Empirically Derived Metadata Ad-Context Alignment Predicts EEG Synchrony

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Abstract

Advertising efficacy benefits from psychological priming, which reflects the relative degree of congruence between aspects of the specific ad and the specific media environment, a measure often referred to as alignment, congruence, or resonance. Such alignment has typically been accomplished using simple, intuitive approaches such as putting humorous ads in comedy programs. To increase the sophistication and effectiveness of resonance-based advertising, here we test the relationship between empirically-derived measures of ad-media resonance and market-level output measures including incremental sales and full funnel branding metrics. Critically, we also evaluated neuroscience metrics known to predict sales effects of advertising as potential mediators. We find that electro-encephalography (EEG) based brain signatures of communication effectiveness (synchrony) – which prior studies have shown best predict market-level outcomes – correlate more strongly with resonance scores than with EEG-based electrical brain signatures of attention, memory, and approach motivation; eye tracking-based fixations and gaze durations on screen; and immediate ad recall and post-study self-reported ad liking. These findings endorse media selection using the canonical set of validated comparators and their resonance scores for specific ads in specific media environments to significantly increase sales and branding success of advertising.

Keywords: TV context, advertisements, EEG, empirically derived metadata, consumer neuroscience

Introduction

The adoption of media optimization by marketers in the 1960s led to the realization that there was a gap in the data being used in media selection. Up until that time, there were three essential predictive metrics used to decide on a media schedule aimed at maximum sales and branding effects (the latter term is used by marketers to represent the psychological predisposition to buying a specific brand):

1. Audience size and characteristics
2. Media cost
3. Reach and frequency of the combined media vehicles selected

A fourth variable sometime subjectively applied as a tiebreaker was the notion of the compatibility between the ad and the media context. The term "endemic advertising" was applied to describe the situation of, for example, advertising golf clubs in a golf magazine. There had always been the reasonable suspicion that this priming effect probably was active to some smaller degree in other situations.

The appearance of media optimizers required quantification for inclusion in the optimizer models, therefore the idea of quantifying context effects arose. Initially, media optimization specialists used the term "media impact weights" and these metrics were generally expressed as indices with base 100. High rated prime time television shows and 60 second ads were taken as the apex at 100 index, while the same environment for 30 second ads was discounted to a lower index. For years, each agency set its own subjective scores on these media impact indices. One agency found that these media impact indices were different for each specific ad (Harvey, 2021), indicating that the value of a media context varied significantly depending on the specific ad creative.

Industry and academic researchers began to do studies in which ads and programs were keyword coded by subjectively selected words such as "funny", "serious", "happy", "sad", and so on. 70 of these studies carried out from the 1970s through the present day were meta-analyzed (Kwon et al, 2021) showed strong consistency of results, indicating an average increase in ad recall of ~15% when, e.g. a funny ad was placed in a funny program. This further supported the idea that media impact indices would best be used based on the specific ad creative and its degree of alignment with each alternative media context.

However some researchers were dissatisfied with the use of arbitrarily selected comparator variables. In the 1990s a study was done in which human coders extracted over 10,000 psychological words from the Oxford Unabridged Dictionary (Harvey and Mu, 2015). A U.S. national probability sample of 10,000 respondents were presented with subsets of these words so as to exhaust the list. A semantic differential scale anchored by "ME" and "NOT ME" at the poles was used for respondents to self-describe themselves in relation to each word. A factor analysis with varimax rotation was used to cluster these words, resulting in 1562 clusters accounting for over 90% of the variance. Using the word within each cluster having the largest loading on the cluster, a list of 1562 metatags was created, and applied by trained human coders to each of 10,000 of the most popular shows on television in 1997. This database was included in an expert system utilizing a Deductive Object Oriented Database (DOOD) called an AI and named CustoMenu, which was part of a media optimizer Opti*Mark that introduced the first set top box data, the first addressable commercials, and the first programmatic trading. Liberty Media and Discovery Communications funded the large-scale deployment of this system to the first wave of adopters of digital set top boxes in the largest cable operator of the time, TCI. Cable subscribers were informed that they could use their remote control channel changers to ask for a program recommendation from an artificial intelligence system. The recommendation came within a second and reflected observed proclivities across the 1562 variables in the set top box data for that household, and excluded from recommendations any programs that the set top box had tuned to in the past. Machine learning was employed to systematically change the weights on the 1562 variables so as to maximize loyal viewing of the recommended programs by giving more weight to variables aggregately implicated in program series adoptions. This resulted in a sixfold increase in the average adoption rate and a distillation of the 1562 variables to a validated set of 265 predictive variables. Today that canonical set are called RMT Value Signals, and are clustered in a hierarchy to 86 Need States and again into 15 Motivations (which turn out to include the 5 Maslow Needs plus ten other Motivations). (Value Signals were originally called "DriverTags")

These 265 variables all relate to qualia, i.e. subjective feelings experienced by human beings and possibly by other living things. They were distilled from every psychology-relevant word in the Oxford Unabridged Dictionary (~13,000 words) and then further distilled by in-market testing in a TV program personalized recommender agent. They fall into five categories (based on careful after the fact inspection, not based on original intention): human values, character and personality traits, moods and emotions, human situations, and content descriptors.

Media researchers Pat Pellegrini and Steven Millman studied these 265 Value Signals in the 2017 U.S. Simmons study and found that they not only were strong predictors of program choice, they are also strong predictors of brand choice across every brand (3830 brands with at least 1000 claimed users) in all 150+ product/service categories studied (Pellegrini et al, 2017). This consistency between the drivers of program choice and product/brand choice aligns with the finding of Neuroeconomics researchers that all choice behavior is calculated the same way in the brain, regardless of the kinds of options which are being considered (Glimcher and Fehr, 2014).

An ARF Cognition Council study (Mattlin et al, 2023) found that 11 of the 15 Motivations had 0.48 r^2 in predicting 6 years of IRI sales data for 19 brands in 3 product categories.

A series of studies by a number of different research companies found that sales and branding metrics were increased significantly when either (a) Value Signals were matched between an ad and a program or (b) Motivations were matched between an ad and a person whose Motivations were inferred from the Internet content they had consumed in the past 30 days as passively measured with privacy protection. (Stipp and Bacon, 2017; Harvey and Shimmel, 2017; Harvey and Karam, 2018; Harvey, 2021)

In the same time frame as these validations against in-market sales and branding effects of the Value Signals, another effort to quantify context effects was underway and dominated industry thought leadership from 2019 to today. This was known as the Attention Economy. This approach singled out visual attention as the one predictor of advertising success that was deemed to be closest at hand. The introduction of webcams on laptops, smartphones, and tablets created a potential sample size of billions of subjects who might be incentivized to permit their eye movements to be tracked during ad exposures in different media environments. ~40 companies arose to offer such measurements. These measurements were used in pretesting new ads as well as in scoring media environments for their average attention durations relative to specific size ad units, but ignoring variations in creative executions. Thus, Company X might score the placement of a 15-second ad in the middle of a streaming program on a major television network watched on a TV screen as having a 70 score, and a video ad providing an opportunity to see a 15-second video ad in a scrolling environment on a smartphone at a 30 score. In some cases these numbers were presented as abstract values and in other cases tied to average seconds of gaze in the general direction of the screen as either absolute seconds or percent of the number of seconds in the ad, or other relative formulations.

As of 2025, nearly all of the top agency holding companies have embedded these attention scores in their tech stacks. Nearly all of them are now looking for other predictive metrics to enhance the sales and branding successes of their clients' campaigns.

This search for additional measures stems from the mixed reactions to the in-market effects of these attention predictors by agencies and especially by advertisers. In a 2025 survey of 51 advertiser executives and 54 agency executives, the Advertising Research Foundation (ARF) found that attention ranked 11th in a list of 14 metrics taken into consideration in the pursuit of the business success of advertising investments. Advertisers were significantly less impressed by attention measures than agencies. When asked what challenges were faced in using attention metrics, the highest ranking response was concerns about accuracy and reliability. This is because – although cherrypicked evidence shows many cases where attention-assisted campaigns had higher awareness scores and other outcome measures (mostly upper funnel) – many results never shown publicly show the opposite, or no difference. This was corroborated by the ARF's own Attention Validation Study which in 2024 indicated that the best of the attention suppliers in predicting which ads were most successful according to the advertiser's own in-market data achieved only an r^2 of only 0.12. When measured against the ability to predict the sales effect specifically (the metric most valued by advertisers in the ARF 2025 survey) the attention suppliers had an r^2 very close to zero (ARF, 2024, pages 32 and 37). Other studies, including one by Playgroundxyz Neuroscience (Bosshard and Harvey, 2024) also show that higher attention measured by eye tracking can improve upper funnel results but higher attention has only weak ability to raise lower funnel results.

Our study was designed to shed light on several questions raised by the industry literature to date:

1. Can EEG measures gauge the degree to which the same ad will perform differently in different ad environments? In other words, how important are context effects? Is the juice worth the squeeze?
2. To what degree can the Value Signals used as a measure of similarity between ad and context predict these differences in performance?
3. To what degree can attention and other measures predict these differences in outcome?

Contributions

This study makes a significant contribution to marketing science and practice by identifying the strongest available predictors of advertising sales and branding effects. In the ideal world, a large-scale probability sample would measure the natural exposure to media and advertising in people's own homes utilizing EEG headbands such as used by Wharton Neuroscience, and would simultaneously measure content and ad exposure, and purchases made by the same panelists. This would generate EEG synchrony measures to be combined with ad-context congruence metrics based on Value Signals, which would provide predictivity of incremental sales and full funnel branding metrics in the 0.9 r^2 range.

This claim of such high predictivity rests upon a series of empirical observations, including (1) the Wharton Neuroscience finding that EEG synchrony has by itself a 0.82 r^2 in predicting ad-produced sales (2) the ARF Cognition Council finding that the RMT Motivations have a 0.59 r^2 in predicting ad-produced sales (Mattlin et al, 2023).

This level of accuracy in guidance will have a significant econometric impact on a mass scale once adopted by the bulk of marketers. Advertising practitioners generally admit to having relatively low degrees of certainty in advance as to the outcomes of their advertising campaigns. The methodology of using natural conditions EEG synchrony plus RMT Value Signals resonance will greatly increase confidence in being able to forecast a return on investment, which will improve the efficiency of the marketing function, impacting approximately 20% of the costs of any business.

Methodology of the Current Study

The remainder of this paper has the following sections: we discuss the experimental design, and report the answers to the three main questions posited above. We then discuss the practical implications of our work for advertisers and conclude with recommendations/plans for further research.

Experimental Design

540 subjects were put through a laboratory procedure in a simulated living room, sitting on a couch, and wearing a Cogwear EEG headband measuring frontal lobes. All subjects saw the same 8 ads. There was one ad representing each of 8 verticals which collectively account for the bulk of national advertising investments in the U.S.

The ten-cell study used the same eight ads in all cells. In each cell except for the control cell, 4 ads were presented after 4 minutes of program content, then this was followed by the next four minutes of program content continuing the same program as before, and then finally the presentation of the other four ads. Ad sequence was randomized for each subject in each cell. 540 subjects were divided equally across the 10 cells. The 10 cells were as follows in terms of media context:

1. Premium streaming network A
2. Premium streaming network B
3. Live sports event
4. Live news C
5. Live news D
6. Primetime broadcast network program
7. Primetime cable network reality program
8. YouTube shorts with pre-roll skippable in 5 seconds
9. Facebook feed video ads
10. Control group – just ads shown, no contexts

All cells presented the stimuli on a TV set except for YouTube and Facebook which – in line with their predominant usage pattern in the real world – were presented on a smartphone. Thus cells 1-7 watched a TV screen and were allowed to watch normally and look away if they felt like it. Cells 8 and 9 watched a smartphone and were allowed to scroll, skip, or do whatever they wanted normally. In cells 1-7, there were 4 minutes of program followed by 4 of the ads plus placebo ads, then a continuation of the same program for 4 minutes, and the other 4 ads plus placebo ads. The number of ads seen in each pod were realistic to the type of television they were watching.

The following measures were taken:

1. EEG synchrony – EEG synchrony was computed as inter-subject correlation (ISC) across participants watching the same stimulus. EEG data were time-frequency decomposed using Morlet wavelets in the alpha band (8–13 Hz). ISC was calculated by correlating the power time series across homologous four prefrontal electrodes between every subject pair,

then averaged within groups to reflect shared neural processing. This metric has been validated against real-world market outcomes and is the most predictive of sales and branding effects.

2. EEG approach: Approach motivation was quantified via frontal alpha asymmetry (FAA). After extracting alpha power from AF7 and AF8 channels, FAA was calculated as the log-transformed power difference: FAA = log(AF8) – log(AF7). Positive FAA indicates approach-related motivation. Time-resolved FAA values were smoothed using convolutional filters and averaged across ad exposures.
3. EEG memory: Memory encoding was operationalized using power-spectral in the theta band (4 – 8 Hz). Time-frequency decomposition was performed at four prefrontal electrodes.
4. EEG attention: Attention was operationalized using power-spectral in the alpha band (8 – 13 Hz). Time-frequency decomposition was also performed at four prefrontal electrodes.
5. Eye tracking fixations: Fixations were defined as gaze points remaining within a spatial threshold for >100 ms. These were extracted using default algorithms in the eye-tracker software. The number and duration of fixations per area of interest (AOI) were computed per frame to index focal visual attention.
6. Eye tracking gaze duration (eyes on screen): Total time that participants' gaze remained within the screen boundaries was computed as total gaze duration, or "eyes-on-screen" time. This serves as an indicator of sustained visual attention and was normalized by total video duration.
7. Value Signals (RMT) ad-context resonance: the overlap of the RMT Value Signals (VS) in the program content leading up to the ad pod, with the ad's VS. For example, if the ad contained 30 VS (out of the battery of 265 total empirically-derived VS in the RMT system) and the program lead-in contained 10 of those same VS, this would calculate to a 33.3% resonance.
8. Immediate ad recall (brand recognition): After exposure, participants completed an open-ended recall task, writing remembered brands from the ads they watched. The total probability of recall rates of each brand across participants was taken.
9. Post-only persuasion: Persuasion was measured post-exposure via self-reported changes in brand attitude. The total probability of post persuasion rates of each brand across participants was taken.

Findings as to the Importance of Context Effects

The degree to which results vary based on where an ad is placed appear to be as large as the variations in results produced across a very large sample of different creative executions. This is illustrated in Figures 1 and 2 by the average of all 8 ads, and how these same ads vary in their composite performance solely on the basis of being placed in different TV program environments. Again, each curve seen below is not one ad, all curves are the same 8 ads averaged together.

Figure 1. Same 8 Ads Averaged Together, How Context Changes Their EEG Approach/Avoidance Response

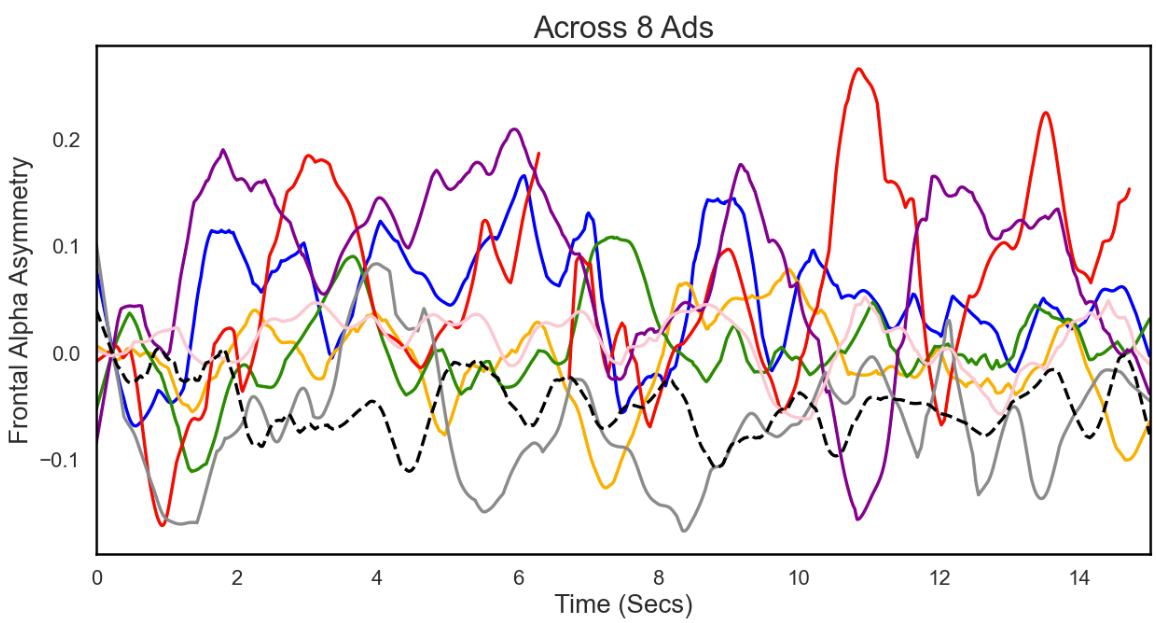
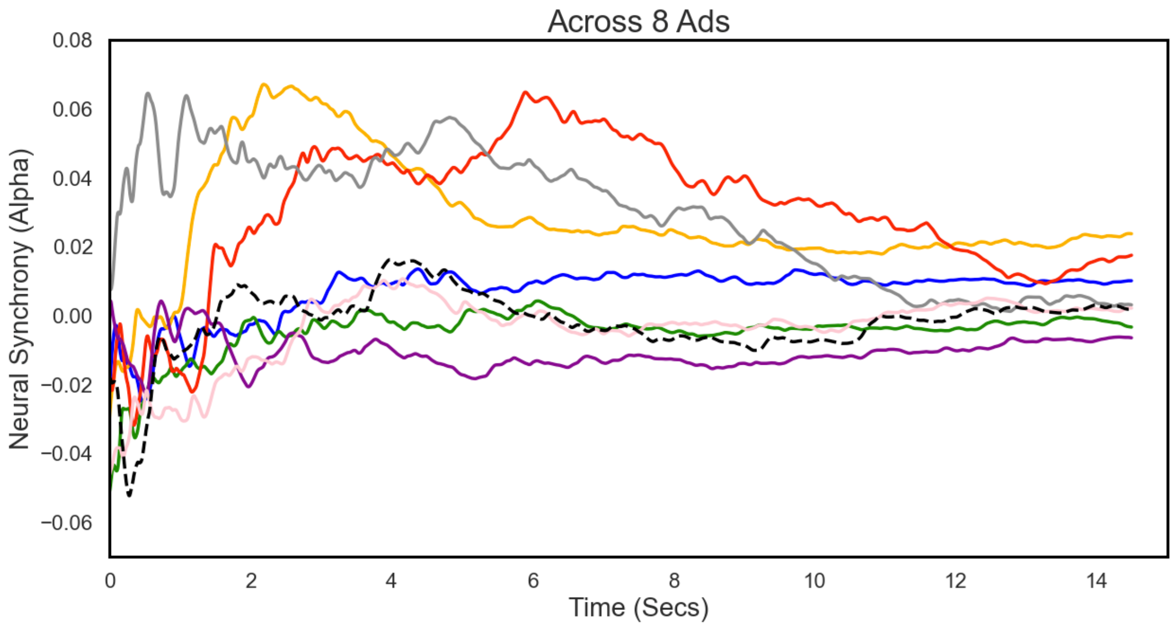


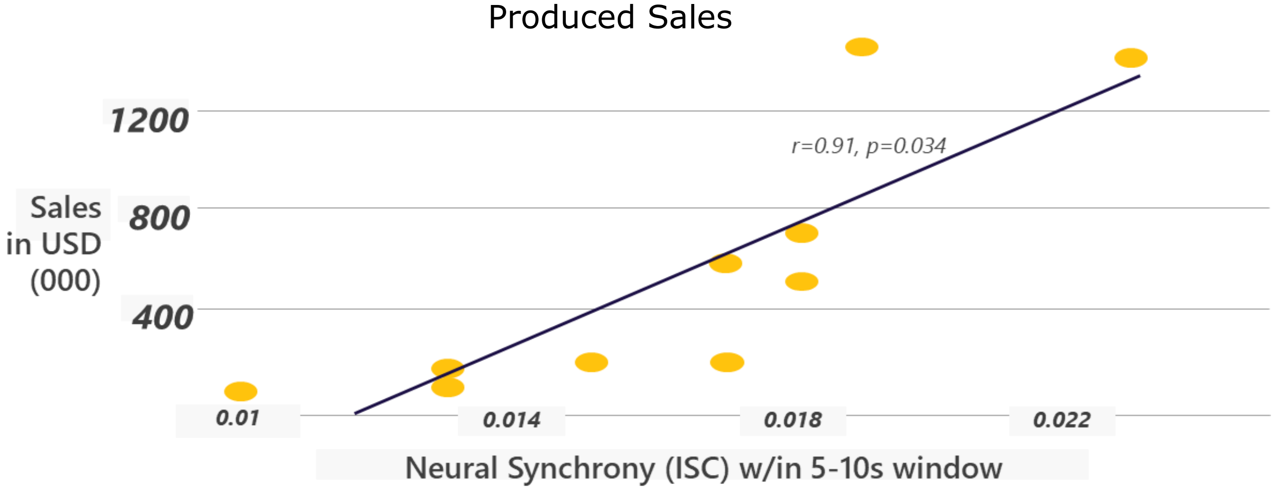
Figure 2. Same 8 Ads Averaged Together, How Context Changes Their EEG Synchrony Response



Findings as to the Predictivity of the Various Measures

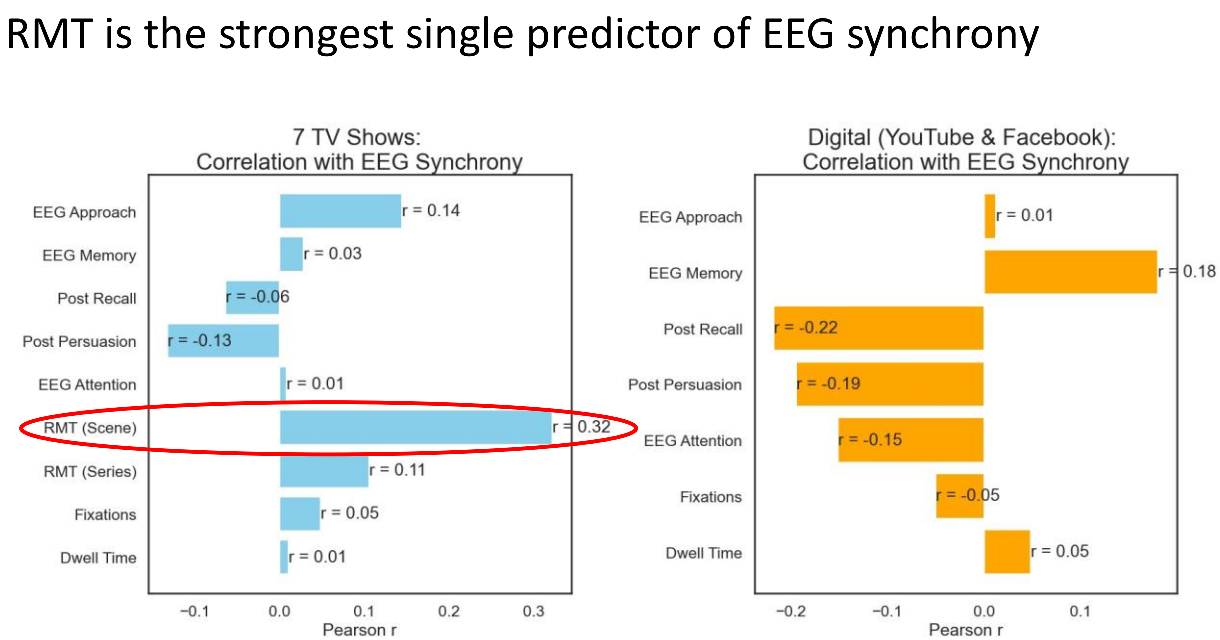
Because the EEG synchrony measure has already been validated by Wharton Neuroscience to predict out of sample, in-market sales results of advertising with r^2 of 0.82, in this study we used synchrony as a proxy for sales effect. We found that RMT Value Signals are more predictive of EEG synchrony than any other of the measures taken in the study.

Figure 3. Wharton Neuroscience Findings of Multiple Proprietary Advertiser Studies: EEG Synchrony Has 0.91 correlation and 0.82 r^2 in Predicting Ad-Produced Sales



In the current study, Wharton Neuroscience found that RMT Resonance between the Value Signals in the ad and the Value Signals in the Context was the only statistically significant predictor of EEG Synchrony:

Figure 4. Wharton Neuroscience Found That RMT Ad-Context Value Signal Resonance Was the Only Statistically Significant Predictor of EEG Synchrony



Note in Figure 4 that both types of eye tracking tested in the study, Fixations and Dwell Time, delivered correlations <0.10, similar to the findings of the ARF study.

Implications for Marketers

This study confirms that context effects are particular to the specific ad creative execution, and are a strong determinant of advertising success, as measured by EEG synchrony. These effects appear to be of about the same order of magnitude as the differences from ad to ad. Taken together, the effect of creative, and the effect of the resonance of the ad to the context, are the dominant factors in ad success.

Visual attention as measured by eye tracking with or without fixations, and attention, memory, and approach/avoidance as measured by EEG, are far less predictive than ad-context resonance as measured by RMT Value Signals in predicting EEG synchrony. It makes sense that RMT resonance is a strong predictor of EEG synchrony, because EEG synchrony and RMT resonance have both been proven to be strong predictors of ad-produced sales.

Given the strength of EEG synchrony in predicting sales effects of advertising, it is the tool recommended for use by marketers in making the most important strategic decisions involving millions of dollars invested in advertising (which ad to use in the Superbowl, whether to make a major change in messaging, etc.). Given the cost and time factors, for day-to-day tactical advertising decisions where EEG synchrony would not be practical, the recommended scalable proxy is RMT Value Signals Resonance between the ad and each alternative media context.

Future Research

In the current phase of planned research work, the authors are engaged in testing how the existing RMT toolset can be made even more effective, by training the RMT AI using the neuroscience data already collected and continuing to be collected in the process of this ongoing project. Wharton AI has joined in the project and two of the authors have developed another method which could be used in conjunction with the other measures (Yun and Platt, 2025).

The authors plan as a next phase of this research to set up a longitudinal panel of people to wear EEG headbands during media usage in their own homes as part of their normal natural activities. The same homes would be measured for media and ad exposure and purchasing. The RMT Value Signals would also be captured in the total data lake emerging from this longitudinal natural exposure panel. It will be possible to see EEG changes from one impression in a specific ad campaign to the next impression on the same person. This will then be relatable to subsequent changes in purchase behavior (and search behavior, website visits, social media statements, etc.) as well as taking into account the RMT VS resonance involved in each ad impression. RMT also has a procedure for measuring the VS profiles of individuals based on their media content consumption, which has been validated to affect advertising sales effects (Harvey, 2021), and this will also be a part of the data absorbed for analysis in the longitudinal study.

Wharton Neuroscience is investigating a possible linkage of these content coding RMT Value Signals with the neurological electrochemical Value Signals which appear in the brain during choice behavior (Glimcher and Fehr, 2014). This will require testing of video content during fMRI measurement with verbal response measures taken of the subject’s qualia subjective experienced feelings and thoughts while watching specific video content to which the RMT VS were attached. The objective is to connect specific RMT VS with specific neurological VS. The hypothesis is that at least some of the neurological VS will be able to be identified by this methodology. The connection of qualia to neurological factual measurement has been an object of interest in psychology since the work of Wilder Penfield in the mid-20th Century.

The current movement driven by the Advertising Research Foundation and others toward closer integration of efforts by academia and industry is a promising development which increases the likelihood that marketing as practiced will become more scientific and therefore more consistently successful in the future.

Citations

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Appendix

Additional analyses were carried out, mostly focusing on the clustered RMT Value Signals, consisting of 87 Need States, further super-clustered into 15 Motivations, to investigate whether any of these additional signals, not used in a resonance/congruence construct, but as signals in their own right, might bear fruit in improving still further the ability of marketers to reliably increase the sales effects of their advertising. These findings although interesting suggest that on their own, simply by including one or another of these qualities in an ad, is not necessarily going to have predictably positive effects. Much more intensive research, such as is being carried out in Canada by Pellegrini at Vividata, is necessary to know what the target audience is motivated by, before including such motivations in one's ads. This finding is supported by the ARF Cognition Council study (Mattlin et al, 2023) which also analyzed RMT motivations present in advertising, and by comparing these data with sales, found a 0.59 r^2 between 11 of the 15 RMT Motivations and IRI sales data for 19 brands in three diverse CPG product categories.

Overview of Correlation Analyses

Pearson correlation analyses were conducted to examine the relationships between psychological constructs (motivations and need states) and EEG metrics across 8 advertisements and 7 television programs (N = 56 observations). Four neural metrics were analyzed: Alpha (Attention), Theta (Memory), frontal alpha asymmetry (Approach), and neural synchrony. Results are presented separately for motivation-based and need-state-based frameworks, as well as for advertisement and television content.

Motivation-EEG Relationship

Advertisement Content. Analysis of 16 motivational constructs revealed moderate correlations with EEG metrics in advertisement content (mean $r = 0.139$). The strongest associations (Table 1) demonstrated that motivational content relates differentially to EEG responses. The pattern of results suggests that certain motivational themes (e.g., “Good life,” “Love”) show inverse relationships with approach-related neural activity. Conversely, these same motivations show positive associations with memory encoding.

Table 1. Top Five Motivation-EEG Correlations in Advertisements

Rank	**Motivation**	**EEG Metric**	**Pearson r**
1	Good life	Approach	−0.479**
2	Love	Attention	−0.466**
3	Love	Memory	0.449**
4	Humanity	Memory	0.439**
5	Humanity	Attention	−0.387*

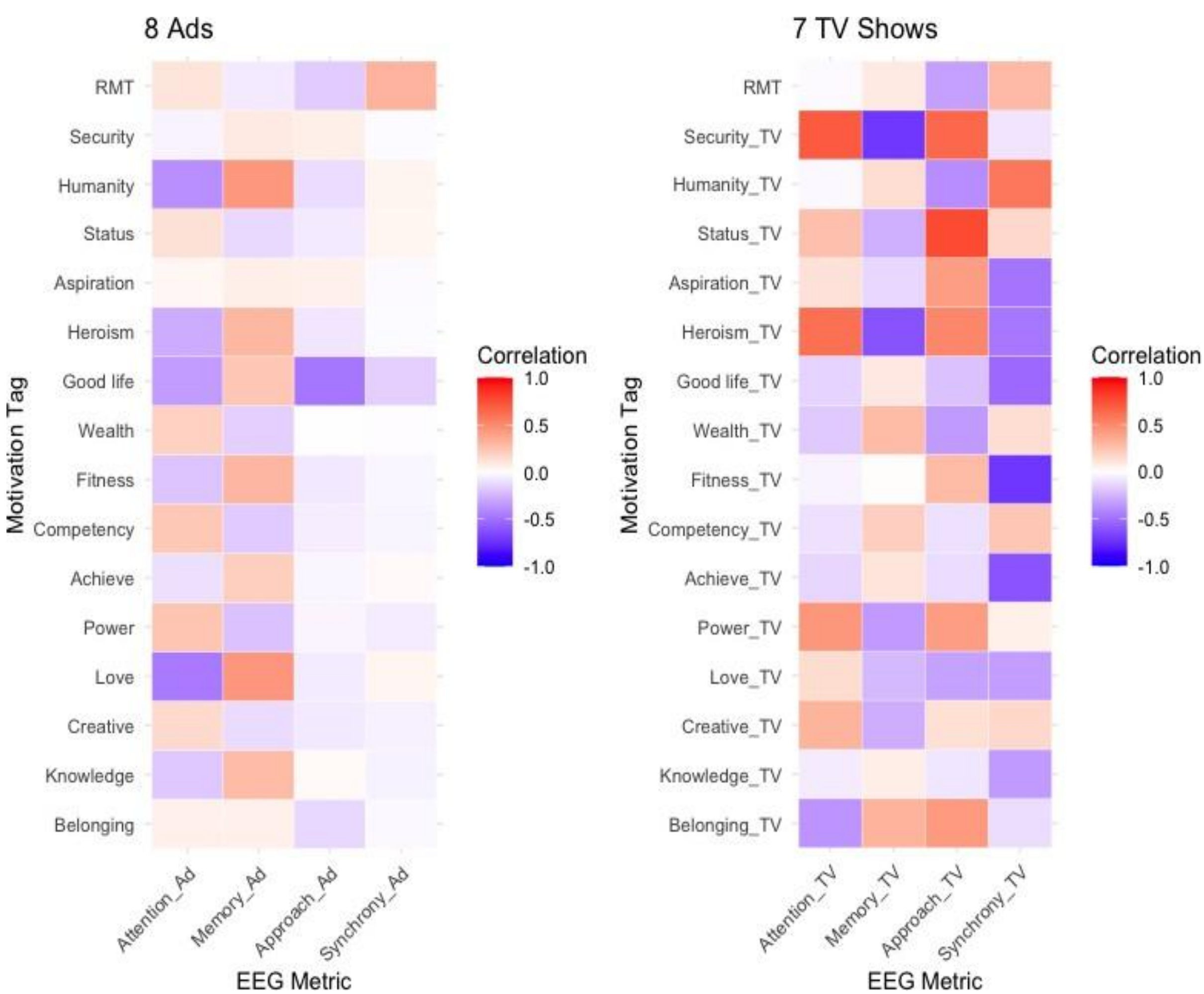
Notes. $*p < .05$, $**\ p < .01$ (two-tailed)

Television Content. Television programming demonstrated substantially stronger motivation-EEG correlations compared to ads (mean $r = 0.288$), with peak correlations approaching large effect sizes. Specifically, status-oriented content elicited the strongest approach-related neural response ($r = 0.772$). Security motivation showed a complex pattern: positive correlations with Attention ($r = 0.701$) and Approach ($r = 0.648$), but a negative correlation with Memory ($r = -0.723$).

Table 2. Top Five Motivation-EEG Correlations in Television

Rank	Motivation	EEG Metric	Pearson r
1	Status	Approach	0.772***
2	Fitness	Synchrony	−0.728***
3	Security	Memory	−0.723***
4	Security	Attention	0.701***
5	Security	Approach	0.648***

Figure 1: Correlation heatmap between motivation constructs and EEG metrics across ads and television programs.



Need State-EEG Relationship

Advertisement Content. The need state framework (67 categories for advertisements) revealed granular associations with EEG responses (mean r = 0.147), with strongest correlations comparable to motivation-based findings. The "Good Times" need to demonstrate a distinctive pattern: strong positive correlation with memory encoding (r = 0.520) paired with strong negative correlation with attention (r = −0.515). In contrast, "Invention" showed the opposite pattern (attention: r = 0.487; memory: r = −0.478).

Table 3. Top Ten Need State-EEG Correlations in Advertisements

Rank	**Need state**	**Neural Metric**	**r**
1	Good Times	Memory	0.520***
2	Good Times	Attention	−0.515***
3	Invention	Attention	0.487**
4	Invention	Memory	−0.478**
5	Savoir Faire	Memory	−0.444**
6	Upscale	Attention	0.443**
7	Teamwork	Attention	0.429**
8	Perfectly Made	Attention	0.432**
9	Effective Worker	Attention	0.429**
10	Human Bonding	Attention	−0.422**

Note. $**\ p < .01$, $***p < .001$ (two-tailed)

Television Content. Television programming demonstrated exceptionally strong need-state EEG correlations (mean r = 0.316), with several associations reaching r > 0.80, indicating large effect sizes and potential predictive utility.

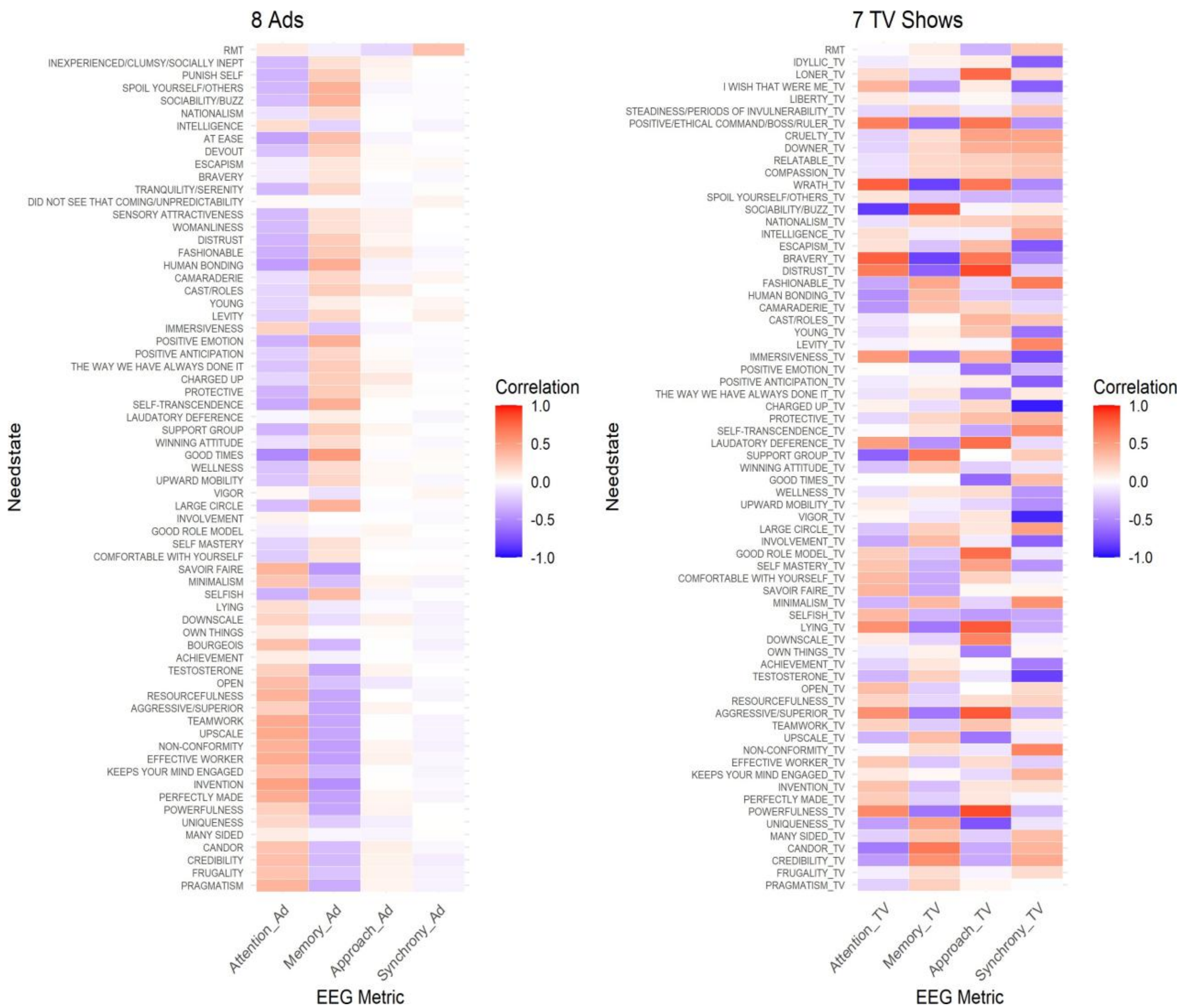
We also found the inverse relationship between arousal-related need states ("Charged Up," "Vigor," "Testosterone") and neural synchrony (r > 0.82). "Sociability/Buzz" showed the desirable dual pattern observed with "Good Times" in ads: reduced attentional demand (r = −0.850) coupled with enhanced memory encoding (r = 0.824). Power-related need states ("Powerfulness," "Aggressive/Superior," "Distrust") strongly correlated with approach-related neural systems (r > 0.80).

Table 4. Top Ten Need State-EEG Correlations in Television

Rank	Need state	Neural Metric	r
1	Charged Up	Synchrony	−0.948***
2	Vigor	Synchrony	−0.920***
3	Distrust	Approach	0.867***
4	Powerfulness	Approach	0.858***
5	Sociability/Buzz	Attention	−0.850***
6	Sociability/Buzz	Memory	0.824***
7	Testosterone	Synchrony	−0.821***
8	Bravery	Memory	−0.817***
9	Wrath	Memory	−0.817***
10	Aggressive/Superior	Approach	0.807***

Note. $***p < .001$ (two-tailed)

Figure 2: Correlation heatmap between need state categories and EEG metrics across ads and television programs.



Comparative Analysis: Content Type Effects

Advertisement vs. Television Correlations. Television content consistently proved stronger psychological-neural correlations than advertisements across both frameworks by a 107-115% increase on average (Table 5).

Table 5. Mean Absolute Correlations by Content Type and Framework

Framework	Advertisement	Television	Difference	Cohen's q
Motivation	r = 0.139	r = 0.288	+0.149	0.31
Need state	r = 0.147	r = 0.316	+0.169	0.36
Combined	r = 0.143	r = 0.302	+0.159	0.33

EEG Metric Comparison. Different neural metrics showed distinct sensitivity to psychological constructs (Table 6). Specifically, Attention and memory showed relatively consistent correlations across content types (0.20–0.29). Approach and synchrony showed dramatic content-type effects: weak correlations in ads ($r < 0.10$) but strong correlations in television ($r > 0.33$).

Table 6. Mean Correlations by EEG Metrics

EEG Metric	Motivation-Ad	Motivation-TV	Need state-Ad	Need state-TV	Overall
Attention	0.197	0.230	0.261	0.280	0.242
Memory	0.206	0.245	0.254	0.287	0.248
Approach	0.095	0.343	0.042	0.327	0.202
Synchrony	0.057	0.335	0.033	0.369	0.199

Resonance Motivation Type (RMT) and EEG Metrics

RMT-EEG Correlation Analysis. Research Measurement Technologies (RMT) quantifies the psychological resonance between the television program context and the embedded advertisement content. As a context-ad interaction measure, RMT provides a single resonance score per observation (N = 56), with higher values indicating greater psychological alignment between the program and ad pairing. RMT showed consistent positive correlations with neural synchrony for both ads (r = 0.322, p = .016) and television programming (r = 0.291, p = .029). This pattern (Table 7) indicates that greater context-content resonance facilitates integrated, immersive neural processing across the entire viewing experience among viewers.

Table 7. RMT Correlations with EEG Metrics

EEG Metric	r	p-value	Interpretation
Synchrony Ad	**0.322**	.016*	Moderate positive
Approach TV	**-0.320**	.017*	Moderate negative
Synchrony TV	**0.291**	.029*	Moderate positive
Approach Ad	-0.172	.207	Weak negative
Attention Ad	0.108	.429	Negligible
Memory-TV	0.089	.518	Negligible
Memory-Ad	-0.066	.629	Negligible
Attention-TV	-0.019	.891	Negligible

Note. *p < 05.

Multiple Regression Predicting Neural Synchrony

The principal component regression (PCR) analyses were conducted separately for the motivational and need-state dimensions to examine their associations with neural synchrony during ad viewing.

For the motivational dimensions, eight principal components accounting for 99.5% of the total variance were entered as predictors. The overall regression model was not significant ($F(8, 47) = 1.24$, $p = .299$), with a modest proportion of explained variance ($R^2 = .17$, adjusted $R^2 = .03$). Among the components, only PC7 significantly predicted neural synchrony in response to ads (β = 0.0045, p = .009), suggesting that a specific latent motivational factor—potentially reflecting status- or agency-related motives based on its loadings—was positively related to neural synchrony during ad exposure.

For the need-state dimensions, eight principal components explaining 100% of the variance were used as predictors. The model was again nonsignificant overall ($F(8, 47) = 0.89$, p = .53), explaining 13% of the variance (R^2 = .13, adjusted R^2 = -.02). However, one component (PC8; β = 0.0040, p = .013) emerged as a significant positive predictor of neural synchrony in response to ads, indicating that a particular need-state factor may contribute modestly to synchronized neural engagement with advertising stimuli.

Together, both models showed limited overall explanatory power, though specific latent components—PC7 in the motivation set and PC8 in the need-state set—were positively related to neural synchrony, implying that distinct psychological clusters of motivational and need-based processes may selectively drive shared neural responses to advertising.