-fixations as fixations).

3. Electroencephalography

Electroencephalography (EEG) is a neuroimaging method for recording the brain's electrical activity through non-invasive scalp electrodes, offering insights into cognitive and affective functions like emotions, memory, and perception. In neuromarketing, EEG analysis includes spectral analysis to examine signal frequencies, hemispheric asymmetry to compare brain hemispheres, and calculation of statistical indices correlated to specific marketing stimuli, making EEG an essential tool in neuromarketing research (Lin et al., 2018; Quiles Pérez et al., 2024). Neuromarketing utilizes EEG to examine the brain's response to marketing stimuli, focusing, mostly, on

four key areas: emotional engagement, attention and engagement, memory encoding, and decision-making. EEG's insights into these neural activities enable the creation of more effective marketing strategies by correlating brain activity patterns with consumer behaviour, aiming to enhance product positioning and advertising (Kalaganis et al., 2021; Rawnaque et al., 2020).

3.1 EEG signal and variables

In order to obtain EEG signals, participants are equipped with an EEG headset, which includes electrodes placed on the scalp to measure electrical activity in the brain. The goal of the analysis of the EEG signal is to capture and analyse the neural responses of participants to marketing stimuli (Quiles Pérez et al., 2024). The collected EEG signals are analyzed using advanced computational methods to find specific patterns or responses associated with the desired marketing stimuli. The most widely brain activity metrics are: the *Approach-Withdrawal index*, the *Global Field Power*, the *Memorization Index*, the *Pleasantness Index*, and the *Interest Index* (Aldayel et al., 2021; Colomer Granero et al., 2016; Oikonomou et al., 2023; Vecchiato et al., 2014).

The Approach-Withdrawal (AW) index measures consumers' motivation towards or against a marketing stimulus by analyzing the asymmetry of activations in the frontal lobe. Greater activity in the left frontal lobe indicates approach-related emotions (i.e. interest, happiness), suggesting positive engagement with the stimulus. Conversely, increased right frontal lobe activity signals withdrawal-related emotions (i.e. disgust, fear), indicating a desire to avoid the stimulus. The Global Field Power (GFP) quantifies the overall electrical activity across the scalp, summarizing the strength and synchrony of brain signals at a given moment. Peaks in GFP signal indicate moments of significant neural engagement. The Memorization Index (MI) quantifies the likelihood that a

stimulus will be remembered or encoded into memory. A higher MI indicates a stimulus is more likely to be memorably encoded, helping marketers create impactful advertisements and branding materials that consumers are likely to remember. The Pleasantness Index (PI) evaluates the emotional valence of a consumer's response, measuring how positive or pleasant a marketing stimulus is perceived. Together, the aforementioned indices provide a battery of brain's metrics of how consumers subconsciously react to marketing stimuli, offering valuable insights for designing more effective and emotionally resonant marketing strategies.

3.2 Sources of cross study variance in EEG studies

Neuromarketing experiments, particularly those utilizing EEG technology, face several technical and methodological challenges that can affect the accuracy and reliability of the results (Georgiadis et al., 2023). First, EEG signals are susceptible to various types of *noise*, including electrical interference from the environment, artifacts from muscle movements (e.g., eye blinks, jaw clenches), and even heartbeats. These noises can obscure the true brain activity signals, making it difficult to interpret the data accurately. Second, *EEG Signals are non-stationary*, i.e., their statistical properties are changing over time. This variability can occur even within a session as a subject's mental state changes due to fatigue, boredom, or varying levels of engagement. Moreover, there can be significant *variability in EEG responses both within a single session, across different sessions, and between different subjects*. This variability can stem from individual differences in brain anatomy, psychological states, and other factors. The quality and relevance of the EEG data depend significantly on the *precise placement* of electrodes on the scalp. Incorrect placement can lead to poor signal quality or the misinterpretation of where brain activity is originating. Standardized electrode placement protocols like the 10-20 system are used to ensure consistency and comparability of data

across studies. Addressing these challenges requires a combination of careful experimental design, rigorous data processing, and analysis techniques, as well as a nuanced understanding of the limitations of EEG technology. By acknowledging and tackling these issues, we can enhance the reliability and validity of neuromarketing findings, leading to deeper insights into consumer behavior and brain function.

4. Best practises for re-assuring cross-study coherence and research reproducibility

In many cases, we as researchers only report the relevant variables to our research question and our own study. However, there are cases where other research questions could be addressed using the same data, only with different variables or data processing. For instance, a meta-analysis might be comparing fixations times or Memorization Indices reported across a number of studies. If there is no information of how those variables and under what settings they have been computing, such a meta-analysis is not possible. Another example is cross-domain collaboration. Assume an eye-tracking study evaluating a food packaging design (Zhang & Seo, 2015) using only the time-to-first fixation as variable, while another study might want to create a tool for predicting consumer attention to a given stimuli (Liu et al., 2023). The latter could be needing the attention heatmaps of the former, however, if the raw data have been discarded, this is impossible.

4.1 Cross study coherence

In order to have coherence between screen-based studies using ET or EEG signals a large number of experiment's parameters/factors must be taken into consideration. First of all, the full experimental protocol, including the number of participants, time/location of the experiment, number of repetitions should always be described in detail. Specifically

in ET studies, we encourage the researchers to always report the particular ET device used, along with all the technical parameters that can be controlled, such as participant distance/angle from the screen/sensor, the sensor technical features such as presumed accuracy, whether per-calibration has been employed and how this procedure took place. Together with the technical details, the algorithms used to process the signal must be communicated as well (e.g., how was fixation time calculated). Finally, the visual material that was shared with participants and the details of how AOI were defined should also be detailed.

In EEG studies respectively, the technical factors related to the EEG's acquisition should be reported in detail. These factors are: the used EEG device, the number of EEG channels and their configuration (montage: bipolar, or referential), the type of EEG electrodes (dry or wet), EEG reference selection, sampling frequency, filtering, and recording of supplementary data such electrooculograms (EOG) signals and eye tracking data. Also, in EEG community it is common to pre-process the signals to remove artifacts and noise, hence in this case the adopted specialized software, such as EEGLAB (Delorme & Makeig, 2004), must be reported together with its configuration.

4.2 Minimum standards for reproducibility

The reproducibility of a study is vital for the progress of science. It is not a secret that the most impactful research studies in relevant research domains have provided open source codes or data. To this direction it is important to provide to the scientific community the raw data of an experiment, as well as the pre-processed data. As described in Sections 2 & 3, all related ET and EEG variables can be extracted by processing the raw data. Furthermore, it is crucial to provide details on how the various adopted ET or brain metrics were calculated. Finally, another important factor affecting reproducibility

is the used software. It is important to provide adequate information related to its configuration and how it is use in the particular study. For data sharing purposes, EEG community have defined some vital standards that must be followed during the release of an EEG dataset to the scientific community. These standards range from the type of files to the overall organization of the dataset. One widely used standard in brain research community is the Brain Imaging Data Structure (BIDS) (Pernet et al., 2019), originally proposed for magnetic resonance imaging data (MRI) and extended to include EEG. This standard is used for organizing and sharing brain imaging study data within and between laboratories. BIDS primarily addresses the heterogeneity of data organization by following the FAIR principles of findability, accessibility, interoperability, and reusability. Most importantly, because BIDS data are highly structured, BIDS also addresses issues related to the reproducibility by allowing the creation of fully automated data analysis workflows.

5. Conclusion

This paper overviewed the main components and use cases of screen-based experiments employing ET and EEG sensors. The core variables extracted in these settings, along with the sources of variances between ET and EEG studies were discussed. To this end, we have discussed the technical details that research works related to the topics of consumer behavior analysis and neuromarketing should take into consideration. We proposed a set of minimum reporting protocol that should be followed in order to promote and facilitate cross data coherence and research reproducibility. We argue that by adopting our proposal as a baseline checklists, we can facilitate the work of the reviewers by requesting specific details in the experimental settings. Last but not least, our proposal can enhance the quality of the articles and their impact to the domain, without introducing additional workload to the researchers.

References

- Aldayel, M., Ykhlef, M., & Al-Nafjan, A. (2021). Recognition of Consumer Preference by Analysis and Classification EEG Signals. *Frontiers in Human Neuroscience*, 14. <https://doi.org/10.3389/fnhum.2020.604639>
- Boerman, S. C., & Müller, C. M. (2022). Understanding which cues people use to identify influencer marketing on Instagram: An eye tracking study and experiment. *International Journal of Advertising*, 41(1), 6–29. <https://doi.org/10.1080/02650487.2021.1986256>
- Colomer Granero, A., Fuentes-Hurtado, F., Naranjo Ornedo, V., Guixeres Provinciale, J., Ausín, J. M., & Alcañiz Raya, M. (2016). A Comparison of Physiological Signal Analysis Techniques and Classifiers for Automatic Emotional Evaluation of Audiovisual Contents. *Frontiers in Computational Neuroscience*, 10. <https://doi.org/10.3389/fncom.2016.00074>
- De Keyzer, F., Dens, N., & De Pelsmacker, P. (2023). The processing of native advertising compared to banner advertising: An eye-tracking experiment. *Electronic Commerce Research*, 23(3), 1921–1940. <https://doi.org/10.1007/s10660-021-09523-7>
- Delorme, A., & Makeig, S. (2004). EEGLAB: An open source toolbox for analysis of single-trial EEG dynamics including independent component analysis. *Journal of Neuroscience Methods*, 134(1), 9–21. <https://doi.org/10.1016/j.jneumeth.2003.10.009>
- Georgiadis, K., Kalaganis, F. P., Riskos, K., Matta, E., Oikonomou, V. P., Yfantidou, I., Chantziaras, D., Pantouvakis, K., Nikolopoulos, S., Laskaris, N. A., & Kompatsiaris, I. (2023). NeuMa—The absolute Neuromarketing dataset en route to an holistic understanding of consumer behaviour. *Scientific Data*, 10(1), Article 1. <https://doi.org/10.1038/s41597-023-02392-9>

- Gheorghe, C.-M., Purcărea, V. L., & Gheorghe, I.-R. (2023). Using eye-tracking technology in Neuromarketing. *Romanian Journal of Ophthalmology*, 67(1), 2–6. <https://doi.org/10.22336/rjo.2023.2>
- Kalaganis, F. P., Georgiadis, K., Oikonomou, V. P., Laskaris, N. A., Nikolopoulos, S., & Kompatsiaris, I. (2021). Unlocking the Subconscious Consumer Bias: A Survey on the Past, Present, and Future of Hybrid EEG Schemes in Neuromarketing. *Frontiers in Neuroergonomics*, 2. <https://doi.org/10.3389/fnrgo.2021.672982>
- Kohout, S., Kruikemeier, S., & Bakker, B. N. (2023). May I have your Attention, please? An eye tracking study on emotional social media comments. *Computers in Human Behavior*, 139, 107495. <https://doi.org/10.1016/j.chb.2022.107495>
- Krafka, K., Khosla, A., Kellnhofer, P., Kannan, H., Bhandarkar, S., Matusik, W., & Torralba, A. (2016). Eye Tracking for Everyone. *2016 IEEE Conference on Computer Vision and Pattern Recognition (CVPR)*, 2176–2184. <https://doi.org/10.1109/CVPR.2016.239>
- Liang, S., Liu, R., & Qian, J. (2021). Fixation prediction for advertising images: Dataset and benchmark. *Journal of Visual Communication and Image Representation*, 81, 103356. <https://doi.org/10.1016/j.jvcir.2021.103356>
- Lin, M.-H. (Jenny), Cross, S. N. N., Jones, W. J., & Childers, T. L. (2018). Applying EEG in consumer neuroscience. *European Journal of Marketing*, 52(1/2), 66–91. <https://doi.org/10.1108/EJM-12-2016-0805>
- Liu, J.-J., Hou, Q., Liu, Z.-A., & Cheng, M.-M. (2023). PoolNet+: Exploring the Potential of Pooling for Salient Object Detection. *IEEE Transactions on Pattern Analysis and Machine Intelligence*, 45(1), 887–904. <https://doi.org/10.1109/TPAMI.2021.3140168>

- Moriuchi, E., & Moriyoshi, N. (2024). A cross-cultural study on online reviews and decision making: An eye-tracking approach. *Journal of Consumer Behaviour*, 23(1), 156–170. <https://doi.org/10.1002/cb.2165>
- Oikonomou, V. P., Georgiadis, K., Kalaganis, F., Nikolopoulos, S., & Kompatsiaris, I. (2023). A Sparse Representation Classification Scheme for the Recognition of Affective and Cognitive Brain Processes in Neuromarketing. *Sensors*, 23(5), Article 5. <https://doi.org/10.3390/s23052480>
- Orquin, J. L., & Wedel, M. (2020). Contributions to attention based marketing: Foundations, insights, and challenges. *Journal of Business Research*, 111, 85–90. <https://doi.org/10.1016/j.jbusres.2020.02.012>
- Pernet, C. R., Appelhoff, S., Gorgolewski, K. J., Flandin, G., Phillips, C., Delorme, A., & Oostenveld, R. (2019). EEG-BIDS, an extension to the brain imaging data structure for electroencephalography. *Scientific Data*, 6(1), 103. <https://doi.org/10.1038/s41597-019-0104-8>
- Pfiffelmann, J., Dens, N., & Soulez, S. (2020). Personalized advertisements with integration of names and photographs: An eye-tracking experiment. *Journal of Business Research*, 111, 196–207. <https://doi.org/10.1016/j.jbusres.2019.08.017>
- Quiles Pérez, M., Martínez Beltrán, E. T., López Bernal, S., Horna Prat, E., Montesano Del Campo, L., Fernández Maimó, L., & Huertas Celdrán, A. (2024). Data fusion in neuromarketing: Multimodal analysis of biosignals, lifecycle stages, current advances, datasets, trends, and challenges. *Information Fusion*, 105, 102231. <https://doi.org/10.1016/j.inffus.2024.102231>
- Rawnaque, F. S., Rahman, K. M., Anwar, S. F., Vaidyanathan, R., Chau, T., Sarker, F., & Mamun, K. A. A. (2020). Technological advancements and opportunities in

Neuromarketing: A systematic review. *Brain Informatics*, 7(1), 10.

<https://doi.org/10.1186/s40708-020-00109-x>

Ronft, S., Friedrich, M. G., & Sofiullah, M. (2023). Effect of product placement labeling on visual product and brand reception – an empirical eye tracking study. *Journal of Marketing Communications*, 0(0), 1–16.

<https://doi.org/10.1080/13527266.2023.2275133>

van der Laan, L. N., Hooge, I. T. C., de Ridder, D. T. D., Viergever, M. A., & Smeets, P. A. M. (2015). Do you like what you see? The role of first fixation and total fixation duration in consumer choice. *Food Quality and Preference*, 39, 46–55.

<https://doi.org/10.1016/j.foodqual.2014.06.015>

Vecchiato, G., Maglione, A. G., Cherubino, P., Wasikowska, B., Wawrzyniak, A., Latuszynska, A., Latuszynska, M., Nermend, K., Graziani, I., Leucci, M. R., Trettel, A., & Babiloni, F. (2014). Neurophysiological Tools to Investigate Consumer's Gender Differences during the Observation of TV Commercials.

Computational and Mathematical Methods in Medicine, 2014, 912981.

<https://doi.org/10.1155/2014/912981>

Vraga, E., Bode, L., & Troller-Renfree, S. (2016). Beyond Self-Reports: Using Eye Tracking to Measure Topic and Style Differences in Attention to Social Media Content. *Communication Methods and Measures*, 10(2–3), 149–164.

<https://doi.org/10.1080/19312458.2016.1150443>

Wedel, M., & Pieters, R. (2008). A Review of Eye-Tracking Research in Marketing. In N. K. Malhotra (Ed.), *Review of Marketing Research* (Vol. 4, pp. 123–147).

Emerald Group Publishing Limited. [https://doi.org/10.1108/S1548-](https://doi.org/10.1108/S1548-6435(2008)0000004009)

6435(2008)0000004009

- Wu, B., Nishimura, S., Zhu, Y., & Jin, Q. (2020). Experiment Design and Analysis of Cross-Cultural Variation in Color Preferences Using Eye-Tracking. In J. J. Park, L. T. Yang, Y.-S. Jeong, & F. Hao (Eds.), *Advanced Multimedia and Ubiquitous Engineering* (pp. 44–49). Springer. https://doi.org/10.1007/978-981-32-9244-4_6
- Zeng, G., Simpson, E. A., & Paukner, A. (2024). Maximizing valid eye-tracking data in human and macaque infants by optimizing calibration and adjusting areas of interest. *Behavior Research Methods*, 56(2), 881–907.
<https://doi.org/10.3758/s13428-022-02056-3>
- Zhang, B., & Seo, H.-S. (2015). Visual attention toward food-item images can vary as a function of background saliency and culture: An eye-tracking study. *Food Quality and Preference*, 41, 172–179.
<https://doi.org/10.1016/j.foodqual.2014.12.004>