Interest as a Proxy of Engagement in News Reading: Spectral and Entropy Analyses of EEG Activity Patterns

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Abstract—Objective measurements of engagement are increasingly sought after by both the media industry and scholar communities to explain what drives people to consume audiovisual contents. However, engagement is a complex construct that, at the psychological level, has been mainly operationalised through indicators of attentional and emotional processes, often overlooking motivational factors. We claim that in the context of news consumption, motivation, operationalised as intrinsic interest for consuming a given content, needs to be factored in together with attentional and emotional processes. The present work provides an objective metric for motivation based on electroencephalographic (EEG) registration of users' neural activity, while they read sets of news pre-classified in terms of their potential interest. We focus on a metric that has been used as an indicator of the degree to which an item or event induces the motivation to approach or escape, the so called frontal alpha asymmetry (FAA). Moreover, in addition to the traditional approach to the analysis of EEG signals, we also introduce a more novel technique based on estimating the entropy of the signals. Results confirm that FAA is indeed a good proxy for objective monitoring of interest in media contents and that entropy analysis, although its interpretation in terms of information processing warrants further investigation, is also sensitive to the manipulation of interest, providing results that complement traditional power spectrum analysis.

Index Terms—User Engagement, News Consumption, EEG, Spectral Analysis, Entropy Analysis, Predictive Modelling

1 Introduction

The construct of *engagement* has become common currency in such diverse domains as entertainment, psychological research, marketing, social media, sports, or education, broadly denoting a high degree of involvement in a given activity, and often associated to a positive and rewarding experience [14], [23], [82]. From a perspective that encompasses research on cognitive psychology, media, and communication, we claim that engagement with media contents lies at the boundary between emotional, attentional and motivational processes, and that the latter have been mostly neglected when trying to operationalise this complex construct. Accordingly, we propose and validate an electroencephalographic metric of interest for news content as a promising indicator of motivational involvement in news consumption.

Engagement can refer to different behavioural aspects, with varying indicators and temporal scopes. For instance, in the fields of marketing and education, engagement often refers to a long term relationship with a brand, or to an intrinsically motivated and prolonged involvement in educational activities. In such cases, research methodologies involve mainly self-reported measures or controlled observations of behaviour during extended periods of time [20], [40]. However, the present work focuses on a shorter temporal scope, aiming to track engaged reading as it unfolds through physiological metrics that provide a high temporal resolution. Reading engagement has been referred both as a general intent on reading and writing, but also as the capacity to focus on text meaning and avoid distractions, and a state of immersion in the narrative [81]. Our own take on the subject relates to the latter two connotations. Nevertheless, this is not to say that basic psychological processes do not play a role in long term engagement and, although the relation between both aspects deserves further research, here we focus on indirect and objective metrics for the online study of human information processing in an everyday life activity.

Traditionally, basic research on human information processing (HIP) has focused on tightly controlled experimental conditions and stimuli to ensure the internal validity of the findings. However, this comes at the cost of limiting external validity and excluding motivational factors from models of cognitive processing. Due in part to a surge of interest in how objective psychological metrics can address the complexity of HIP in a variety of technology and media oriented contexts, contemporary cognitive scientists are faced with the challenge of working with increasingly complex stimuli resembling real-life conditions and with constructs such as engagement or immersion, which aim at unveiling the factors that lead to compelling experiences for users [67] of media and entertainment products. In terms of HIP, such constructs are often ill-defined because they break the usual divide-and-conquer strategy in HIP research and tackle the interplay between different cognitive processes like attention and emotion, both of which are regarded indicators of engagement and immersion [22]. In fact, such

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Manuscript received April 19, 2005; revised September 17, 2014.

constructs tend to be used interchangeably [67].

In the context of human-agent interaction, engagement has been defined either as the attention paid for the subject to the interaction [72], as the value attributed by the subject to the interaction [61], or as the interaction process itself [70]. Some studies have also considered engagement as a binary variable (either it is present or absent), whereas in other cases engagement has been characterised as a continuous variable [22]. Furthermore, engagement has been used to account for both the cognitive and hedonic aspects of user interactions, and considers the characteristics of systems (e.g., usability, aesthetic appeal, interactivity), users (e.g., level of felt involvement, positive affect), as well as their interaction at the system level [51]. Recent works have began to explore a unified framework for studying engagement [4], [5], [7], [22], [51], [52], [72]. Thus, an obvious way to better characterise the construct of engagement and disentangle it from overlapping constructs is to depart from a putative description of the key psychological processes involved in the specific target activity. In the case of news reading, in addition to the cognitive and hedonic aspects mentioned above, a key aspect of engaging readers is that they have an interest to acquire information on the issue addressed by the news, and interest is precisely a key indicators of intrinsic motivation [75]. Going back to the previous example, when trying to test the immersiveness of a given content or device, the role of an intrinsic motivation to undergo an immersive experience is nowhere as evident as in the case of reading news.

However, there is little consensus on which are the best empirical indicators of interest, which has been defined as an “an emotional state linked to the participant’s goal of receiving and elaborating new and potentially useful knowledge” [57], and has been operationalised mainly by means of subjective self-report methods [2], [4], [5], [51], [52], [53], [54]. In turn, we propose to consider a promising electroencephalographic metric that has been directly linked to intrinsically motivated approach behaviours, the Frontal Alpha Asymmetry (FAA), which we predict will be directly related to the degree of interest of the news being read by participants in our study.

In what follows, we provide a brief introduction to previous research on psychological indicators of interest and present our own experimental work, which involves testing the utility of the FAA metric as a neural correlate of motivation to engage in the consumption of media contents. In our study, a sizeable sample of users interacts with an unstructured, heterogenous collection of online news that vary in their levels of a priori potential interest, and we observe the effects of this manipulation of interest with respect to the FAA and the self-reported measures of engagement. In addition, we examine how certain entropy indices reflect differences in the irregularity of EEG data of engaged news readers and demonstrate how to determine the level of engagement of news readers by modelling their neural activity, in a predictive modelling task.

2 Related Work

The benefits of exploring the neural correlates of interest in news consumption are several. First, objective experimental methods can complement self-reported methods that introduce important limitations in the user experience research [63]. Self-report methods, such as questionnaires and interviews, rely on subjects’ awareness of their own mental processes, which is very limited in the majority of cases [50], [56], and are often distorted by cognitive biases (e.g,. social desirability bias). This impairs the capacity of self-report methods for accounting for subtle and dynamic cognitive/emotional processes. In order to overcome these constraints, user experience research has turned to objective psychological measurements to thoroughly evaluate user experience [7], [46], engagement with video games [44], or video quality assessment [6]. The main aim of the present study is thus to define an objective metric for interest by probing its neurophysiological underpinnings with electroencephalographic measures.

Amongst the various techniques available, we chose EEG because it offers insights into the brain activity related to diverse cognitive and emotional processes with a high temporal resolution, which is lacking in self-report methods. Research on user experience using EEG methods has typically focused on the analysis of power spectral density (PSD) of frequency bands such as the delta (1-4 Hz), theta (4-8 Hz), alpha (8-13 Hz), beta (13-30 Hz) and gamma (36-44 Hz) bands [60]. Given that we are working with unstructured stimuli, blocked designs are preferable over event-related ones, as we have not precise control over the timing of the target responses. Developing indirect measures of engagement based on neural activity can be particularly useful as a complement of behavioural measures of user engagement, such as click data [1], [2], [3], [7], in the context of (relatively) passive media usage like news reading, watching audiovisual content, or searching the Web. While some activities (e.g. playing a video game) are likely to demand to the subject the performance of observable behaviours, from which information about her engagement can be extracted, other activities involving the use of computer mediated media are more passive (e.g. reading online news or watching YouTube videos) and, therefore, are better tackled with electrophysiological techniques.

2.1 Interest, Motivation, and Frontal Alpha Asymmetry

Davidson’s [15] model of motivation proposes that human behaviour is driven by two motivational systems. The first one, known as the *approach* system, is activated in the presence of desirable stimuli, facilitates appetitive behaviours, and is related to positive emotions. The second one, known as the *withdrawal* system, reacts when aversive stimuli are encountered, is involved in avoidance behaviours, and is associated to negative affect. The activity of the approach system produces a relatively higher activation of the left frontal cortex which can be measured by means of EEG. Specifically, the levels of FAA have been considered as a consistent index of approach activation [13], [28]. FAA refers to the difference in the degree of cortical activation of the alpha band (8-13 Hz) in the frontal cortex, between the right and left hemispheres of the brain. FAA is computed by subtracting the level of alpha power in the right frontal cortex to the level of alpha power in the left frontal cortex. Lower levels of alpha power indicate a higher allocation of cortical resources and express the relative activation of the right frontal cortex [13].

FAA has proven to be a reliable measure for analysing user experience in a diversity of contexts. Previous research has shown that it can be serve as a correlate of the pleasantness of TV commercials [77], for comparing the motivational activation facilitated by different technologies in news reading [65], or even for predicting purchase decisions [64]. However, to our knowledge, previous research has not considered the utility of the FAA measure as a correlate of the interest experienced by the subject towards information. We hypothesise that since interest, as defined above [57], is linked to the goal of elaborating on new information, it should involve the activation of the motivational approach system, which, in turn, should be evidenced by an increase in FAA.

2.2 Interest, Information Processing, and Changes in Brain Activity Bands

Besides the hypothesised motivational approach, indicators of interest can be extracted from other aspects of HIP that are also amenable to EEG measurement. Since interest is related to an active elaboration of potentially useful knowledge, it seems plausible that it should impact the amount of resources devoted to its processing. More specifically, it is likely that interest for a given information is also associated to the activation of mechanisms for enhancing the processing and storage of such information. For example, HIP involves selecting and encoding information, that is, elaborating mental representations of it in working memory [36] which can be subsequently stored in long-term memory. The allocation of working memory resources to information encoding is signalled by increases in the theta and gamma power bands [55], [68]. Thus, if as hypothesised before, the subjective interest is related to an enhanced information encoding, this should be signalled by increases in the theta and gamma bands.

Previous research has proposed further neural correlates of interest. Smith and Gevins [72] reported that decreases in the lower band of alpha, in the frontal region, are related to interest towards television commercials. Additionally, several studies [27], [37] have linked the beta band to cognitive processing. Therefore, there is evidence suggesting that the effects of subjective interest in neural activity may be visible in the theta, alpha, beta, and gamma power bands.

3 User Engagement in Online News Reading

Some prior works [72], [77] have addressed the issue of obtaining measures of user engagement with passive media (mostly television programs or commercials) from the viewpoint of neural activity. However, operationalisation of user engagement through these channels is hindered, amongst others, by the differential effects of formal and structural features of the media, which may confound with the effects of user interest expressed over the semantic content of the media. The reason for that, is because audiovisual media provides a continuous stream of sensory stimulation through iconic representations of the reality, like images and sounds [84]. Some of the physical attributes of such representations (e.g. scene changes, attractive characters, etc.) can elicit automatic attentional and emotional responses [36] that, in turn, may promote engagement. However, written text is just symbolic representation that lacks many of the attributes of iconic representation. In written text, the presence of formal attributes that automatically affect the allocation of attention resources is minimal. Hence the context of text reading allows to inspect the neural correlates of interest with a smaller risk of encountering confounding factors related to the iconic representation of the reality. Previous research has analysed neural correlates of engagement in audiovisual contents [72], [77], but, with few exceptions using very experimental paradigms like the one described in [9], the brain activity associated to interest in written texts remain mostly unexplored.

The domain of online news provides a context ripe for exploring interactive-rich user experiences, since it embodies a range of behaviours (e.g., browsing, searching, reading), cognitive processes (e.g., deciding what to read, evaluating the content or way in which it is delivered) and affective (e.g., motivations) constituents of online interactions. Moreover, news content is often bundled with user-generated content, like comments and opinions about the news articles, all which promote social awareness and participation. Nevertheless, the perception of a news article quality may be different for every individual, as individuals vary in their backgrounds and personal tastes.

Our lab-based approach allowed us to jointly analyse the affective and attention characteristics of engagement with online news articles. To this end, we conducted a controlled user study and recorded the EEG signals from 57 participants who read online news articles that induced either strong interest or dullness, thus promoting diametrical levels of engagement. In addition, we collected subjective qualitative information using questionnaires aimed at measuring two putative components of engagement, namely, affect and focused attention.

4 Materials and Methods

4.1 News Dataset

Initially, our dataset contained 383 news articles crawled from Yahoo News US, over a period of two weeks, from three different genres: crime and law, entertainment and lifestyle, and science. All news articles appeared in the same format and retained their original look and feel. We first filtered our dataset and kept those news articles that contained between 300-600 words, to mitigate any effects of large variations in article length. We then randomly selected 40 articles from each genre and asked an external group of judges to rate them on a 5-point interestingness scale. Following that, we averaged the reported scores, ranked the articles per genre, and picked the top three and bottom three as our candidates for interesting and dull news articles respectively. This final selection of 18 news articles $(6\times 3 = 18)$ was used in our study. The judges were average readers from the same demographics pool where we selected our participants to simulate the average interest in the news.

4.2 Participants

Fifty-seven (57) participants (female=28, male=29) were recruited through a campus-wide ad. Participants were free

TABLE 1: I-PANAS-SF [76]

Positive Affect (PAS) Items	Negative Affect (NAS) Items
active	afraid
alert	ashamed
attentive	hostile
determined	nervous
inspired	upset

TABLE 2: FA scale [52]

1. I forgot my immediate surroundings while performing the news reading task.
2. I was so involved in my search task that I ignored everything around me.
3. I lost myself in this reading experience.
4. I was so involved in my news reading task that I lost track of time.
5. I blocked out things around me when I was completing the news reading task.
6. When I was performing this news reading task, I lost track of the world around.
7. The time I spent performing the news reading task just slipped away.
8. I was absorbed in my news reading task.
9. During this news reading task experience I let myself go.

from vision-related conditions and were able to read what was displayed on the computer screen without difficulty. Also, participants aged from 18 to 47 and were of mixed nationality. Participants were all proficient with the English language (18.18% intermediate level, 68.18% advanced level, 13.63% native speakers). To avoid any adverse effects because of language-specific bias, we evaluated their English language fluency prior to the study.

4.3 Design

The experiment involved a mixed-design with two independent variables: article genre (three levels: “crime and law”, “entertainment and lifestyle”, “science”) and task interestingness (two levels: “interesting”, “dull”). The primary dependent variable was participants’ level of engagement as determined by the self-report data (i.e., questionnaires) and the EEG signals collected.

The study consisted of two online news reading tasks: one involving reading an interesting news article and one involving reading a dull news article. To select these two articles, every participant was asked (prior to the study) to rank, for each of the three genres we examined, six news titles according to their interestingness. More specifically, the participants were asked to assign the most interesting news title to the first position, the next most interesting news title to the second position, and so on. Then, we selected the top-ranked news article for the interesting task and the bottom-ranked news article for the dull task, thus tailoring interestingness to each participant. The news titles that were ranked by our participants came originally from a larger pool of news articles (see Section 4.1).

Finally, the participants were asked to read the news articles as they would normally do in their natural setting, and they were allowed to stop reading at any point in time they felt like. To control for order effects, the news article genre and the task assignment were counterbalanced using a Latin Squares design.

4.4 Apparatus

4.4.1 Self-Report Measures of Engagement

A psychometric scale was used to probe the pragmatic and hedonic qualities of their user experience: the User Engagement Scale (UES) [54]. The UES is a multi-dimensional survey instrument that measures user engagement with technology. More specifically, it examines the cognitive (felt involvement, focused attention, perceived usability) and affective (positive and negative affect) aspects of interactions.

Affect accounts for the hedonic experiences, as well as the motivations that influence and sustain our engagement during computer-mediated activities [79]. The Focused Attention (FA) scale gauges users’ feelings of energised focus and total involvement, which is often accompanied by loss of awareness of the outside world and distortions in the subjective perception of time (as they are being drawn into the experience). All questions were all forced-choice type and appeared in random order to reduce potential ordering effects. The UES was administered at post-task.

I-PANAS-SF. The International Positive and Negative Affect Schedule Short Form (I-PANAS-SF) [76] was used to measure the affect at pre-task and post-task (Table 1). I-PANAS-SF is a 10-item version of PANAS [79] that measures affect changes. It includes 5 items measuring positive affect (PAS) and 5 items measuring negative affect (NAS). Participants were asked to respond on a 7-point Likert scale (1: very slightly or not at all, . . . , 7: extremely) their agreement to the statement: “You feel this way right now, that is, at the present moment”, for each item. In our setting, we collected information regarding the participants’ affect state both at pre- (pre-PAS, pre-NAS) and post-task (post-PAS, post-NAS). Finally, affect was also measured by asking the participants to respond to the question “Overall, did you feel positive or negative while completing the news reading task?”.

Focused attention. The FA is a 9-item subscale (Table 2), part of a larger scale for measuring user engagement [52]. FA has been used in past studies [42], [52], [53] to evaluate users’ perceptions of time passing and their degree of awareness about what took place outside of their interaction with the given task. To measure FA, the participants were instructed to report on a 7-point Likert scale (1: strongly disagree, . . . , 7: strongly agree) their agreement to each item listed in Table 2.

Interest. To validate the effectiveness of our experimental manipulation, we measured the perceived article interest at post-task by asking the participants to state on a 5-point Likert scale their agreement to a set of questions, such as “I found the news article interesting to read”. The reported scores were converted into binary judgments by assigning disagreement or neutral opinion to the dull condition and agreement to the interesting condition. The binary judgments were then compared against the pre-task labelling of the news articles’ interestingness. The Chi-Square test revealed a significant association ($\chi^2 = 29.52, p < .001$) between the two measures, with a strong positive relationship ($\phi = .518, p < .001$), which confirms the effect of our experimental manipulation. The follow-up analysis is based on the controlled levels of article interestingness, as determined by our experimental manipulation.

4.4.2 *Emotiv EPOC Wireless EEG Headset*

EEG data were recorded using the Emotiv EPOC Wireless EEG Headset [17]. The Emotiv EPOC is a low-cost, consumer grade Brain-Computer Interface (BCI) kit that consists of (1) a wireless EEG headset device for acquiring EEG signals, and (2) the SDK for pre-processing, annotating and visualising the signals. The Emotiv EPOC collects data from 14 active sites and two bipolar reference electrodes positioned at the mastoids, using the international 10-20 system montage [60]. The electrodes were placed in the positions AF3, AF4, F3, F4, FC5, FC6, F7, F8, T7, T8, P7, P8, O1, and O2. Each of the electrodes is connected to an Analog-to-Digital Converter (ADC) for sampling EEG signals with an internal sample rate of 2048 Hz, which is automatically filtered and down-sampled to 128 Hz. The effective bandwidth of Emotiv EPOC is 0.16-43 Hz, with digital notch filters at 50 Hz and 60 Hz for removing noise. In addition, the SDK provides a packet count functionality to prevent data loss, a writable marker trace for single-trial segmentation tasks, and real-time sensor contact to ensure quality measurements. During our experiment, a unique marker value was inserted to the marker trace to signal the onset and offset of each online news reading task, and discriminate the tasks from the resting periods.

4.5 Procedure

The user study was carried out in a laboratory setting. The participants sat in a quiet room, facing the computer used to perform the online news reading tasks. At the beginning of each session the participants were informed about the purpose of the study, addressing potential privacy issues and outlining the experimental procedure. Then, they were asked to complete a demographics questionnaire. Upon completing the demographics questionnaire and the pre-task I-PANAS, the electrodes for the measurement of the EEG signals were fitted.

Each participant performed two online news reading tasks, one for each article interestingness condition. During the online news reading tasks, the participants were presented with two web browser windows: (1) a window showing the online news article and (2) a window indicating the steps to follow along with the main questionnaire. Participants were instructed to read the online news article at their own pace and for as long as they wanted. Upon finishing reading the online news article, they were asked to switch to the questionnaire and answer the relevant section. The same procedure was repeated for the second online news reading task. At post-task, the participants had to complete the I-PANAS and FA scales. At the end of the session, the electrodes were removed, the participants were debriefed and they were compensated with a 20€ gift card.

5 EEG Data Acquisition and Analysis

5.1 EEG Data Processing

From our original sample of 57 participants we excluded 7 participants for which the recording of EEG was affected by technical problems. Moreover, in the remaining 50 participants we identified a few cases where the EEG recordings from one news reading task were incomplete, resulting in a final sample 91 news reading tasks (47 interesting and 44 dull).

The raw EER signals were processed using the EEGlab library [16] in Matlab. At first, EEG signals were filtered using a bandpass filter (1-45 Hz) and artefacts were filtered automatically using the Automatic Artifact Removal plug-in for EEGlab [24]. The signal of each participant, per condition, was split into 20-second segments. For each such segment we removed the channels whose PSD deviated more than 4 SD from the mean of the channels. Since the time spent reading the news articles varied amongst participants, the number of segments was not equal for all the participants and conditions and ranged between 7 to 43 (M = 20.27, SD = 9.08). In total, we analysed 1845 segments for each measure (FAA and power bands).

Next, we computed the log mean PSD for each segment using the spectopo function in EEGlab (512-point window length, non-overlap), with a resolution of 0.125 Hz. The resulting power estimates were averaged for each frequency band we considered in our study, i.e., theta, alpha, beta, and gamma. The FAA was calculated for each segment by averaging the estimates of alpha power of the prefrontal and frontal left electrodes (FC3, F3, and F7), and then subtracting it from the average of the estimates of alpha power of the prefrontal and frontal right channels (FC4, F4, and F8).

Since most of the processes associated to attention and working memory in the context of user engagement research have been observed in frontal (including prefrontal) and occipital regions, we also calculated the average value of PSD for each band in each of these two areas. To this end, we averaged the values of the prefrontal and frontal channels (FC3, FC4, F3, F4, F7 and F8) for each power band to obtain an estimate of the power of each band in the frontal region. Finally, we averaged the values of the occipital channels (O1 and O2) to obtain an estimate of the power of each band in the occipital region.

5.2 Multilevel Modelling

We analysed the EEG data by means of mixed multilevel models, a method that allows dealing with some specificities of psychophysiological data (violation of sphericity, nested data, autocorrelation of residuals) more effectively compared to traditional statistical methods such as ANOVA [35], [73]. For our analysis, we used the R package nlme [59] and our approach for the model construction was the one described by [10], [11], [35]. Initially, we fitted a series of two-level models, in which measurements for each condition (level 1) were nested within participants (level 2). A random intercept for participants was included in the models since it improved model fitting, as shown by comparing the models with and without these factors in a likelihood test [10]. The models also accounted for the autocorrelated structure of the data by including the corAR1 function. Initially, we built a model (Model 1) for FAA data, as well as for the average power of each one of the frequency bands (theta, alpha, beta, and gamma) in the frontal area, on one hand, and in the occipital area, on the other hand. This first model (Model 1) for each measure included only the interestingness condition as a fixed factor.

Next, we fitted a series of models for each frequency band while other factors were added as predictors, to assess if the magnitude of each power estimate is related to interest when controlling for the effects of those predictors. Besides the variable interestingness, the models accounted for FA (Model 2), the differences in PAS and NAS at pre- and post-task (Model 3), the overall assessment of the experience (Model 4), the genre of the news articles (Model 5), as well as all the aforementioned predictors altogether (Model 6). For Model 4, given that the overall assessment of the experience is a factorial variable (three levels: "neutral", "negative", "positive"), we set the neutral level as the baseline and compared the two other levels to it. Similarly, for Model 5, crime news was set as the baseline level and the other two levels (entertainment and science news) were compared against it. Since the self-report data of one participant were loss due to technical failure, we also excluded the EEG data corresponding to this participant in Models 2 to 6. Thus the sample for these models is 1813 segments instead of the 1845 segments used for Model 1.

5.3 Entropy Analysis

We also investigated the ability of entropy features to discriminate between varying levels of user engagement with online news articles. To this end, we computed three different entropy measures (see Sections 5.3.1, 5.3.2, and 5.3.3) using the spectopo output (Section 5.1) for each power band considered in our study.

Entropy has been extensively used in signal processing and pattern recognition applications. In information theory, entropy measures the disorder or uncertainty associated with a discrete, random variable, i.e., the expected value of the information in a message. In bioinformatics, entropy-related measures have been used to study the scaling behaviour of EEG [30], quantify the level of order in EEG signals or participants under different stages of sleep [21], or during anaesthetic induction [38], [41]. For example, in [84], the authors demonstrate that entropy decreases when a patient is at anaesthetic status because the EEG signals have a lower complexity, and vice versa. Entropy analysis has been also applied in conjunction with a measure of depth of anaesthesia (DOA), using various entropy indices like Approximate entropy (ApEn) [19] and Sample entropy (SampEn) [29], [80].

Entropy statistics provide an improved evaluation of time series irregularity, with increasing values corresponding to intuitively increasing process complexity and activation of different centres of the brain, such as, for example, the cognitive activation observed while interacting with an engaging stimuli. On the contrary, low entropy indicates the reduction of irregularity in the EEG signal (e.g., all the power condensed into a single frequency bin) and could be explained by a decrease of dynamical complexity of part of the brain; in other words, a lower entropy indicates more self-similarity in the time series [71].

5.3.1 Shannon entropy

Shannon entropy [69] allows to estimate the average minimum number of bits needed to encode a string of symbols in binary form (if *log* base is 2) based on the alphabet size and the frequency of symbols. Given a finite time series $X(t) = (x_t\colon 1 \leq t \leq T)$, the Shannon entropy can be expressed as

$$\mathrm{H}(X) = \sum_i P(x_i) I(x_i) = -\sum_i P(x_i) \log_b P(x_i), \tag{1}$$

where I is the information content of X, $I(x)$ is the random variable, and b is the base of the logarithm used.

5.3.2 Approximate entropy

The ApEn [58] expresses the (logarithmic) likelihood of similar patterns to be followed by similar observations. In other words, it quantifies the amount of regularity and the unpredictability of fluctuations in a time series. A low value of the entropy indicates that the time series is deterministic, whereas a high value indicates randomness.

Let's consider a time series $X(t) = (x_t\colon 1 \leq t \leq T)$. Given parameters m and r, where m is the length of the compared data and r specifies a filter factor (vector comparison distance), we define ApEn as

$$\mathrm{ApEn}(m, r) = \Phi_m(r) - \Phi_{m+1}(r) \tag{2}$$

We compute the entropy for $m = 2, \ldots, 5$. We set $r = 0.2$ SD, where SD is the standard deviation of the sequence values. The ApEn can be computed for any time series, chaotic or otherwise, at a low computational cost, and even for small data samples ($T < 50$).

5.3.3 Sample Entropy

The SampEn [66] is a modification of the ApEn, used extensively for assessing the complexity of a physiological time-series signal. SampEn introduces several improvements to the ApEn [38], such as eliminating self-matches and exhibiting signal length independence. A difference to ApEn is that it calculates for each individual component the total number of template well-matches prior to the logarithmic operation.

The first step of calculating SampEn is the same as ApEn. Given a time series $X(t) = (x_t\colon 1 \leq t \leq T)$, the parameters m and r, and a distance function $d[X_m(i), X_m(j)] (i \neq j)$, we count the number of template matches (pairs), when the embedding dimension is m and $m+1$, that have distance $d < r$. We define the SampEn to be

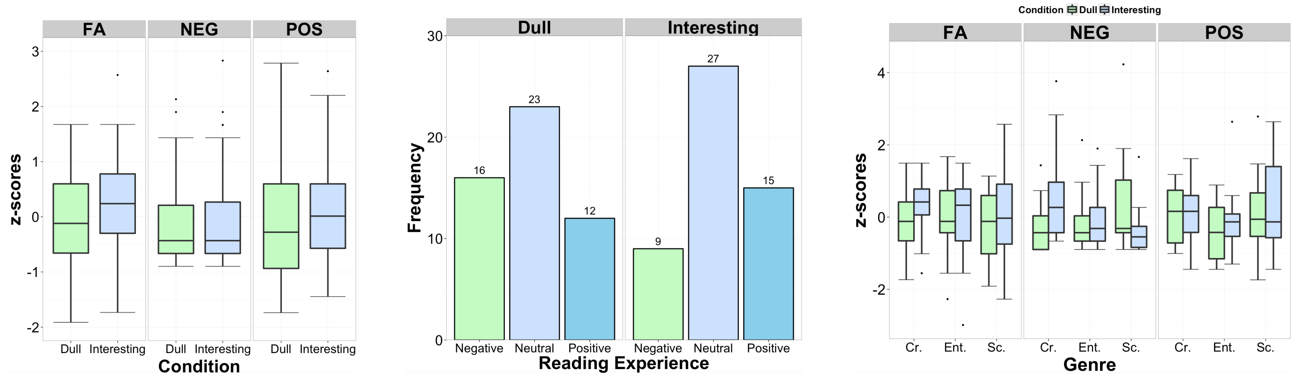
$$\mathrm{SampEn}(m, r) = -\log \frac{p_{m,r}}{p_{m+1,r}} \tag{3}$$

Given that SampEn is based on ApEn, its parameter selection procedure is similar to that of ApEn.

6 Results

6.1 Self-report Data

Our analysis was based on scores gathered by 51 participants who performed the two news article reading tasks. A series of t-tests was conducted to determine whether the reported scores for FA, post-NAS, and post-PAS scores were significantly different across the two experimental conditions ("interesting", "dull"). The t-test results did not indicate any significant differences in FA ($t(50) = 1.30, p = .19, d = .26$) or post-NAS, ($t(50) = .40, p = .69, d = .08$). However, we observed a marginally significant difference for post-PAS ($t(50) = 1.86, p = .07, d = .37$). Therefore,



(a) Variation of user engagement measures across conditions

(b) Overall experienced affect across conditions

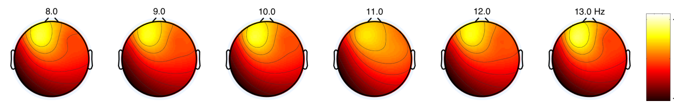
(c) Variation of user engagement measures across conditions (interaction with news genres)

Fig. 1: Descriptive statistics on self-report data.

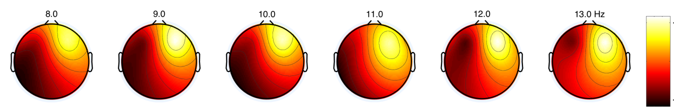
TABLE 3: Results of the ANOVA analysis

Dependent variable	Independent variable	*F*	*df*	*p*
Focused attention	Genre	.43	2	.65
	Condition	1.14	1	.30
	Genre * Condition	.56	2	.57
Negative affect	Genre	.72	2	.49
	Condition	.09	1	.76
	Genre * Condition	4.81	2	.01*
Positive affect	Genre	2.35	2	.10
	Condition	1.29	1	.28
	Genre * Condition	.18	2	.83

$^{*}p < .05$



(a) Dull news article



(b) Interesting news article

Fig. 2: Example (participant 50) of the relative activation (for different frequency bands in Hz) of the frontal channel (FAA) across the experimental conditions.

participants did not report being more immersed or having experienced a more positive or negative affect in any of the experimental conditions (Figure 1a).

Next, we examined whether the overall news reading experience reported at post-task by the the participants was determined by the experimental condition. For both experimental conditions ("interesting", "dull"), and in the majority of cases, the news reading experience was rated as neutral (Figure 1b). Overall, the reading of interesting news articles facilitated a more positive experience (15 positive responds, 9 negative responds), while the reading of dull news articles resulted in a generally negative experience (12 positive responds, 16 negative responds). The results of a Chi-square test ($\chi^2(2) = 2.61, p = .27$) showed no significant relationship between the two variables, suggesting that, in general, participants' experience did not differ significantly across the two experimental conditions.

Finally, we examined whether the self-report data on FA, post-NAS and post-PAS were genre-dependent, and, in addition, if there was an interaction between the experimental condition and genre in the reported scores. To this end, we applied a series of two-way ANOVAs to test for such effects. The results, summarised in Table 3, show no significant main effects for genre or condition, over any of the three variables. Interaction effects for genre by condition were also non-significant in the case of FA and post-PAS, although a significant interaction was found in the case of post-NAS. As we can observe in Figure 1c, the "interesting" condition elicited a stronger negative experience for the crime genre, while in the case of the science genre the negative affect was stronger for the "dull" condition. We hypothesise that the exposure to crime news content, which is generally associated to gloomy and unsettling events, may eventually engage the readers but at the same time result in a negative reading experience. However, the fact that none of the post-hoc paired comparisons with Tukey correction revealed any significant effects ($p > .05$), limits our confidence to this interpretation.

6.2 EEG Multilevel Models

Here we report the results of our modelling task presented in Section 5.2. Table 4 shows the results of the models that were fit using only the independent variable interestingness as a predictor of the power estimates. We note a significant increase in FAA and a significant decrease in the power of beta and gamma bands, of the frontal region, across the experimental conditions. More specifically, these oscillations in the power spectrum indicate that an increased interest in the news article is associated to higher levels of FAA and lower levels of frontal beta and gamma power. An example of the relative activation of the frontal channel (FAA) across the experimental conditions is shown in Figure 2.

As discussed in Section 5.1, for each of the variables that are known correlates of interest (FAA, frontal beta, and frontal gamma) we fitted a model and explored whether the interestingness condition is a significant predictor of it, while controlling for all other factors. Table 5 presents

TABLE 4: Performance of models

	FAA	Frontal Theta	Occipital Theta	Frontal Alpha	Occipital Alpha	Frontal Beta	Occipital Beta	Frontal Gamma	Occipital Gamma
Fixed factors									
Intercept	1.12^{***}	4.42^{***}	4.33^{***}	2.22^{***}	3.16^{***}	-0.95^{*}	-1.09^{**}	-5.50^{***}	-5.98^{***}
Interest	0.35^{**}	-0.28	0.03	-0.13	-0.20	-0.35^{*}	-0.09	-0.35^{*}	-0.08
Random factors									
Intercept	0.78	2.91	2.94	2.75	2.70	2.88	2.67	3.05	2.89
Residuals	1.26	2.47	2.05	2.13	1.87	1.87	1.82	2.26	2.17
N observations	1845	1845	1845	1845	1845	1845	1845	1845	1845
N participants	50	50	50	50	50	50	50	50	50

$^{\dagger}p < .1$; $^{*}p < .05$; $^{**}p < .01$; $^{***}p < .001$
Note. Coefficients for fixed factors are expressed in natural log of PSD. Random factors are expressed in SD.

TABLE 5: Summary of the models of FAA

	Model 2	Model 3	Model 4	Model 5	Model 6
Fixed factors					
Intercept	1.44^{***}	1.31^{***}	1.08^{***}	0.89^{***}	085^{*}
Condition	0.23^{*}	0.20^{*}	0.21^{**}	0.22^{*}	0.29^{*}
FA	-0.01	-	-	-	0.00
post-PAS	-	0.01^{*}	-	-	0.00
post-NAS	-	0.00	-	-	-0.03
Overall Exp: Positive	-	-	0.19	-	0.29
Overall Exp: Negative	-	-	0.08	-	0.33
Genre: Entertainment	-	-	-	0.37^{**}	$0.49^{\dagger}$
Genre: Science	-	-	-	0.44^{**}	0.55^{**}
Random factors					
Intercept	0.72	0.73	0.71	0.73	0.70
Residuals	1.18	1.18	1.18	1.18	1.18
N observations	1813	1813	1813	1813	1813
N groups	49	49	49	49	49

$^{\dagger}p < .1$; $^{*}p < .05$; $^{**}p < .01$; $^{***}p < .001$

TABLE 6: Summary of the models of frontal beta

	Model 2	Model 3	Model 4	Model 5	Model 6
Fixed factors					
Intercept	-1.55^{*}	-1.18^{**}	-0.64	-0.73	-1.19
Condition	-0.31^{*}	$-0.26^{\dagger}$	-0.31^{*}	$-0.29^{\dagger}$	-0.37^{*}
FA	0.02	-	-	-	0.02
post-PAS	-	-0.02^{*}	-	-	-0.02
post-NAS	-	-0.02	-	-	0.04
Overall Exp: Positive	-	-	$-0.62^{\dagger}$	-	$-0.69^{\dagger}$
Overall Exp: Negative	-	-	$-0.50^{\dagger}$	-	-0.75^{*}
Genre: Entertainment	-	-	-	-0.29	-0.07
Genre: Science	-	-	-	$-0.40^{\dagger}$	-0.33
Random factors					
Intercept	2.91	2.91	2.89	2.89	2.88
Residuals	1.84	1.84	1.84	1.85	1.83
N observations	1813	1813	1813	1813	1813
N groups	49	49	49	49	49

$^{\dagger}p < .1$; $^{*}p < .05$; $^{**}p < .01$; $^{***}p < .001$

a summary of the coefficients of these models for FAA. First, we see that the interestingness condition is related to significant increases in FAA in all cases. Second, we observe that Model 3 exhibits a significant positive relationship with post-PAS and FAA, while Model 5 is positively associated with the entertainment and science news genres. On the other hand, model 6, which contains all the predictors, indicates that the entertainment and science genres are significant predictors of FAA, even when controlling for the remaining factors (only with marginal significance in the case of entertainment).

Furthermore, Table 6 presents a summary of the coefficients of the models for frontal beta. Our analysis revealed that the interestingness condition predicted significant decreases in frontal beta when controlling for FA (Model 2), overall experience (Model 4), as well as in the model that accounted for all predictors (Model 6). For the remaining cases (Models 3 and 5), the interestingness condition only reached marginal significance: $p = .07$ and $p = .06$, respectively. The self-reported assessment of the overall experience (both positive and negative) was also related to significant, as well as marginally significant, decreases in frontal beta (Models 4 and 6). Also, in Model 3, a significant decrease in frontal beta was found to be related to post-PAS and a marginally significant decrease was found to be related to the entertainment news genre in Model 5.

Last, Table 7 shows significant decreases in the frontal gamma associated to the interestingness condition when the

TABLE 7: Summary of the models of frontal gamma

	Model 2	Model 3	Model 4	Model 5	Model 6
Fixed factors					
Intercept	-5.98^{***}	-5.61^{***}	-5.08^{***}	-5.41^{***}	-4.91^{***}
Condition	$-0.31^{\dagger}$	-0.26	-0.34^{*}	$-0.29^{\dagger}$	-0.43^{*}
FA	0.01	-	-	-	0.01
post-PAS	-	-0.01	-	-	0.00
post-NAS	-	-0.03	-	-	0.05
Overall Exp: Positive	-	-	$-0.71^{\dagger}$	-	-0.85^{*}
Overall Exp: Negative	-	-	-0.81^{**}	-	-01.16^{**}
Genre: Entertainment	-	-	-	-0.13	-0.32
Genre: Science	-	-	-	-0.15	-0.35
Random factors					
Intercept	3.08	3.08	3.04	3.07	3.05
Residuals	2.25	2.25	2.24	2.25	2.23
N observations	1813	1813	1813	1813	1813
N groups	49	49	49	49	49

$^{\dagger}p < .1$; $^{*}p < .05$; $^{**}p < .01$; $^{***}p < .001$

effects of the overall experience assessment (Model 4) were controlled, as well as when the effects of all the predictors together are controlled (Model 6). When controlling only for post-PAS and post-NAS (Model 3), the interestingness condition did not appear to be a significant predictor of frontal gamma power. However, when controlling either only for FA (Model 2) or the news genre (Model 5), the interestingness condition reached marginal significance ($p = .08$ and $p = .09$, respectively). Decreases in the frontal gamma were also observed when the overall experience was reported as positive or negative, compared to neutral (Model 6).

6.3 Entropy Analysis

Since in the context of user engagement research most of the processes associated to attention and working memory have been observed in frontal (including prefrontal) and occipital regions, we also consider several entropy indices for each band in these two areas. To this end, we averaged the values of the prefrontal and frontal channels (FC3, FC4, F3, F4, F7 and F8), as well as the occipital channels (O1 and O2), for all power bands. Then we computed the Shannon, ApEn, and SampEn entropies which, as discussed in Section 5.3, have been operationalised successfully in prior research.

The dependent t-test was applied to determine if there are statistically significant differences of the entropy scores with respect to our experimental conditions (interesting, dull). Our analysis revealed that the SampEn was the entropy measure that discriminated best the frequency bands across news reading tasks of varying interestingness. More specifically, for the FAA, the SampEn was significantly higher for the interesting condition ($M = 2.12, SE = .12$) than to the dull condition ($M = 1.44, SE = .07$), $t(35) = 4.04, p < .001$. Furthermore, the SampEn computed for the frontal alpha was found to be significantly higher for the interesting condition ($M = 2.94, SE = .13$) than to the dull condition ($M = 2.53, SE = .14$), $t(35) = 2.07, p < .05$. Similarly, the occipital alpha exhibited higher levels of entropy in the interesting condition ($M = 3.09, SE = .12$) than to the dull condition ($M = 2.62, SE = .13$), $t(35) = 2.37, p < .05$.

When examining the occipital gamma, the SampEn was found to be significantly higher for the interesting condition ($M = 1.70, SE = .05$) than to the dull condition ($M = 1.11, SE = .11$), $t(39) = 2.60, p < .001$. Last, the SampEn was found to be significantly higher for the frontal gamma for the interesting condition ($M = 2.62, SE = .13$) than to the dull condition ($M = 2.27, SE = .11$), $t(35) = 2.39, p < .05$. For all other entropy indices and frequency bands, the dependent t-test did not indicate any significant changes.

TABLE 8: Features used for the prediction of user engagement in the online news reading tasks

Features	Values
Segment	$i \in \{1, \ldots, N\}$
FAA	8 - 13 Hz (frontal alpha right - frontal alpha left)
Frontal theta	4 - 8 Hz
Occipital theta	4 - 8 Hz
Frontal alpha	8 - 13 Hz
Occipital alpha	8 - 13 Hz
Frontal beta	13 - 30 Hz
Occipital beta	13 - 30 Hz
Frontal gamma	36 - 44 Hz
Occipital gamma	36 - 44 Hz

TABLE 9: Class distribution

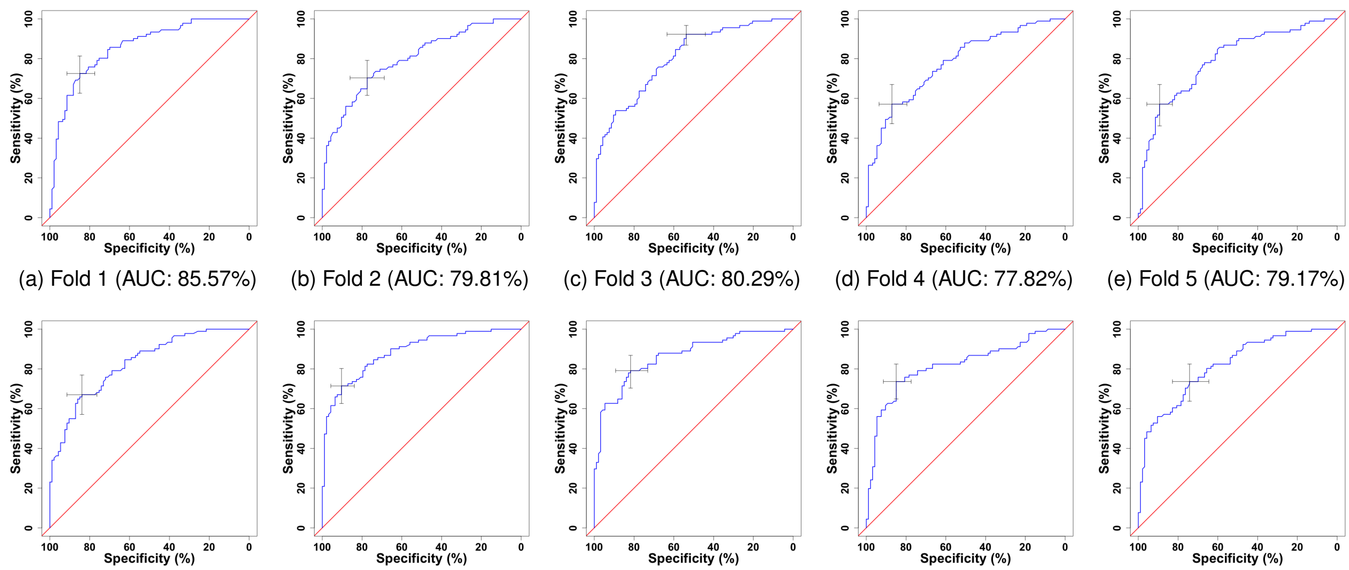
Class	# Examples	Perc.
Interesting	934	50.62%
Dull	911	49.38%

7 Prediction Task

As a side contribution, we demonstrate that it is feasible to predict the level of engagement of users reading news of varying interestingness by modelling their neural activity. We pose the problem as a two-class classification problem (Table 9 shows the class distribution) and our classification target is the task interestingness, which in our context is a proxy of user engagement. To this end, we train a random forest (`RF`) classifier[1] and use as our feature set the average values of PSD for each band in the frontal and occipital regions (Table 8), which were computed over 91 EEG recordings (47 interesting and 44 dull) from 51 participants. We compare our model against a baseline classifier (`Baseline`) that always predicts the majority class in the training set.

Prior to training our models, we performed feature selection using a wrapper method. The wrapper method

1. https://cran.r-project.org/web/packages/randomForest/index.html



(a) Fold 1 (AUC: 85.57%) (b) Fold 2 (AUC: 79.81%) (c) Fold 3 (AUC: 80.29%) (d) Fold 4 (AUC: 77.82%) (e) Fold 5 (AUC: 79.17%)

(f) Fold 6 (AUC: 82.74%) (g) Fold 7 (AUC: 88.52%) (h) Fold 8 (AUC: 86.48%) (i) Fold 9 (AUC: 81.51%) (j) Fold 10 (AUC: 81.52%)

Fig. 3: The Receiver Operating Characteristic (ROC) curves for the model trained on each fold.

evaluates multiple models using procedures that add and remove predictors until finding the optimal combination that maximises the model's performance. More specifically, we used a recursive feature elimination algorithm[2] that fits all predictors, then ranks each predictor according to its importance, and finally retains the top-ranked predictors which are re-fitted to the model in the next iteration. To get performance estimates that incorporate the variation due to feature selection, we applied a 10-fold cross-validation and used the Area Under Curve (AUC) as the performance measure to optimise. By applying this step, we excluded noisy features that do not contribute to the accurate discrimination of our classes.

Next, we performed a 10-fold cross-validation using stratified sampling, to create balanced splits of the data that preserve the overall class distribution. In each fold, we retained 90% of our data for training and 10% for testing. Additionally, we held out a small subset of our training data for fine-tuning the classifier's hyperparameters (e.g., ϵ-threshold, number of trees, minimum size of terminal nodes, maximum number of terminal nodes). We then applied the optimal parameter values to our final model and evaluated its performance against the test set. Table 10 shows the feature importance in terms of the mean decrease in accuracy.

For assessing our models' performance, we considered the standard IR metrics of precision, recall, and accuracy. Traditionally, the most frequently used metrics are accuracy and error rate. However, metrics like accuracy can be deceiving in certain situations and are highly sensitive to changes in data. Hence, we also computed the F-Measure, which combines precision and recall as a measure of the effectiveness of classification in terms of a ratio of the weighted importance on either recall or precision, as determined by the β coefficient (we use $\beta = 1$). Finally, we computed the area under the curve (AUC), which makes use of the proportion of two single-column-based evaluation metrics, namely true positive (TP) rate and false positive (FP) rate.

TABLE 10: Feature importance

Features	Mean Decrease (Accuracy)	Mean Decrease (Gini)
Segment	.0285	79.68
FAA	.0263	99.24
Frontal theta	.0301	94.47
Occipital theta	.0274	93.84
Frontal alpha	.0234	83.41
Occipital alpha	.0324	95.52
Frontal beta	.0294	90.56
Occipital beta	.0360	93.54
Frontal gamma	.0377	97.31
Occipital gamma	.0302	94.27

Table 11 shows the micro-average performance scores for our `RF` model and the `Baseline`, and across all ten folds. As we can observe, our model outperformed the `Baseline` in almost all cases (i.e., for the positive class, the negative class, and the combined weighted average class prediction) but the *recall* of the positive class, where the `Baseline` help the best performance since it always predicts the majority class. More specifically, for the positive class, our model introduced an improvement over the `Baseline` that ranges between $8\% - 18\%$ across all performance metrics. For the negative class, our model help an improvement of 72%, in terms of the F-Measure, over the `Baseline` which failed completely to predict the negative class. Most importantly, when considering the weighted average performance of the models, and with respect to F-Measure, our `RF` model introduced a notable improvement of 41% over the `Baseline`. Finally, we consider the performance of our `RF` model (77.82%-88.52%) with respect to the AUC achieved for each fold (Figure 3) which, given existing assessment conventions, appears to be promising.

2. https://cran.r-project.org/package=caret

TABLE 11: Performance metrics for the `RF` model and `Baseline` (bold typeface denotes the best result)

Performance metrics	RF	Baseline
Pos. class		
Precision	**0.72**	0.54
Recall	0.78	**1.00**
F-Measure	**0.75**	0.67
Neg. class		
Precision	**0.76**	0.00
Recall	**0.69**	0.00
F-Measure	**0.72**	0.00
Weighted. avg.		
Precision	**0.74**	0.25
Recall	**0.74**	0.50
F-Measure	**0.74**	0.33
Accuracy	**0.74**	0.50

8 Discussion and Conclusions

The present work aimed at providing an objective metric for interest, an indicator of the motivational component of engagement that can be used during passive media consumption without the biases and the lack of temporal resolution of subjective self-reported methods. It represents a first exploratory step in order to elaborate operational definitions of interest in news-based interactions or other contexts, with an emphasis on its effects on neural activity. More specifically, through a controlled experiment, we recorded the EEG signals from 51 participants who read news articles that induced either strong interest or dullness, thus promoting diametrical opposite levels of engagement. After preprocessing the acquired EEG signals, we (1) analysed the relationship between spectral power and engagement, (2) investigated the ability of different entropy measures to discriminate between varying levels of engagement, and (3) performed a predictive task where we used the power estimate of each frequency band as our feature set to learn a `RF` classifier that can predict when the news reader is engaged or not.

Foremost, our findings indicate an association between news interestingness and levels of FAA, even when controlling for the effects on FAA of other variables like attention, positive and negative affect, overall assessment of the experience or news genre. The fact that FAA was found to be independent of the emotional valence supports the idea that we are measuring a different component of information processing, namely, the motivational component of engagement. Note that this is so even in the case of interaction with negative stimuli, while in most real-life contexts emotionally negative stimuli results in behavioural avoidance (i.e., our natural tendency is to withdraw from emotionally negative situations), in the context of information interaction, such as in our news reading tasks, people who consume both positive and negative content could be equally engaged. This suggests that physiological measures of emotional valence, such as facial electromyography or heart rate [63], should at least be complemented with the FAA metric when used as indicators of interest.

Therefore, our analysis contributes to a deeper understanding of the psychological nature of engagement. In our methodology, we applied the approach-avoidance model of motivation [15] and considered FAA as a correlate of approach motivation. Our findings highlight that, in the context of engagement with news reading, approach motivation must be factored in. Therefore, we argue that future research on user engagement could benefit from applying the behavioural approach-avoidance model of motivation rather than the more commonly used bi-factorial model of emotions [12], where motivational activation is equated to emotional responses.

With respect to our multilevel modelling, our analysis did not indicate any significant differences in the theta and alpha power bands across the experimental conditions, neither for the frontal nor the occipital regions. Regarding the alpha power band, previous research on audiovisual messages suggests that engagement can be associated to decreases in the frontal alpha power [72], a result that was not replicated in our study. A possible explanation of this is that the authors of [72] considered only the lower part of the alpha (8-9.5 Hz), whereas we analysed the complete alpha spectrum (8-13 Hz). Another possible explanation is that the neural correlates of engagement may be different in the case of audiovisual and textual stimuli. The lack of engagement effects on any of the power bands in the occipital region (mostly associated with visual processing) suggests that the visual processing of the interesting and the dull news was similar. This interpretation seems reasonable given that there were no considerable differences in the formal aspects of both conditions, reinforces our argument that the components of engagement should be tied to the features of the task at hand, and provides a testable prediction that can guide further research on this issue.

Moreover, we considered the possibility that interest could be associated to a higher allocation of working memory for stimuli encoding, and that this would be exhibited in higher levels of theta and gamma activity [55], [68], in the interesting condition. However, we did not find any significant increase in the theta or gamma bands, neither in the frontal nor the occipital region, suggesting no difference in the allocation of working memory. Also, we observed a decrease in the frontal gamma in the dull condition which goes against our original hypothesis. Similarly, since beta activity has been related to the occurrence of cognitive processes, one would expect that it increases when reading interesting news, but our findings point out to the opposite direction.

Also, in previous research, the frontal gamma power band has been linked to the activity of the brain default network [8]. The brain default network is a neural network that is activated when we are not focused in tasks demanding our attention [25], [47], and whose activation underlies mind-wandering [47] and boredom [48]. Considering this evidence, a possible explanation of our findings is that reading dull news produces a lower allocation of attention. This leads to the activation of the brain default network that produces the subjective experience of mind-wandering or boredom, which would explain the higher levels of frontal gamma observed in the dull condition. Furthermore, to deal with boredom and stay focused on the news reading task, our participants may have needed to exert a more top-down control of attention. Frontal beta activity has been associated to top-down control of behaviour [74] and to the maintenance of the current sensorimotor state [18]. Therefore, higher level of beta activity for the dull reading task can be interpreted as a consequence of making a cognitive effort to maintain the focus of attention. In other words, the interaction with interesting news content is characterised by an automatic allocation of attention [78]. Of course, these are tentative explanations that will require further testing, but our results are consistent with this interpretation.

Overall, the significant effects of engagement over FAA and frontal beta and gamma challenge the lack of significant effects in the self-report data (e.g., FA, post-NAS, post-PAS, overall experience). This clearly highlights the utility of indirect measurements like EEG in the context of user engagement research, especially considering that the measures of brain activity were obtained with a low-cost device.

Regarding our entropy analysis, we noted variations in the SampEn measure for several power bands and across the different experimental conditions. We consider SampEn as an indicator of regularity, i.e., how reproducible the signal is at different times, with lower SampEn suggesting that the values remain similar and higher SampEn indicating irregular and less predictable activation patterns.

When examining the SampEn of the FAA, we observed significantly higher values for the interesting condition than the dull condition. The reduction of irregularity in the FAA in the dull condition could be attributed to a less complex electrophysiological behaviour. This suggests that the differences in the degree of cortical activation between the right and left hemispheres were consistently lower in the dull condition, as compared to the more irregular patterns observed in the interesting condition. Given that FAA relates to motivation, the observed differences indicate that it is consistently lower in the dull condition, whereas in the interesting condition it exhibits a higher - yet more variable signal. One obvious interpretation of the latter is that when readers are interacting with engaging news content some parts of the content result in peaks in the FAA and others in valleys, but overall the average level is higher than to the dull condition.

Furthermore, our analysis of the SampEn in the frontal alpha revealed increased irregularity in the interesting condition. According to recent findings, entropy can increase with internal processing demands that are involved in inhibitory top-down control. Hence, the observed high entropy could be attributed to the internal processing demands in response to engaging stimuli that may have promoted creative ideation. A similar pattern was observed for the SampEn in the occipital alpha which, based on prior research [72], was found to be inversely correlated to the amount of neurones involved in performing a task. In general, amplitudes of alpha waves diminish when subjects open their eyes and are attentive to external stimuli. Our entropy analysis appears to be in line with these findings and, although we did not observe significant differences in the occipital alpha across conditions, we found a lower - on average - occipital alpha in the interesting condition that is characterised by higher irregularity.

When considering the occipital gamma, we found the SampEn to be significantly higher for the interesting condition than to the dull condition. In the past, gamma oscillations have been proposed to play an important role for object representations in the visual system [31], but also for working memory maintenance [32], [55] and long-term memory recall [49]. In our analysis, we interpret the higher SampEn of the gamma power band as the result of cognitive activation of the occipital region. We argue that the observed activation may have been induced by the recall or maintenance of memory representations due to the cognitive processing of interesting news content.

Regarding frontal gamma, there has been increasing evidence that gamma oscillations are involved in a variety of cognitive processes like visuospatial focused attention [33], visual perception, learning and memory [33]. Based on the theory proposed in [39], individual memories are stored by the spatial pattern of cells that fire within a given gamma cycle and different memories become active in different gamma cycles. The high SampEn of the gamma frequency observed in the interesting condition, which is indicative of gamma frequency oscillations, may reflect the increasing complexity of the memory-related processes, i.e., multiple memories fire during each cycle. Another possible interpretation of the oscillatory activity in gamma, as indicated by the high SampEn, is that it occurs spontaneously when subjects are in a state of focused attention [27].

Generally, entropy statistics provide an improved evaluation of time series irregularity, with larger values corresponding to increasing process complexity and activation, such as, for example, the cognitive activation observed while interacting with engaging stimuli. However, we want to emphasise that, although the interpretation of our entropy analysis is not as straightforward in all cases, our goal here is to demonstrate the practical utility of certain entropy indices as simple and easy to apply methods for discriminating between the neural effects of engaging vs. dull news content. Indeed, our experimental results prove the potential applications of this branch of statistics in reflecting differences in the irregularity of EEG data of engaged news readers, which can complement the information offered by traditional PSD analyses.

Finally, in our predictive modelling task, we demonstrated the feasibility of yet another approach to predict the level of engagement of news readers by modelling their neural activity. Despite our simple feature set and our relatively noisy signals, our `RF` model achieved a good prediction accuracy and managed to outperform the `baseline`. This improvement was observable for several performance indicators, with the most important being the AUC. The AUC is a particularly useful performance measure because it provides a visual representation of the relative trade-offs between the benefits (reflected by true positives) and costs (reflected by false positives) of classification in regards to data distributions. The AUC scores reflect a good performance for our `RF` model and provide the first positive evidence of user engagement prediction in the context of our study.

9 LIMITATIONS

As previously discussed, in this work we have addressed one of the many facets of the engagement construct. More specifically, we analysed correlates of interest which, while being a central part of cognitive engagement, do not cover the full spectrum of this phenomenon. We focus on an online measure of engagement; that is, observable modulations of users' brain activity when cognitively engaged. Other aspects of engagement could have a different temporal dimension such as, for instance, visiting a webpage everyday could also be considered as a type of cognitive or behavioural engagement, developed over a number days.

Furthermore, our measure of interest does not address the aspects of engagement that do not occur concurrently with exposure to the stimuli. Also, we did not analyse the impact of interest, or its EEG correlates, on another basic psychological process, memory for the information, which could provide a more comprehensive view of the psychological processes involved in cognitive engagement.

Another potential limitation concerns the novel technique based on estimating the entropy of the signals. Although the entropy indices proved to be sensitive to our experimental manipulation of interest and provided significant results that complement traditional power spectrum analysis, the interpretation of the entropy signals in terms of information processing warrants further investigation.

A further possible limitation of this work is that we only obtained self-reported measures of emotional valence and attention, which may be biased. For instance, participants could have reported that they were equally attentive to interesting and dull news just to satisfy the experimenters' expectations. This could raise doubts about the accuracy of self-reported measures, and, in turn, about the weak relationship between interest and perceived attention or emotional valence. Further research could also consider indirect measures of these aspects, such as psychophysiological methods (e.g. facial electromyography for emotional valence, heart rate for attentional responses) in order to explore more deeply this issue.

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