

Do EEG Metrics Derived from Trailers Predict the Commercial Success of Movies? A Systematic Analysis of Five Independent Datasets

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Abstract

This research explores whether neural activity in response to movie trailers is consistently related to commercial success for the movies they promote. A systematic analysis of electroencephalography (EEG) recordings from a large sample of participants ($n = 188$) viewing a large set of movie trailers ($k = 161$) originating from multiple and internationally diverse datasets was performed. Several metrics that have previously been associated with commercial success—alpha, theta, beta, and gamma oscillations; alpha asymmetry; and intersubject correlations—were investigated. Only gamma activity was predictive of commercial success (box office revenue) above and beyond characteristics of the movie and self-reported liking. Importantly, the predictive power of gamma activity generalizes to new movies: Out-of-sample predictions improve significantly with gamma activity as a predictor. In addition, the findings provide initial evidence that mental processes associated with understanding and comprehension may underlie this gamma response. For movie marketing, the findings suggest that gamma activity elicited by movie trailers can be used to optimize trailers for maximum understanding and to inform prerelease marketing decisions. This work represents a significant step forward for the field of consumer neuroscience by confirming the value of EEG-derived metrics in predicting marketing-relevant outcome measures.

Keywords

neuromarketing, consumer neuroscience, EEG, movies, advertising, gamma, prediction

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Consumer neuroscience, the application of neuroscientific tools and methods to marketing theory and practice, has become increasingly popular since its inception almost 20 years ago (for reviews, see, e.g., Ariely and Berns 2010; Plassmann et al. 2015; Smidts et al. 2014). In recent years, researchers in consumer neuroscience have started to investigate the possibility of using neural data in response to marketing stimuli collected from a relatively small group of individuals (a “neural focus group”; Falk, Berkman, and Lieberman 2012) to predict behavior of a larger group. The term “neuroforecasting” has been adopted to describe this phenomenon (Genevsky, Yoon, and Knutson 2017). Most of these neuroforecasting studies have used functional magnetic resonance imaging (fMRI); for an overview, see Knutson and Genevsky (2018). Across these fMRI studies, activity in the brain’s valuation network, in particular activity in the nucleus accumbens and medial prefrontal cortex, has been found to predict aggregate, market-level behavior

such as song downloads (Berns and Moore 2012), microlending success (Genevsky, Yoon, and Knutson 2017), public health campaign success (Falk et al. 2016), virality of news articles (Scholz et al. 2017), advertising elasticity (Venkatraman et al. 2015), ad-related click-through rates (Schmälzle et al. 2020), and online video views (Tong et al. 2020).

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In parallel to the work on neuroforecasting with fMRI, recent studies have addressed the question of whether electroencephalography (EEG) can also be employed to predict market level success (for a review, see Hakim and Levy 2019). EEG is a relevant method in this context, not only because of its much lower cost as compared with fMRI (Ariely and Berns 2010), but also because EEG has a superior temporal resolution in comparison to fMRI, which makes it particularly well suited for analyzing dynamic stimuli such as TV commercials and movies. The combination of these advantages makes EEG the most used neuroscience method in neuromarketing practice today, particularly in ad testing (Smidts et al. 2014).

Neuroforecasting of movies' box office success has been one target for consumer neuroscience research using EEG: In several studies (Barnett and Cerf 2017; Boksem and Smidts 2015; Christoforou et al. 2017), neural activation elicited by movie trailers has been used to predict the commercial success of the movies promoted by these trailers. Movie trailers are the focal communication format for promoting movies (Henning-Thurau and Houston 2019), and much research has examined the advertising role of trailers (see, e.g., Basuroy, Desai, and Talukdar 2006; Elberse and Anand 2007; Elberse and Eliashberg 2003). Movie trailers not only are an advertisement for the movie but also let the audience consume part of the product in advance. Consequently, movie trailers give consumers information on the content of the movie and thus inform their decisions on whether to watch a movie in the future (Henning-Thurau and Houston 2019). Although the global box office revenue for all movies released across the world reached \$41.1 billion in 2018 (Motion Picture Association of America 2019), most movies are not profitable (De Vany and Walls 1999). With such high stakes, the quality of movie trailers is of paramount importance to attract audiences to watch the upcoming movies. It is therefore worthwhile to investigate whether and which neural metrics are informative for movie marketing advertising decisions and whether these metrics can also be applied effectively in producing and optimizing the trailer before its release.

Neuroforecasting with EEG

EEG measures the potential for electrical current to pass between two sites, expressed in voltage, and these measurements of electrical properties reflect the summed activity in millions of neurons at the surface of the brain (Luck 2014; Stern, Ray, and Quigley 2001). Since the inception of EEG by Hans Berger in 1929, it has been noted that changes in an individual's engagement with a particular stimulus co-occur with changes in frequency (i.e., the number of oscillations per second) and amplitude of the EEG signal. This observation has resulted in a convention defining oscillations in the EEG signal in terms of frequency bands, which are typically associated with different mental processes, such as attention, reward, memory, and approach motivation. In the current article, we focus on specific frequency bands, or power metrics, that have been studied extensively in the cognitive neuroscience literature: theta (4–

8 Hz), alpha (8–12 Hz), beta (13–20 Hz), and gamma (>20 Hz) oscillations, and (frontal) alpha asymmetry. In addition to activity within frequency bands, more recently brain states also have been examined using the level of neural similarity *across* subjects viewing the same stimulus (intersubject correlations [ISCs]).

Dmochowski et al. (2014) were among the first to show that EEG measures in a small sample could predict behavior at the aggregate population level. In their study, neural similarity across a limited number of viewers predicted population-level audience preferences in terms of tweet frequency during an episode of a popular television series (*The Walking Dead*) and population ratings of advertisements broadcasted during the Super Bowl. Another study on Super Bowl commercials demonstrates that EEG activity in the theta band measured from a small sample of viewers could be used to predict the number of YouTube views of these commercials (Guixeres et al. 2017). Moreover, while Venkatraman et al. (2015) find the strongest effects of predicting market-level success as measured by ad elasticity from their fMRI measures, they also report a moderate relationship between ad elasticity and EEG alpha band activity and frontal alpha asymmetry. Finally, in a study using machine learning on EEG data to predict YouTube metrics, prediction accuracy increased by 12.7% when EEG metrics (most prominently alpha and beta oscillations) were added to survey-based predictions (Hakim et al. 2020).

Of particular interest for the current article are three studies in which EEG activity elicited while watching movie trailers was measured to investigate whether it related to population-wide commercial success of the movies these trailers promoted. In a seminal study, a whole-brain (data-driven) analysis revealed that EEG activity in the gamma band during trailer watching was associated with commercial success of the movies as expressed in terms of U.S. box office revenue, beyond self-reported liking of the trailer (Boksem and Smidts 2015). In a second study, in which participants wore a mobile EEG cap while sitting among the audience in an actual movie theater, the neural similarity measured in activity in the alpha band, referred to as cross-brain correlation (CBC), predicted future free recall of the movie trailers and prospective market-level sales of the corresponding movies six months later (Barnett and Cerf 2017). In a third study, neural similarity measured in the gamma band while participants watched trailers predicted the movies' sales performance on opening weekends and up to four weeks after the initial release of the movie (Christoforou et al. 2017).

However, even though all three of these studies used movie trailers as stimuli, they differed on the exact measure they tried to predict (gross U.S. box office revenue, opening weekend sales, sales in the first four weeks, average weekly ticket sales) and on the EEG measure that was found to be predictive of this market-level outcome measure (gamma band activity, two different measures of neural similarity). It is therefore difficult to establish what measures are predictive of movie success in general, independent of the particular dataset and metrics that are used. Moreover, the numbers of participants

and stimuli in these studies were relatively small, potentially leaving them underpowered.

The current study is the first attempt at an aggregated analysis investigating which EEG metrics are consistently related to the same outcome measure of market-level success, for the same type of stimulus (movies). Here, we present a reanalysis of the raw data from the three studies on movie trailers that have been published to date: Boksem and Smidts (2015), Christoforou et al. (2017), and Barnett and Cerf (2017). In addition, we collected data in two additional studies that have not previously been published. We extracted metrics reported in the original published articles and other metrics that have been associated with market-level outcomes in past research and that are also used in neuromarketing practice, and we related these metrics to our outcome measure of interest (gross U.S. box office revenue; see the Web Appendices for results using opening weekend revenue as an alternative outcome measure). This “mega-analysis” (Costafreda 2009) thus offers the benefits of an increased sample size, in terms of both participants and stimuli, a standardized analysis pipeline, consistency in EEG metrics, and a standardized population-level metric of market success.

The EEG Metrics of Interest and the Mental Processes They May Reflect

EEG metrics included in the analyses of the current study are alpha, beta, theta, and gamma oscillations; alpha asymmetry; ISC; and ISC in the alpha band specifically, referred to as CBC. We will briefly introduce these metrics here (for a more exhaustive discussion, see Web Appendices A and B).

ISC quantifies the level of neural similarity across participants viewing the same stimulus. Peak correlations in neural activity are expected to occur at moments in a movie where engagement (a cognitive state defined operationally by “emotionally laden attention”) is highest (Dmochowski et al. 2012, p. 2). Previous research has related neural similarity to performance on a final exam among students attending a class (Meshulam et al. 2021), to learning performance associated with educational videos (Cohen et al. 2018), to the memorability of audiovisual narratives (Cohen and Parra 2016), to the level of (emotional) engagement of movie scenes (Hasson et al. 2004; Nummenmaa et al. 2012), and to engagement and subsequent recall of television or oral story narratives (Song, Finn, and Rosenberg 2021). Importantly, ISC has been shown to forecast population-level preferences for TV shows and commercials (Dmochowski et al. 2014).

CBC is a version of ISC in which EEG alpha power (oscillations in the 8–12 Hz range, as discussed subsequently) time series are correlated across participant pairs. Here, an a priori decision is made to consider only activity in the alpha band, across all electrodes. CBC has previously been related to market-level success of movies (Barnett and Cerf 2017).

In addition to synchronization across participants, individual-level brain activations as reflected in different frequency bands have been associated with a host of mental

processes. There is a large literature showing a negative association between alpha activity (8–12 Hz oscillations) and attention (e.g., Klimesch et al. 1998; Van Diepen, Foxe, and Mazaheri 2019) or more generally between alpha activity and information processing (Pfurtscheller and Lopes Da Silva 1999) or arousal (Simons et al. 2009). Indeed, alpha activity evoked by commercial ads has been shown to be negatively correlated with self-reported arousal, as well as with the ads’ ability to grab attention (Eijlers, Boksem, and Smidts 2020). Asymmetry in the alpha band has been associated with approach and avoidance motivation (Coan and Allen 2004), such that a decrease of activity in the alpha band across left frontal areas is associated with pleasant stimuli in general and with the judged pleasantness of TV commercials in particular (Shestiyuk et al. 2019; Vecchiato et al. 2011). Venkatraman et al. (2015) report moderate relationships between alpha asymmetry and market level success as measured by ad elasticity.

Beta activity (13–20 Hz oscillations) has been related to various cognitive processes, but most notably to memory (Lundqvist et al. 2016; Miller, Lundqvist, and Bastos 2018) and reward processing (Cohen, Elger, and Ranganath 2007; Marco-Pallares et al. 2008). Of particular relevance for the present study, individual preferences for movie trailers and commercials has been found to be associated with activity in the beta frequency band (Boksem and Smidts 2015; Shestiyuk et al. 2019). Furthermore, Lucchiari and Pravettoni (2012) have observed that while beta activity seems to be modulated by the experience of pleasure associated with a favorite brand, theta (4–8 Hz oscillations) modulation seems to reflect the lack of this experience. Activity in the theta band has been associated with negative valuation more generally and has been shown to predict consumer choices (Telpaz, Webb, and Levy 2015). Theta band activity has also been related to memory for TV commercials (Vecchiato et al. 2010). In addition, EEG activity in the theta band measured from a small sample of viewers has been used to predict the number of YouTube views of these commercials (Guixeres et al. 2017).

Finally, gamma band activity (>20 Hz oscillations) has been related to numerous functions associated with top-down cognitive control (Engel, Fries, and Singer 2001), most prominently processes that match sensory input to stored memory associations (i.e., understanding; Herrmann, Fründ, and Lenz 2010). Moreover, gamma activity has been associated with a lateralized network in the brain, including the temporoparietal junctions and the bilateral inferior frontal gyri, involved in understanding and meaning making (Samogin et al. 2020). Importantly, gamma activity while watching movie trailers has also been found to predict movie sales in the general population (Boksem and Smidts 2015).

To summarize, the different EEG metrics considered in this study are associated with different underlying mental processes. ISC (and CBC) have mainly been associated with engagement with the stimulus, that is, the extent to which a stimulus resonates similarly across individuals. Activity in the alpha band is associated with attention, but also with arousal and information processing more generally, while asymmetric frontal

activation in this frequency band is associated with approach/avoidance motivation. Theta activity is associated with memory performance, but also with (negative) valuation. Beta activity has been associated with positive valuation, but also with memory formation, and gamma activity has been associated with cognitive control, understanding, and meaning making.

As is evident from the preceding paragraph, although different frequency components of the EEG are associated with different mental processes, there is no one-to-one mapping of these mental processes onto specific frequency bands: Frequency bands can be associated with several mental processes, and these processes can be associated with several frequency bands. This makes it difficult, if not impossible, to infer mental processes from observed EEG oscillations. This is called the “reverse inference problem” (Poldrack 2006): While it is possible to relate specific manipulations of mental processes to changes in observed EEG oscillations (forward inference), it is not possible to relate observed EEG oscillations to specific mental processes (reverse inference).

However, while reverse inference cannot be used for hypothesis testing, it can be used for hypothesis generation. For example, foreshadowing our main findings, if we find that gamma oscillations obtained from participants viewing trailers predict the commercial success of movies, we cannot draw firm conclusions as to which mental processes evoked by those trailers resulted in those movies being successful or not. However, prior literature does enable us to generate testable hypotheses regarding underlying mental processes: If gamma activity is associated with commercial success and the literature suggests that gamma activity is associated with understanding, then perhaps trailers that evoke relatively strong gamma responses are those that are most easily understood. Therefore, we include a follow-up experiment (described subsequently, in Part 2) in which we test such a hypothesis.

Aims of the Current Study

In the current study, we examine whether neural activity, represented by seven EEG metrics (oscillations in the alpha, beta, gamma and theta frequency range; alpha asymmetry; ISC; and CBC) recorded from a relatively large sample of participants ($n = 188$) in response to watching a large set of movie trailers ($k = 161$), is associated with populationwide success of the corresponding movies expressed in terms of gross U.S. box office revenue. In addition to the large sample size, large stimulus set, and standardized analysis pipeline afforded by our mega-analysis approach, this work adds to the current literature in four important ways.

First, despite the compelling results presented in previous research on the association between EEG metrics and aggregate population-level choice (ticket sales for movies), it has become clear that a single finding cannot be taken as sufficient support for any theory or hypothesis. The importance of conducting replications has been stressed by several authors who have questioned the validity of numerous findings in neuroscience and

psychology (e.g., Botvinik-Nezer et al. 2020; Ioannidis 2005). The most promising way of addressing these issues is to attempt to replicate findings from previous studies, as the probability of a finding being true increases with the number of replications. Here we take up this challenge, not only by reanalyzing three published datasets in a uniform and systematic manner, but also by adding two independent, previously unpublished datasets to further validate the association between EEG metrics and aggregate population choice.

Second, our current approach differs from analyses in previous EEG studies on movie trailers as it tests for out-of-sample prediction accuracy, instead of just establishing correlational relationships between brain and behavior. This out-of-sample prediction leads to a more conservative inference of the brain-behavior relationship than does correlation, thereby increasing the probability of successful replication in the future (Shen et al. 2017). More practically, establishing predictive models with high accuracy is required to convert insights from neuroimaging to applications in practice (Gabrieli, Ghosh, and Whitfield-Gabrieli 2015). That is, for neuromarketing practice it is of much greater value to be able to predict the (relative) box office success of a yet unreleased movie than to merely be aware that a particular EEG metric is somehow related to market-level success. Our analysis of five individual datasets enables us to train a regression model on a training set of four independent samples and then evaluate the predictive performance on the remaining sample using cross validation. Testing the predictive importance on independent samples provides the most accurate estimate of the generalizability of the models.

Third, for findings to be of value for academics and practitioners alike, we need to show not only that EEG measures predict consumer choices but also that these measures provide unique added value in terms of predictive power beyond traditional measures. That is, because we know that self-report measures often perform quite well in predicting preferences and choice, we need to demonstrate that neural data can actually capture unique information about marketing stimuli that can be of added value in combination with traditional measures such as self-reported preferences and characteristics of the stimulus.

Therefore, we investigated whether neural activity is predictive of movie success above and beyond in-sample liking as well as several characteristics of the movies that are likely to have an effect on their success at the box office: the genre of the movies, production budget (e.g., Bharadwaj et al. 2017; Eliashberg, Elberse, and Leenders 2006), popularity of the director and actors (i.e., star and director power; Ainslie, Drèze, and Zufryden 2005; Liu, Mazumdar, and Li 2015), and whether the movies are sequels or are based on prior works (e.g., books, TV shows; Basuroy and Chatterjee 2008). Note that several other factors, such as user-generated content on social media and other word-of-mouth effects (e.g., Lu, Dinner, and Grewal 2023), may also be associated with movie success. However, our focus here is particularly on information that is available prior to the trailers’ release and also

Table 1. Design Parameters of the Five Studies Included in the Mega-Analysis.

Items	Study 1	Study 2	Study 3	Study 4	Study 5
Participants (n)	29	39	39	10 + 13	58
Age (mean)	22	20	22	22	34
Female (%)	55	46	38	41	48
Male (%)	45	54	62	59	52
Total no. of trailers	56	18	60	15	13
Views per participant	18	18	20	14/16	5
Views per trailer	4–8	39	3–20	10/13	4–8
Box office revenue (million \$)	4–121	1–92	6–127	14–333	8–234

Notes: Study 1: Boksem and Smidts (2015); Studies 2 and 3: new data; Study 4: Christoforou et al. (2017); Study 5: Barnett and Cerf (2017). In Study 4, the stimulus set of 15 trailers was split into two subsets: one set of eight trailers and one of seven trailers. Participants were randomly assigned to view one of the subsets. Participants viewed the stimulus subset twice in this study, but to keep conditions constant across studies, we included only the first presentation of the trailers in the analysis. Because the two subsets were viewed by different participants, they are considered separate studies in our analyses.

under control of the producer, because we are interested in whether measures derived from the EEG signal can be used to predict a movie's success prior to its release, when pretesting and optimizing trailers can still have an effect.

Fourth, instead of relying on reverse inference to interpret brain activations, in the follow-up experiment described in Part 2 we use reverse inference to generate, and subsequently test, hypotheses about the mental processes evoked by trailers that are reliably associated with commercial success. This approach generates actionable insights into how to best execute a trailer to maximize box office returns.

Part 1: Predicting Commercial Success with EEG Metrics

Study Design Parameters

In the current study we performed a reanalysis of three published studies and two new datasets. Here we provide a brief overview of the design parameters for the five datasets; for a more exhaustive account, refer to Web Appendix C.

Participants. All participants had normal or corrected-to-normal vision and were fluent in English. Combining the five studies resulted in an overall sample of 188 participants. Refer to Table 1 for an overview of the different sample sizes per study and other design parameters for the five studies included in this mega-analysis.

Stimuli. Across all studies, the stimuli consisted of 161 official movie trailers in English. Refer to Table 1 for the total number of trailers per study, how many trailers each participant viewed, and how many views the trailers received in each study. Web Appendix C provides an exhaustive overview of how trailers were selected for each study. The commercial success as expressed in terms of gross U.S. box office revenue of the movies that all the trailers promoted varied between \$1.4 million and \$333.2 million (median = \$45.5 million, $M = \$57.1$ million, $SD = \$52.2$ million). Opening weekend revenue varied between \$30,000 and \$94.3 million (median = \$14.1 million, $M = \$18.0$ million,

$SD = \$18.3$ million). The evaluations of the movies that the trailers promoted as expressed by IMDb ratings varied between 3.1 and 8.3, and the average evaluation was similar across studies (median = 6.1, $M = 6.6$, $SD = .73$ on a scale of 1–10). See Web Appendix D for an overview of all the movies included in the mega-analysis.

Data Collection and Measurements

Prior to the start of all data collection sessions, participants first received information and instructions about the tasks, and consent forms were obtained from all participants. In Studies 1–4, the participants were seated in a comfortable chair, the electrodes were applied, and the data recording was prepared. In Studies 1–3, the recording occurred in an electrically shielded, sound-attenuated room that was dimly lit. Study 4 took place in a designated experimental room far from noise and well lit with artificial light. For Studies 1, 2, and 3, a 19-inch PC monitor was positioned at 1.80 meters from the participants, while for Study 4 the distance from the monitor to the participants was 60 centimeters because of the simultaneous collection of eye-gaze data. In Studies 1–4, the stimuli were presented randomly to the participants. After the presentation of each trailer, an on-screen question was presented asking the participants to indicate the degree to which they liked the movie (trailer) on a scale of 0–10 for Studies 1, 2, 3 and on a scale of 1–10 for Study 4. Recordings of Study 5 took place in a movie theater. Participants sat among the regular audience wearing mobile EEG caps. Two participants who chose the same movie were seated together. Ratings of how much participants liked the trailer were only collected upon free recall after the feature movie (several hours later), so these data were not compatible with the other studies.

EEG recordings and preprocessing. For a detailed description of how the EEG data were recorded and processed, see Web Appendix E. Briefly, we performed preprocessing of the EEG data in MATLAB (MathWorks) and BrainVision Analyzer software (Brain Products). Data were downsampled to 256 Hz, rereferenced, and filtered with a 1 or 1.5 Hz low-cutoff

filter and a 50 or 60 Hz notch filter. Eye-movement and electro-myography artifacts were corrected. The EEG data were then segmented, and standard artifact detection and rejection criteria were applied to these segments.

For the power-based metrics, we then decomposed the data into different frequencies (1–128 Hz or 1–125 Hz) using a fast Fourier transform. Following this, we averaged the frequency data across all segments for each video, and for each participant separately. To create the five EEG metrics (theta, alpha, beta, and gamma oscillations and alpha asymmetry), we sampled neural activity from specific clusters of electrodes (see Web Appendix F), per frequency band, based on the literature (as previously presented in the introduction to this article and in Web Appendix A). Note that power-based metrics could not be calculated for Study 5. Due to the setup of this study, for most participants data were collected on only one trailer. In combination with the absence of a baseline, no normalization can be applied in the form of z-scoring or baseline correction. Unfortunately, nonnormalized power values are not informative about the cognitive state, because power can also be influenced by skull thickness and orientation of the source, among other factors. Therefore, only the ISC and CBC metrics were calculated for this dataset.

ISCs were computed using correlated component analysis, similar to that described in Cohen and Parra (2016). CBC (see Barnett and Cerf 2017) was calculated as the moment-to-moment synchrony in alpha activity (7–12 Hz) across participants watching the same trailer. Power spectral density of alpha activity was calculated using a short-time Fourier transform on the raw EEG signal. For a given participant pair, the Pearson correlation was calculated on the alpha power time series. The analysis was repeated for every possible pairwise combination of participants and then averaged across these pairs. Finally, the data were averaged across time to obtain a single value of neural similarity for each trailer. Values were z-scored per study.

Self-reported liking. Liking scores were obtained on a 10-point or 11-point scale. They were z-transformed per participant and then were averaged over participants and subsequently z-scored per study. In contrast with the other studies, in Study 5 liking scores were not obtained immediately after viewing the trailers. We therefore set liking scores for Study 5 to 0 (the mean liking score of all studies).

Movie Characteristics

Budget. The estimated production costs per movie were scraped from the IMDb website. The budget of the movie is expected to contribute to a qualitatively better movie and by extension also a better trailer. Indeed, budget is well known to be a strong predictor of box office returns (e.g., Bharadwaj et al. 2017). Budget was added to the regression model as a predictor variable, to examine whether EEG data can predict commercial success beyond the effects of budget.

Genre. Although effects of genre on box office returns are not always observed in prior literature (Hennig-Thurau, Houston, and Sridhar 2006), we took the genre of the movie that the trailer promoted into account in the analysis to control for the effect of movie genre on total U.S. box office returns. Because the five studies reported here were conceived independently from each other and were not intended to be combined in a single article, there are inconsistencies in how genres were operationalized in the original independent studies. Therefore, to align the operationalizations of genres across these studies, we recoded the genres associated with each movie. We did this by scraping IMDb for the genres listed for that movie (most often three). This resulted in 19 unique genres across the movies in our set. We then reduced this set by first excluding genres that occurred fewer than ten times in our set and second by removing genres that almost always co-occurred (e.g., “adventure” almost always co-occurred with “action,” and “horror” with “thriller”). Finally, we made sure that removing genres did not result in leaving any movie unclassified; we therefore combined the “comedy” and “family” genres. This resulted in assigning the movies/trailers to a set of genres consisting of action, biography, drama, mystery, thriller, and family/comedy. Web Appendix G shows the descriptives of U.S. box office returns per genre.

Star power. We operationalized actor and director recognition as the number of awards (Oscars plus Golden Globes) won prior to the movie’s release. For actor recognition we took the total number of awards won prior to the movie’s release by the three main actors as listed on IMDb.

Sequels and adaptations. Prior research has demonstrated that sequels may have a positive effect on box office revenue (Basuroy and Chatterjee 2008). In addition, movies that are an adaptation of prior work may have a head start in the eyes of the moviegoing public because they have already captured a certain level of public awareness and familiarity, which may increase box office revenue. To control for these factors, we coded, for each of the 161 movies in our set, whether the movie is a sequel and whether it is based on a book, TV series, or video game.

Control variables. In addition to the variables of interest described previously, we also included a number of variables of no interest in our statistical models. In particular, we used as control variables the number of views a trailer received in the study, the number of trailer views per participant in a study, the mean age of the participants in a study, the number of different genres shown per study, and whether the study was published or not. For reasons of clarity, and because these variables are not of direct interest (they are mainly artifacts of how the trailers were selected and the composition of the sample), we omit the estimates from these variables from the tables in the “Results” section.

Statistical Analyses

Model fitting. To determine whether the EEG metrics provide unique information about commercial success beyond the movie characteristics and self-reported liking, we fitted two linear mixed effects models (fitlme function from MATLAB) with U.S. box office revenue as our dependent variable. In the first, restricted model, we regressed box office revenue onto the dummies for the six genres, budget, star power, whether the movie was a sequel or adaptation, self-reported liking, and control variables, and added a random intercept for study. In a second model, we added one of the seven EEG metrics as predictors to the restricted model and report fixed effects for the added EEG metric. This was repeated for every EEG metric.

After examining the ability to explain commercial success by each EEG metric separately, we added the significant metrics to a linear model simultaneously using forward selection (p -value for inclusion .05). We compared the goodness of fit between the final model and restricted model by conducting a likelihood-ratio test, and we report the fixed effects of predictors from the second, full model.

Note that most analyses are performed on Studies 1–4, because the power-based metrics could not be calculated for Study 5 (see the “EEG recordings and preprocessing” section). The data from Study 5 are included for a comprehensive examination of CBC and ISC across the five studies. The final models that include all metrics are examined using Studies 1–4. Furthermore, the two subsets of trailers in Study 4 are considered two independent studies with their own random intercept, since they were viewed by different groups of participants (see Web Appendix C). Note also that in all models we include the predictors of no interest described previously in the “Control variables” section.

Out-of-sample prediction. The final model was then used to make out-of-sample predictions. In addition to being a good fit for the current dataset, the model also needs to be able to make predictions on a different dataset obtained from a different group of participants. This is especially relevant in the context of EEG, where signals can vary across participants for reasons unrelated to the presented stimulus.

We used a fivefold cross-validation approach in which four of the five datasets (Studies 1, 2, 3, 4a, and 4b) were used to fit the final model, which was then used to predict the U.S. box office revenue for the movies from the dataset that was left out. Leaving out all trailers from the same dataset provides us with a test set that is independent from the training set. After repeating this five times (once for each fold), we then correlated the predicted box office revenue for the movies thus obtained with the actual box office revenue as a measure of predictive accuracy. Results of the model including the EEG metrics are compared with the same model without EEG metrics, to examine whether including EEG metrics improve predictions.

The predicted commercial success for a trailer was estimated using a model fitted on data of all studies except for the study

Table 2. Fixed Effects for the Final Model Predicting Self-Reported Liking (Studies 1–4).

Predictor	Estimate	t-Value	p-Value	d.f.
Action	–.34	–1.60	.113	130
Biography	.20	.70	.483	130
Comedy	–.29	–1.02	.311	130
Drama	.48*	2.57	.011	130
Mystery	.60*	2.37	.019	130
Thriller	.11	.56	.577	130
Actor awards	.07	1.65	.102	130
Director awards	.04	.45	.655	130
Sequel/adaptation	$.10 \times 10^{-2}$	.01	.995	130
Budget	$.27 \times 10^{-2}$	1.36	.178	130
Alpha asymmetry	.15*	1.98	.050	130
ISC	.24**	3.08	.003	130

* $p < .05$.

** $p < .01$.

*** $p < .001$.

from which the trailer originated. This means that the random intercept cannot be estimated for the study of that trailer. U.S. box office revenue was therefore z-standardized per study for this analysis, thereby removing the differences in range between studies and the need for random intercepts. This also means that we are not able to make predictions of absolute U.S. box office revenue; we rather test the ability to make predictions in a relative sense. As a test statistic to evaluate the accuracy of predictions we use the correlation between the actual and predicted box office results. The presence of a difference in correlation coefficients for the model with and without EEG is inferred using Hotelling’s test of equality for dependent correlation coefficients (Hotelling 1940).

Results

Predicting in-sample preferences. Before we test whether EEG metrics evoked by movie trailers can predict population-level preferences for these movies (U.S. box office revenue), we first look at whether these metrics can predict the individual preferences (i.e., the self-reported liking of the trailers) for movies of the study participants from which the EEG was recorded. We first fitted a restricted model containing only the movie characteristics (genre, budget, sequel/adaptation, and star power) and the control variables. We found that only genre was a significant predictor of self-reported liking (participants liked movies more if they were of the drama or mystery genre), while star power had a marginally significant effect.

Next, EEG metrics were added to this restricted model, one at a time to avoid multicollinearity issues. We found that, in addition to the movie characteristics, both alpha asymmetry ($b = .16$, $t(131) = 2.06$, $p = .042$) and ISC (for Studies 1–4: $b = .24$, $t(131) = 3.13$, $p = .002$; for Studies 1–5: $b = .23$, $t(144) = 3.15$, $p = .002$) were significant predictors of self-reported liking. EEG metrics were then added one by one to the restricted model using forward selection: The most

Table 3. Fixed Effects for Restricted Model Predicting Commercial Success (U.S. Box Office Revenue) by Movie Characteristics, Liking, and Control Variables (Studies 1–4).

Predictor	Estimate	t-Value	p-Value	d.f.
Action	−8.84	−1.19	.235	131
Biography	−1.36	−.14	.893	131
Comedy	20.69*	2.04	.043	131
Drama	3.17	.47	.640	131
Mystery	7.88	.85	.397	131
Thriller	9.62	1.44	.152	131
Actor awards	.88	.61	.546	131
Director awards	−1.60	−.52	.608	131
Sequel/adaptation	5.74	.95	.346	131
Budget	.53***	7.63	.000	131
Liking	.62	.23	.827	131

* $p < .05$.** $p < .01$.*** $p < .001$.

Notes: Similar results were obtained for Studies 1–5; see Web Appendix H.

significant EEG metric was added, after which the model was estimated again. This was repeated until all significant ($p < .05$) predictors were added to the final model. The final model includes only ISC and alpha asymmetry as significant EEG metrics predicting self-reported liking (Table 2). The likelihood ratio test shows that including these metrics improves the fit of the model significantly ($\chi^2(2) = 13.34$, $p = .001$), increasing explained variance from an adjusted R^2 of .07 to .13, as compared with the restricted model.

Predicting population-level preferences. To test whether EEG metrics evoked by movie trailers can predict population-level preferences for these movies, we first fitted a restricted model containing movie characteristics, self-reported liking, and the control variables as predictors of commercial success (U.S. box office revenue). As shown in Table 3, we found that genre (comedies generate higher box office returns) and particularly budget are significant predictors of U.S. box office revenue. Indeed, we found that a model containing only budget as a predictor explains 50% of the variance in box office revenue, which is toward the higher end of what is observed in prior research (see, e.g., Bharadwaj et al. 2017). Star power and self-reported liking ratings, however, were not significant predictors.

Next, EEG metrics were added to the restricted model, one at a time. Only gamma activity was found to be significantly related to U.S. box office revenue (Table 4). In fact, a model including only gamma activity as a predictor already explains 34% of the variance in box office revenue. Also noteworthy is that the effect of CBC (found to predict box office revenue in the study by Barnett and Cerf 2017) was not significantly related to box office revenue in our mixed-effects model across the five studies (Table 4). Inspecting the results for each study individually shows that the effect of CBC is strongest in Study 5 (Web Appendix I). Study 5 uses the dataset in

Table 4. Fixed Effects for EEG Metrics When Added to the Restricted Model of Movie Characteristics and Liking, per Metric Separately.

Predictor	Estimate	t-Value	p-Value	d.f.
Alpha	.37	.13	.900	130
Beta	1.51	.54	.593	130
Gamma	10.08***	3.82	.000	130
Theta	1.73	.61	.542	130
Alpha asymmetry	−1.80	−.67	.505	130
ISC (Studies 1–4)	−.40	−.14	.888	130
CBC (Studies 1–4)	−2.55	−.95	.345	130
ISC (Studies 1–5)	$-.96 \times 10^{-2}$	$-.32E^{-2}$	.998	143
CBC (Studies 1–5)	−1.72	−.60	.547	143

* $p < .05$.** $p < .01$.*** $p < .001$.**Table 5.** Results for Fixed Effects in the Final Model Predicting U.S. Box Office (Studies 1–4).

Predictor	Estimate	t-Value	p-Value	d.f.
Action	−5.60	−.79	.433	130
Biography	.24	.03	.981	130
Comedy	19.21*	1.99	.049	130
Drama	3.87	.60	.551	130
Mystery	10.62	1.20	.234	130
Thriller	9.20	1.44	.151	130
Actor awards	1.99	1.40	.165	130
Director awards	−.24	−.08	.936	130
Sequel/adaptation	4.30	.74	.460	130
Budget	.48***	7.20	.000	130
Liking	.71	.26	.793	130
Gamma	10.08***	3.82	.000	130

* $p < .05$.** $p < .01$.*** $p < .001$.

which Barnett and Cerf (2017) originally reported the CBC effect, a result that we reproduce here.

Subsequently, EEG metrics were added one by one to the restricted model using forward selection: The most significant EEG metric was added, after which the model was estimated again. This process was repeated until all significant ($p < .05$) predictors were added to the final model. This process resulted in a final model that includes only gamma activity as a significant EEG metric (Table 5). The likelihood ratio test shows that entering the gamma metric improves the fit of the model significantly ($\chi^2(1) = 13.90$, $p < .001$), increasing explained variance from an adjusted R^2 of .53 to .57. Similar results are found when we use opening weekend revenue as the dependent variable (Web Appendix J).

To further illustrate the findings, the relationship between gamma activity and U.S. box office revenue is plotted per study in Figure 1 as a Pearson correlation between box office revenue and residuals of the model excluding gamma activity. It shows that the relationship is positive in all studies.

Web Appendix K shows an additional analysis on the effect of excluding trailers that were presented in more than one study,

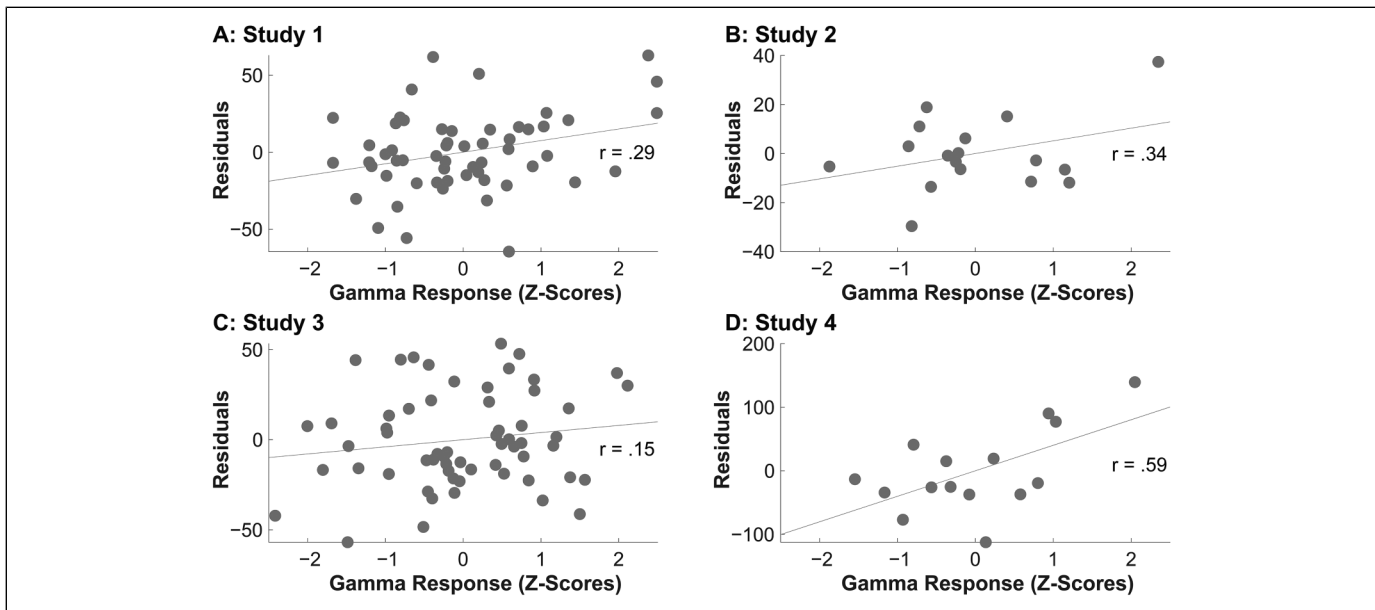


Figure 1. Relationship Between the EEG Gamma Metric and Residuals of the Model Predicting U.S. Box Office Revenue Without Gamma Activity (r = Pearson Correlation).

yielding similar results and demonstrating the robustness of the gamma effect.

Finally, we ruled out the possibility that gamma activity is related to genre instead of box office revenue. Gamma activity could, for instance, be increased for comedies, which in turn might generate higher box office results. A model with genre as the independent variable and gamma as the dependent variable shows that gamma activity is not related to any of the genres (all $p > .160$; see Web Appendix L, Table L1). Furthermore, we tested whether differences in colorfulness, saturation, luminosity, and video length can explain differences in gamma activity. Results presented in Web Appendix L, Table L2, show that this is not the case.

Out-of-sample prediction of box office. In the previous analyses we found that a model with movie characteristics, liking, and gamma activity as predictors was the best fit to the data. As a next step, we examined whether the model is not only a good fit for the current dataset but can also make predictions about new data. We examined to what extent we can predict U.S. box office revenue for one of the studies using data from the other studies. Making predictions for a different study is of particular relevance in the current situation, where trailers are viewed by a different group of participants in every study.

We applied a fivefold cross-validation approach in which four of the five datasets (i.e., Studies 1, 2, 3, 4a, 4b) were used to fit a linear model with genre, budget, sequel/adaptation, star power, and liking as predictor variables, and this model was then used to predict the box office revenue of the movies in the remaining dataset. Results of this model are compared with the same model with gamma activity included, to examine whether including the EEG metric improves predictions.

The correlation between predicted and actual U.S. box office revenue increased significantly when gamma activity was included in the model (Hotelling's $t(145) = 2.85$, $p = .005$). The prediction by movie characteristics and liking correlated $r = .48$ with actual box office revenue, whereas the correlation increased to $r = .57$ when gamma activity was included in the model, showing that predictions of commercial success increase when gamma activity is included.

Discussion

We performed a systematic reanalysis of multiple datasets investigating which EEG metrics are consistently related to commercial success for movies. We combined data from five studies in which neural activity in response to movie trailers was investigated. We examined which of seven conceptually relevant metrics (theta, alpha, beta, and gamma activity; ISC; CBC; and alpha asymmetry), extracted from the EEG signal, are predictive of in-sample preferences, and particularly of populationwide success of the corresponding movies, above and beyond available prerelease information on production budget, genre, star power, sequel/adaptation, and self-reported liking of the trailers. We found that, while alpha asymmetry and ISCs predicted in-sample liking of the trailers, only the effect of gamma activity was significantly related to commercial success expressed as U.S. box office revenue. Importantly, accuracy of out-of-sample predictions significantly increased when gamma activity was added as a predictor.

Predicting in-sample preferences. We found that asymmetric alpha activity over the frontal cortex (greater alpha activity over the right hemisphere as compared with the left

hemisphere) was associated with greater self-reported liking of the trailers. This finding fits well with the idea that alpha asymmetry is associated with positive valence and approach motivation (Harmon-Jones, Gable, and Peterson 2010), and also with previous findings in a marketing context in which it was observed that TV commercials that were liked better by participants also evoked a more pronounced alpha asymmetry (Vecchiato et al. 2011).

In addition, ISCs were associated with in-sample liking of the movie trailers. This suggests that trailers that are processed more similarly across participants are also (on average) more liked in that particular sample of individuals. The intuition is that if a stimulus is processed similarly in different individuals' brains, this means that they were all focused on the same thing (here the movie trailer). In contrast, when participants' minds wander, brain responses will be highly idiosyncratic and ISC will be low. Indeed, as ISC has been associated with engagement (Dmochowski et al. 2012), a straightforward, although slightly circular, interpretation would be that engaging trailers are generally liked better (see also Hasson et al. 2004; Nummenmaa et al. 2012; Song, Finn, and Rosenberg 2021).

None of the other metrics were found to be associated with individual preferences—not even beta activity, which has previously been found to predict in-sample liking of movie trailers (Boksem and Smidts 2015). While beta activity has indeed been associated with reward processing (Marco-Pallares et al. 2008) in general and with preferences for commercials (Shestiyuk et al. 2019) and brands in particular (Lucchiari and Pravettoni 2012), this association does not generalize across the datasets in the current mega-analysis.

Predicting market-level preferences. Although alpha asymmetry and ISC were found to predict in-sample preferences for movie trailers, they were not predictive of market-level success of these movies. Instead, we found that only gamma oscillations could significantly, and out of sample, predict the box office results for the movies across the datasets in our current mega-analysis.

Previous research has found a positive relationship between ISCs and engagement-related outcome measures. We hypothesized that increased ISC, and therewith increased engagement, should relate to better box office results. However, no such relationship was observed in the current study. Not finding a consistent relationship may be attributed to several factors. The ISC metric might only be predictive for specific stimuli or outcome measures. This explanation seems unlikely, given that the results were obtained using various stimuli and outcome metrics including movie stimuli (Dmochowski et al. 2012) and audience preferences (Dmochowski et al. 2014). Another explanation for the absence of an effect of ISC might be the low number of views for some trailers. The decomposition method may require larger sample sizes per trailer. Cohen and Parra (2016) note that ISC can be calculated reliably on as few as 12 stimuli. In the current study, however, even fewer stimuli were used to calculate ISC for some trailers. To test this potential concern, we repeated the analysis on a subset of

the trailers for which at least 12 views were available (see Web Appendix M). Again, no evidence of a relationship between ISC and box office revenue or opening weekend revenue was found. Note, however, that the number of trailers was reduced substantially for this analysis (from $k = 161$ to $k = 74$). Therefore, we cannot exclude the possibility that the absence of an effect of ISC in this analysis might be due to the low number of trailers used.

While a relationship between movie success and an alternative measure of neural similarity (CBC) was found by Barnett and Cerf (2017), this relationship was not present in any of the other datasets in the current analysis. We did reproduce the two correlations reported by Barnett and Cerf (2017) using our CBC data and their outcome measures (see Web Appendix N, Figure N1, Panels A and B). This confirmed that the actual CBC measures in the original study and in this reanalysis were identical and that the absence of a strong effect of CBC is not due to differences in the analyses. As an additional check we also calculated CBC only on channels that gave the largest effects in the original study (Web Appendix O), but the results did not improve. Instead, we may conclude that the association between CBC and movie success does not generalize well to different data.

Importantly, however, we note two caveats that may explain the lack of effect of CBC in Studies 1–4. First, we examined U.S. box office revenue, whereas the largest effect was found for average weekly ticket sales in the original publication by Barnett and Cerf (2017). Weekly ticket sales are inherently an interesting measure since this measure is not as sensitive to how long a movie runs in theaters, which may introduce variance in gross box office revenue that is not directly associated with the quality of the movie. However, using weekly ticket sales as a measure makes less sense for movies that were released longer ago. We did not have access to this metric for all movies in our set to fully test the effects for this metric.

Secondly, and more importantly, the data from Barnett and Cerf (2017) were collected in a field setting that was markedly different from the setting of the other studies (in the theater vs. in the lab), and participants evaluated only a few trailers (vs. several trailers in other studies). CBC might only be predictive when trailers are watched in a setting where other viewers are present, compared with letting participants watch the stimuli individually. Such a conclusion would have important practical implications in that preferably trailers should be tested in both conditions. Since nowadays trailers are mostly viewed individually online, similar to how they were viewed in Studies 1–4, CBC seems in general a less suitable metric for predicting success of new movies. Future studies could investigate whether neural synchronization metrics such as CBC are in general more strongly elicited in social settings, and whether they may also be more predictive of market-level success if collected in more social settings.

Of all EEG metrics, only gamma activity was found to be a robust predictor of commercial success above and beyond in-sample liking and characteristics of the movies. Gamma

activity has been related to various mental states associated with top-down cognitive control in general and with the matching of sensory input to stored memory associations (Engel, Fries, and Singer 2001; Herrmann, Fründ, and Lenz 2010), the process through which understanding and meaning are created, in particular. Indeed, gamma oscillations have been localized to a lateralized network in the brain, including the temporoparietal junctions and the bilateral inferior frontal gyri, involved in understanding and meaning making (Samogin et al. 2020). This association also aligns with the bilateral distribution of the gamma effect as observed in the study by Boksem and Smidts (2015) (on which we based the cluster as used in the current study), and the putative role of gamma activity in the integration of information across different brain areas in different stages of (perceptual) processing during the viewing of a trailer (Samogin et al. 2020).

As noted in the introduction, however, one must be careful when interpreting the relationships between EEG metrics and psychological constructs because of the reverse inference problem (Poldrack 2006). When a psychological construct has been shown to be related to particular neural activity in prior studies, this does not imply that those particular psychological processes were necessarily engaged when this neural activity is observed in a different context. This is especially the case for complex stimuli such as commercials and trailers, in which there is less control over the presence and absence of various kinds of stimulus features. Indeed, as suggested in the preceding section and in the introduction, gamma activity has been associated with many different mental processes, so confirming the involvement of particular mental processes through the measurement of gamma activity is not possible. However, reverse inferencing can aid in generating hypotheses about the mental processes involved.

Part 2: Mental Processes Underlying the Gamma Response

To obtain some initial insight into the mental processes underlying the gamma response, we selected trailers that elicited either a high or low gamma response. New participants then watched these trailers and subsequently responded to a survey asking about their feelings and experiences while watching each trailer. Trailers were drawn from the two most common genres in our set: action and drama. To test whether effects were specific to gamma responses, we followed the same procedure for an EEG component unrelated to gamma activity, and with putatively different associated mental processes. Thus, we also selected trailers that elicited either high or low alpha responses.

Methods

Participants. We recruited 185 participants (87 female, 98 male; $M_{\text{age}} = 19.8$ years, $SD = 1.1$) from the university population. All participants provided written informed consent for their

Table 6. Survey Items and Loadings on the Two Varimax-Rotated Factors.

Items	Factor 1	Factor 2
"When watching the trailer, it was easy to keep my attention focused on the trailer"	.80	.35
"When watching the trailer, I easily got distracted and my mind wandered off" (reverse-coded)	.68	.35
"I found it easy to understand and comprehend what was happening in the trailer"	.34	.83
"The trailer did not make sense" (reverse-coded)	.31	.74
"I was entirely absorbed by the trailer while watching"	.85	.31
"The trailer was engaging"	.84	.32
"The trailer has a clear story line"	.30	.83
"It was difficult to figure out how events in the trailer were related" (reverse-coded)	.15	.81
"The trailer was arousing"	.52	.10
"The trailer evoked an emotional reaction"	.57	.18
"The trailer has appealing visuals and sound"	.72	.14
"The trailer was interesting"	.84	.33

Notes: Bold formatting indicates significant factor loadings.

participation. The study was approved by the local internal ethical review board and was conducted according to the Declaration of Helsinki. Participants received course credit for their participation. None of the participants took part in any of the other studies reported in this article.

Stimuli. Trailers for this experiment were selected based on the gamma and alpha responses they elicited in the EEG experiment reported in the main study. We selected two sets of trailers, one set from the action genre and one set from the drama genre. From each genre we selected two trailers high on gamma activity and also high on alpha activity, two trailers high on gamma but low on alpha activity, two trailers low on gamma but high on alpha activity, and finally two trailers low on both gamma and alpha activity. The levels of alpha and gamma activity were manipulated within each subject, while genre was manipulated between subjects. Thus, the final set consisted of 16 trailers (8 for each genre). These 16 trailers and their associated gamma and alpha responses were all from Study 1; see Web Appendix D.

Survey items. The survey asked participants about their feelings and experiences while watching each trailer. We asked about mental constructs that have been associated with gamma or alpha responses in previous literature (see Web Appendix A). Specifically, we asked about attention, absorption and engagement, meaning and comprehension, clarity of the narrative, arousal, emotions, visual appeal, and whether the trailer was interesting. See Table 6 for the items. Responses could be given on a continuous rating scale ranging from "not at all"

to “very much so.” In addition, we asked whether participants had seen the trailer before and whether they had seen the movie.

Procedure. Participants each watched eight trailers in random order from the same genre (i.e., genre was manipulated between subjects). After watching each trailer, they responded to the survey items listed in Table 6. Finally, we asked them how often they go to the cinema in a year, what their favorite genres are, and how critical trailers are in deciding whether to go see a movie or not, in addition to demographic variables. The experiment lasted just under 30 minutes. After completing the experiment, participants were thanked and debriefed.

Analysis. To uncover any latent factors underlying the responses to the survey items, we performed an exploratory factor analysis. The Bartlett sphericity test indeed shows that the items are significantly correlated ($\chi^2 = 14,172.33$, $p < .001$) and that the data could be sufficiently described by two factors with eigenvalue > 1 (total extracted variance 66%). Varimax-rotated Factor 1 displays high loadings on items related to attention, engagement, visual appeal, and interest, while Factor 2 displays high loadings on comprehension, meaning making, and clarity of the narrative (see Table 6 for all factor loadings). We label Factor 1 as “Attention” and Factor 2 as “Understanding.” Next, we ran multilevel hierarchical regressions with random intercepts for participants and genres, with the average gamma and alpha response per trailer (as evoked in response to these trailers in Part 1, Study 1) as predictors of interest, and Attention and Understanding as dependent variables. Additional predictors were participants’ gender, favorite genres, moviegoing frequency, and self-reported importance of trailers for moviegoing decisions.

Results

Attention. We found that the alpha ($b = -.50$, $t = -2.58$, $p = .010$) and gamma ($b = -.134$, $t = -2.23$, $p = .026$) responses were negatively associated with Attention. Including other predictors such participants’ gender, favorite genres, moviegoing frequency, and self-reported importance of trailers revealed that importance of trailers ($b = .439$, $t = 2.96$, $p = .004$) and whether the preferred genre included “action” ($b = .279$, $t = 2.73$, $p = .007$) were additional significant predictors of Attention.

Understanding. We found that the gamma response was positively associated with Understanding ($b = .429$, $t = 6.93$, $p < .001$), while the alpha response was negatively associated with Understanding ($b = -.050$, $t = -2.50$, $p = .013$). Of the additional predictors, again whether the favorite genre included “action” was positively associated with Understanding ($b = .208$, $t = 2.52$, $p < .013$).

Overall, the results indicate that while alpha and gamma responses were associated with both Attention and Understanding, (high) gamma activity is mainly associated with Understanding and (low) alpha activity is most strongly associated with Attention.

Discussion

We found that the levels of gamma activity elicited by the trailers as reported in Part 1 was associated with the self-reported understanding of the events depicted in the trailer and how these events were related to form a coherent narrative in Part 2. For example, for trailers that elicited a high gamma response, participants agreed more with statements such as “I found it easy to understand and comprehend what was happening in the trailer” and “The trailer has a clear story line.” In contrast, the level of alpha activity elicited by the trailers in Part 1 was associated with self-reported attention in Part 2: For trailers that elicited a more pronounced reduction in alpha activity (suppressed alpha power is associated with increased attention; Van Diepen, Foxe, and Mazaheri 2019), participants reported stronger agreement with statements such as “When watching the trailer, it was easy to keep my attention focused on the trailer” and “The trailer was engaging.”

Thus, we can provide some initial evidence that the increased gamma response that is predictive of higher box office returns is associated with processes such as understanding, meaning making, and comprehension: Successful trailers are easier to understand and have a clear story line (see also Barnett and Cerf 2017). This suggests that if one wants to be successful in promoting a movie, the trailer should clearly depict the movie’s story line and should be easy to comprehend. Indeed, understanding the movie trailer’s narrative is almost a necessary condition for being able to decide whether one would like to watch the movie. This dovetails with findings by Karray and Debernitz (2017), who extensively coded trailers and found that the creative content, in particular the appeal of the movie plot as conveyed by the trailer, had a positive effect on expected financial return of the movie. They also found that the number of trailer scenes negatively affected returns, suggesting that such trailers may become too complex for viewers to easily understand and recall.

Of note, in this small set of movies ($k = 16$) we did not observe a significant association between Understanding and box office revenue (see Web Appendix P), although the association was in the expected direction. In contrast, gamma activity, even across only 16 trailers, was marginally significant in predicting box office revenue. These findings may suggest that, even though gamma activity is strongly associated with Understanding, gamma response is a richer measure, and self-reported understanding cannot be taken as a comprehensive behavioral proxy of gamma activity. Of course, this study lacks sufficient statistical power to make strong claims, which we discuss as a limitation in the “General Discussion” section.

Although we found gamma activity to be most strongly associated with Understanding and alpha activity with Attention, gamma activity also correlated with Attention and alpha activity with Understanding. Typically, attention is an antecedent of understanding (one needs to pay attention in order to understand something), and also here we find that reductions in alpha activity (i.e., increased attention) are associated with increased understanding. In contrast, things that are difficult

to understand (i.e., that are disfluent) typically require much attention, and here we find that high levels of self-reported attention can be negatively associated with the gamma activity that reflects Understanding.

Taken together, these findings may suggest that the more easily participants could make sense or meaning of the trailer, the more successful the movie ultimately was at the population level. Of course, alternative explanations are possible. For example, it may be that movies that have very simple and straightforward story lines to begin with are more successful in general. However, our results suggest that even when we control for genre such as action or drama, the gamma effect holds, such that even within a particular genre, trailers that are more easily understood are associated with higher box office returns. We return to this point when discussing potential future directions.

General Discussion

Contribution and Implications

The current work makes several important contributions, both methodological and substantive. First, by making use of the large sample size, large stimulus set, and standardized analysis pipeline afforded by our mega-analysis approach, we were able to perform a high-powered replication of reports of associations between EEG activity on the one hand and commercial success of movies on the other. Such a replication is important, since recently the reproducibility of many findings across different scientific disciplines has been questioned (e.g., Botvinik-Nezer et al. 2020; Ioannidis 2005). To avoid building further research on fragile ground, replications are necessary to validate novel insights and hypotheses. We contribute to this by showing that across five datasets, the association between gamma power and box office success holds, while other metrics, such as ISCs, do not generalize as well to different datasets (or measurement conditions), and still other often used metrics, such as frontal alpha asymmetry, were not found to be predictive at all.

Second, instead of just establishing correlational relationships between brain and behavior, our current cross-validated prediction approach (leaving out data from an entire study as a test set) allows for out-of-sample prediction, resulting in a more rigorous inference of the brain–behavior relationship and thus increasing the probability of successful replication in the future (Botvinik-Nezer et al. 2020). Importantly, establishing predictive models with high accuracy is required for translating insights from neuroimaging studies to applications in practice (Gabrieli, Ghosh, and Whitfield-Gabrieli 2015). That is, for findings to be of value for neuromarketing practice, it is imperative to be able to predict the (relative) box office success of a yet unreleased movie, much more so than merely showing that a particular EEG metric is somehow related to market-level success.

Third, we show the relevance for movie marketing decisions by finding not only that gamma band activity predicts consumer choices, but also that this metric provides unique added value in

terms of predictive power beyond traditional measures. That is, we demonstrate that neural data can capture unique information about marketing stimuli. This is important because the extensive literature on movie marketing indicates that certain characteristics of movies, such as their production budget, star power, and genre, already perform quite well in predicting preferences and choice. For neuroimaging methods to be worth their use in practice, it is crucial to show the value added. In the current study we find that adding gamma activity to the model increases the predictive accuracy of box office revenue by 19% (from $r = .48$ to $r = .57$). This difference may not seem very large, but the baseline (predicting box office revenue from genre, star power, and in particular production budget) is already very high. Also, being able to predict box office success just a little bit more accurately can already have substantial impact in informing decisions on advertising spending. The observed estimate of the effect of gamma activity (10.08) implies that an increase of one standard deviation in gamma band activity would be associated with an increase of over \$10 million in box office revenue (keeping other variables constant). Given the average box office revenue of \$57.1 million, this increase in gamma band activity would thereby be associated with an increase of roughly 18% of the total returns of the movie. This indicates the potential value of optimizing the trailer for boosting awareness and sparking interest in the movie.

One practical implementation of our findings could be that several versions of a trailer are produced and then pretested by measuring gamma responses to these different versions. The version for release could then be selected by comparing these gamma responses: The version with the highest gamma response resonates the most with the audience and may therefore attract more people to the cinema. Pretesting several versions of trailers is managerially insightful because it also enables one to disentangle the impact of the composition of the trailer on gamma activity from the effect of movie content and appeal conveyed by the trailer on gamma activity. Finding a low gamma response to all versions of the trailer may constitute a warning signal that the movie itself may not be very appealing, and that a low response is not due to having designed a bad trailer given the (potentially great) movie material. Alternatively, the gamma response evoked by the selected “best” trailer can be compared with the response evoked by past trailers; if the trailer compares favorably, it is likely that the movie will do relatively well, and vice versa. This may inform marketing decisions, for example about advertising spending or the number of screens in theaters.

It should be acknowledged, though, that since the trailer is an excerpt of the movie, optimizing the gamma band activity of the trailer itself has limits. A relevant topic for further research, in particular for neuromarketing practice, is to study to what extent gamma band activity is driven by the inherent quality of the already produced movie in comparison to improvements to the trailer composed, given the available movie material. Additionally, understanding which attributes or features of the movie trailer affect the gamma response would be of significant value for guiding the design and optimization of trailers.

As a fourth contribution, we provide initial evidence of the underlying mental processes that make trailers successful. While previous work (Boksem and Smidts 2015) has already suggested that gamma responses elicited by movie trailers are associated with market-level success of movies, here we were able to relate these gamma responses to latent processes such as understanding, comprehension, and sense making, providing more actionable insights for practitioners. Our work complements previous work in marketing on what makes trailers successful (e.g., Karray and Debernitz 2017) by confirming that ease of understanding the story line and low levels of complexity (Barnett and Cerf 2017) seem to be important drivers of the predictive brain response.

Fifth, we want to stress that the approach taken here is only possible through open science, the sharing of both data and the code for analyzing the data, making results transparent and accessible to all levels of an enquiring society. The practice of keeping data and code as proprietary, which is still relatively common in academia and the de facto norm in neuromarketing practice, has been blocking scientific progress for many years. Therefore, we have uploaded the data collected in our lab (Studies 1–3) and scripts of all analyses reported in this article to a publicly accessible repository (<https://osf.io/auyr5/>) such that future studies may benefit from and build on the current work.

Limitations

In addition to the contributions listed previously, the current work also has its limitations. A first limitation is that, while we show that we can predict movie success out of sample, we were able to predict success only in a relative sense. That is, for new movie trailers we are able to predict which movies will do well and which ones less so, all relative to the other movies in the sample. Absolute revenue amounts in dollars are difficult to estimate; since EEG power measures bear no absolute meaning, values can typically only be interpreted relative to other stimuli or to a baseline. For neuromarketing practice, this would imply that absolute box office returns of new trailers can only be estimated by means of comparison with brain activity in response to existing trailers with known associated commercial success. Existing trailers with varying movie success will have to be presented to participants along with the new trailers of interest. Box office returns of new trailers could then be estimated by scaling results according to responses to the existing trailers.

A related limitation may be that, even though this mega-analysis enables us to sample a relatively large range of movies with a large range of commercial success across common genres, the movies included in our sample remain a very small subset of all movies and genres released and may therefore be somewhat biased. For example, while we are able to predict box office revenues with gamma activity, predicting extreme responses on the outcome variable (i.e., blockbuster movies) may not be possible because the linear relationship between gamma activity and box office success may break down at the extreme ends of the distribution. This

is because in our training sets (particularly for Studies 1–3) blockbuster movies were explicitly excluded. In addition, all box office revenues were standardized in our analysis. Therefore, predicting revenues for movies that fall far outside of the range of our dataset may not be possible. Future studies could explicitly test associations between gamma activity and box office revenue for blockbusters, for genres not included in our study, such as horror or animated movies, and for movies that are sequels as these were explicitly excluded in Studies 1–3 and therefore underrepresented in our dataset.

A third limitation may be that EEG metrics are inherently noisy measures. That is, the signal-to-noise ratio is typically low, which potentially has important implications for the reliability of these metrics. The current mega-analysis allows for an improved signal-to-noise ratio, and thus reliability, by testing a large number of stimuli that were viewed multiple times. However, while some trailers were viewed many times in this dataset, some received only a limited number of views (see Web Appendix C, Figure C1). Remarkably, not much is known about the reliability of EEG measures when processing naturalistic, dynamic stimuli such as movie trailers, and thus it is unclear how many views per stimulus are required to obtain reliable metrics. Here we controlled for the number of views per trailer in our analyses and used cross validation to show robustness of the gamma metric predicting commercial success. Nevertheless, we call for future studies to provide evidence for reliability of EEG metrics associated with dynamic naturalistic stimuli (e.g., movie trailers, commercials).

Fourth, although we showed that EEG metrics, and more specifically activity in the gamma band, contributed significantly beyond prerelease information on genre, budget, sequel/adaptation, star power, and in-sample liking of the movie (trailer) in predicting box office revenue, this in-sample liking is measured in a sample that is much smaller than is typical for a consumer response panel and likely not highly representative of the population. This may have contributed to our finding that liking was not a significant predictor of commercial success across the included studies. Expanding on our work, future research could examine the contribution of neural activity beyond self-report measures collected in larger samples (e.g., in online panels).

A final limitation may be that our main dependent measure is U.S. box office revenue, while four out of the five reported studies used non-U.S. participants. While this issue is unlikely to introduce spurious results (if anything, it should be easier to predict local box office revenue), it could obscure associations between EEG metrics and box office success. We therefore partly reanalyzed our data with local box office revenue (when available) as a dependent variable. We found that the gamma responses of local participants also were significantly related to local box office revenue, while other metrics were not (see Web Appendix Q).

Future Directions

An outstanding question for further consumer neuroscience research is whether the results are specific for movie trailers

as a stimulus and box office revenue as a dependent variable. It may be that other metrics predict success for other types of dynamic stimuli (such as commercials) or other measures of commercial success (e.g., number of streams, viewing times, click-through rates, word of mouth). If the fMRI literature is anything to go by, it is not unlikely that different metrics may indeed predict different market-level outcome variables (Knutson and Genevsky 2018): For example, while activity in the nucleus accumbens predicts song downloads, advertising elasticity, and crowdfunding success (Berns and Moore 2012; Genevsky, Yoon, and Knutson 2017; Venkatraman et al. 2015), medial prefrontal cortex activity predicts call volume in response to health campaign messages and ad-related click-through (Schmälzle et al. 2020), and activity in the temporal lobes predicts market-level ad recall (Chan et al. 2019) and click-through rates (Couwenberg et al. 2017). Future studies could test the same set of EEG metrics used in the current work but apply it to different stimulus types and investigate different market-level responses.

For movie marketing, it would be especially relevant to study the relationship between EEG metrics and the amount of word of mouth that a trailer generates. Several studies have shown the importance of word of mouth on predicting box office revenue of movies (e.g., Gelper, Peres, and Eliashberg 2018; Liu 2006). A trailer's gamma band activity might be effective in generating buzz on social media, thus indirectly driving box office results. Further research could also test to what extent a trailer's neural metric contributes to predictions of box office revenue based on information extracted from the movie script (Eliashberg, Hui, and Zhang 2014) or its synopsis and narrative (Toubia et al. 2018). Additionally, given the potential of AI-driven design of advertising stimuli (e.g., Jansen et al. 2023), it will be interesting to investigate whether EEG-based metrics provide optimization guidance beyond AI-driven trailer design.

Another potential direction for further research would be to explore the dynamics of activity in the gamma band over time within a stimulus. Perhaps the peaks in activity more strongly contribute to the predictive effect of gamma than the average gamma activity used in the current study (see, for example, the peak-end rule, positing that people tend to rely heavily on the intensity of peak and final moments; e.g., Do, Rupert, and Wolford 2008). It might be informative to see whether such a peak is related to responses to specific types of scenes or particular events in the narrative. Currently, maximizing average gamma band activity in response to movie trailers, for example, by cutting out scenes with low gamma responses, would potentially already be an effective strategy for marketing practice, potentially increasing understanding and consequently revenue.

In addition to providing movie producers with an implicit measure to pretest the quality of trailers (i.e., the gamma response), our results also generate hypotheses regarding the underlying mechanisms associated with successful trailers (i.e., understanding). We provide an initial test of this hypothesis by showing that for trailers that evoke high gamma response,

participants indeed also reported better understanding and comprehension of the narrative of the trailer. An important topic for future research would be to show that this finding also holds for yet-to-be-released movies to rule out any effect of familiarity with the movie. Additionally, it would be interesting to show that self-reported measures of understanding and comprehension could also predict box office success. Our preliminary analysis suggests that understanding may indeed relate positively to box office returns, but that the association between gamma activity and box office revenue is much stronger (see Web Appendix P). This may suggest that gamma activity is a richer measure that captures more than understanding alone and again demonstrates that there is no one-to-one correspondence between brain measures and mental states. Nevertheless, a high-powered study including a large sample of movies and participants may offset the relative lack of predictive power of self-reported measures of understanding and show these measures to be viable proxies of EEG measures.

Finally, the current work uses *a priori* selected metrics that have been related to psychological processes or outcome measures that are conceptually relevant for predicting consumer behavior. Instead of using predefined metrics, a data-driven approach might be used (for instance, see Boksem and Smidts 2015; Hakim et al. 2020), enabling potentially new metrics to be established or current metrics to be fine-tuned. Small differences in frequency bands or channel locations could increase predictive power, something that cannot be found using the current approach.

Conclusion

In summary, we performed a systematic reanalysis of five datasets investigating which EEG metrics are consistently related to commercial success for movies. We found that gamma band activity was predictive of populationwide success of the corresponding movies, above and beyond traditionally available pre-release information on budget, the genre of the movie, star power, sequel/adaptation, and self-reported liking of the trailers. Importantly, the findings show that the predictive power of gamma activity generalizes to different data and that out-of-sample predictions improve significantly when gamma response is added as a predictor. In addition, we provide initial evidence for why some trailers perform better than others: Those that clearly convey the movie's story line and are easy to understand will be more successful. We believe that this work represents a significant step forward for the field of consumer neuroscience, not only by confirming the value of brain-derived measures in predicting real-world outcome measures, but also by showing the value of open science.

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