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Abstract

Naturalistic stimuli can elicit highly similar brain activity across viewers. How do naturalistic educational materials engage human brains and evoke learning desire? Here, we presented 15 audiovisual course clips (each lasting about 120 s) to university students and recorded their neural activity through electroencephalography (EEG). Upon finishing all the video viewings, subjects ranked 15 courses in order of learning desire and reported the reasons of high learning desire (i.e., "value" and "interest"). The brain activity during the video viewing was measured as the neural similarity via inter-subject correlation (ISC), that is, correlation between each subject's neural responses and others'. Based on averaged learning desire rankings across subjects, course clips were classified with high vs. medium vs. low motivational effectiveness. We found that ISC of high effective course clips was larger than that of low effective ones. The ISC difference (high vs. low) was positively associated with subjects' learning desire difference (high vs. low). Such an association occurred when viewing time accumulated to about 80 s. Moreover, ISC was correlated with "interest-based" rather than "value-based" learning desire. These findings advance our understanding of learning motivation via the neural similarity in the context of online education and provide potential neurophysiological suggestions for pedagogical practices.

Keywords: naturalistic stimuli, learning desire, neural similarity, inter-subject correlation (ISC), electroencephalography (EEG)

Significance Statement

This study shows that naturalistic educational materials with high motivational effectiveness elicit larger neural similarity across learners than less effective ones. Importantly, the neural similarity serves as a sensitive predictor of learners' course-learning desire. It is suggested that the use of emerging electroencephalography-derived inter-subject correlation approach works with evaluating the quality of audiovisual educational materials. Hence, such a novel approach is promising to provide neurophysiological information for pedagogical practices.

1. Introduction

Learning desire is an important prerequisite for human learning to occur. How to evoke learning desire is a persistent concern in the field of educational psychology and pedagogy (Todd, 2013). Recently, online courses have brought a tremendous transformation into education, as evidenced by their use in many open learning systems, such as Coursera and Khan Academy (Copley, 2007; Waldrop, 2013). Compared with the traditional classroom learners, online learners experience lower-level interactivity and thus are more susceptible to quiting learning or dropping out courses (Kizilcec, Bailenson, & Gomez, 2015; Szpunar, Khan, & Schacter, 2012). Therefore, evoking learning desire is of great importance, especially in the context of online education (Keller & Suzuki, 2004; Visser, 1998). To this end, one of the good practices is to comprise audio-visual materials at the course introductory phase (Grant & Thornton, 2007; Kay, 2012).

Currently, there are two main hypotheses that account for potential factors contributing to learning desire. First, the "value-based" hypothesis (Atkinson, 1957; Eccles *et al.*, 1983), proposes that helping learners perceive the value (e.g. utility-value) will effectively promote learning desire. The perceived utility-value of courses influences course enrollment decisions (Canning *et al*., 2018; Updegraff, Eccles, Barber, & O'Brien, 1996) and academic achievements (Hulleman, Godes, Hendricks, & Harackiewicz, 2010). Second, the "interest-based" hypothesis (Krapp, 2002; Hidi & Renninger, 2006), postulates that guiding learners to develop interest will effectively boost learning desire. Interest, as the saying goes, is the best teacher. Interest contributes to learners' further study (Ainley, Hillman, & Hidi, 2002; Harackiewicz, Barron, Pintrich, Elliot, & Thrash, 2002; Mitchell, 1993; Renninger & Hidi, 2002; Schiefele, 2009) and improves learning performance (Rotgans & Schmidt, 2014).

In the context of online education, learning desire evoked by audio-visual educational materials has been rarely studied from the neural perspective. To decode human brain activity during real-world experiences, previous studies have measured individuals' neural responses to discrete and simplified artificial stimuli; these responses comprise electroencephalography (EEG)-derived event related potentials and functional magnetic resonance imaging (fMRI)-derived blood-oxygenation-level-dependent (BOLD) signals (Spiers and Maguire, 2007). Beyond all that, emerging neuroscience research has started to measure the neural similarity (i.e. group-level similar neural responses) to concrete and complex naturalistic stimuli from a "collective-brain" perspective. Indeed, when exposed to the same stimulus, individual brains tend to "tick collectively" in synchronized spatiotemporal patterns (Hasson, Nir, Levy, Fuhrmann, & Malach, 2004). The neural similarity can be quantified by inter-subject correlation (ISC), that is, correlation between individual subject's neural responses and others' (Cohen *et al*., 2018). Using ISC approach, previous fMRI research reveals that movie viewing elicits highly similar neural activity across viewers (Hasson *et al*., 2004). Within several-minute narratives, time-resolved ISC peaks during the viewing of scenes with high emotional arousal and valence (Hasson *et al.*, 2004; Nummenmaa *et al.*, 2012). Moreover, ISC is indicative of the powerfulness of political speeches (Schmälzle, Häcker, Honey, & Hasson, 2015) and the effectiveness of anti-alcohol public service announcements (Imhof, Schmälzle, Renner, & Schupp, 2017).

Apart from fMRI-derived ISC, previous EEG studies have captured significantly correlated components during the watching of movie clips, TV series and commercials (Dmochowski, Sajda, Dias, & Parra, 2012; Dmochowski *et al.*, 2014). Correlated components were extracted from multi-channel EEG time series to maximize the correlation based on a

signal decomposition method (Dmochowski *et al.*, 2012). EEG-derived ISC has been found to indicate attentional engagement during the narrative video viewing (Cohen, Henin, & Parra, 2017; Dmochowski *et al*., 2012) and preferential attitudes towards SuperBowl commercials (Dmochowski *et al*., 2014). In a recent study, learners were asked to attentively or inattentively watch online educational videos, during which their brain activity was measured (Cohen et al., 2018). EEG-derived ISC discriminates between the attentive and inattentive viewings and predicts the learning performance. In a real-world classroom, EEG-derived ISC has also been found to associate with engagement and attentional modulation (Poulsen, Kamronn, Dmochowski, Parra, & Hansen, 2017).

Building upon previous findings, the EEG-derived ISC approach holds the potential to uncover the neural underpinnings during the natural processing of audio-visual educational materials. In current study, we recorded EEG signals while learners were viewing audio-visual course clips. The ISC approach was adopted to examine the neural similarity across learners. Upon finishing all the video viewings, subjects ranked 15 courses in order of learning desire and reported the reasons of high learning desire (i.e., “value” and “interest”). The viewing of course clips was expected to prompt significant neural similarity across learners because brains tend to “tick collectively” during natural vision (Hasson *et al.*, 2004; Dmochowski *et al.*, 2012). Moreover, considering the potential links from the neural similarity to the effectiveness of naturalistic materials (Imhof *et al*., 2017; Schmälzle *et al*., 2015), subjects’ attentional engagement (Cohen *et al*., 2017; Domochowski *et al*., 2012; Poulsen *et al*., 2017) and preferential attitudes (Domochowski *et al*., 2014), we expected that the neural similarity could be indicative of the motivational effectiveness of course clips, and serve as a predictor of learning desire. Specifically, we hypothesized that (*i*) ISC should be higher for course clips ranked with high vs. low learning desire, and that (*ii*) the ISC

difference (high vs. low) should be positively correlated with subjects' learning desire difference (high vs. low). Finally, to provide neurophysiological suggestions for why some naturalistic educational materials elicited high learning desire, we explored the association between ISC and potential reasons (e.g. "value", Hulleman, Durik, Schweigert, & Harackiewicz, 2008, and "interest", Harackiewicz *et al*., 2002).

2. Methods

2.1 Subjects

Fifteen subjects (three males, mean age 21 years, range 18 – 25 years) were recruited through public announcement at the East China Normal University, China. All of them were right-handed, in good health, with normal or corrected-to-normal vision, and with no history of neurological or psychiatric disorders. Monetary compensation was afforded for their participation. The study was approved by the Committee on Human Research Protection of East China Normal University (HR 064-2017). All subjects provided a written, signed informed consent prior to the experiment.

2.2 Materials

Fifteen courses from Massive Open Online Courses (MOOCs, http://www.icourse163.org) were selected based on three criteria: (1) being designed by National Key Universities to ensure the production quality; (2) covering various topics in humanities, social sciences and natural sciences; (3) online enrollments of those courses were various (see details in **Table 1**). We focused and selected the introductory parts of those several-hour online video courses (e.g. https://www.icourse163.org/course/WHU-85001), since the initial learning phase exerts an important effect on learning desire (Keller & Suzuki, 2004; Visser, 1998). The selected

course clips were then edited (i.e., 1-s fade-out, resolution 1280 × 720) using Movie Maker (Windows, Microsoft Corporation). The duration of each course clip lasted approximately for 120 s ($M \pm SD$: 127 ± 41 s, range: 57–215 s).

2.3 Procedures

During the experiment, subjects were individually seated in front of a 19.5-in monitor in an electromagnetic-sound-shielded room, wearing earphones and an EEG recording cap (**Fig. 1A**).

There were fifteen trials corresponding to fifteen course clips. One trial entailed the following steps. First, a course title together with its pre-assigned course number (see details in **Table 1**) appeared for 3 seconds, followed by a 1-s fixation. Next, subjects watched a course clip. After that, subjects provided answers to "Do you like the introduction?" and "Do you want to learn the course?" (1–100, from "not at all" to "very much", until response; **Fig. 1B**). Controlled by E-prime software (version 2.0; Psychology Software Tools Inc., Pittsburgh), the presentation order of trials (course clips) was randomized across subjects.

Upon finishing fifteen trials, fifteen course titles with their course numbers were presented together on the screen. Subjects were then instructed to rank the fifteen courses in order of their learning desire from 1 (most) to 15 (least). To do so, subjects wrote down corresponding course numbers besides a column of rankings (1–15) with paper and pen (**Fig. 1C**). Upon finishing the course ranking, subjects were asked to rate on a 4-point scale from 1 (strongly disagree) to 4 (strongly agree), on potential reasons that their high learning desire was attributed to. Two items testing most concerned reasons, "value" and "interest", were included: "learning the introduced course is useful for me" (Hulleman *et al.*, 2010) and "I am interested in the introduced course" (Nuutila, Tuominen, Tapola, Vainikainen, & Niemivirta,

2018). As suggested by the pre-collected data from independent raters (see section 2.6), subjects reported reasons only for their Top 2 courses (i.e. those were ranked with 1 and 2). To note, learning desire rankings of courses were later reversely coded (i.e., 16 minus original rank), such that larger rankings indicated higher course-learning desire.

(Insert **Fig. 1** here)

2.4 EEG data acquisition and preprocessing

Brain signals were recorded via a 64-channel EEG apparatus (NeuroScan, El Paso, TX), in accordance with the international 10/10 system. The electrooculograms (EOGs) were recorded via four auxiliary electrodes. Two horizontal electrodes were placed lateralized to two eyes, while the other two vertical electrodes were placed over the upper and lower sides of the left eye. Data collected from the two horizontal electrodes and the two vertical electrodes were synthesized respectively and merged into one horizontal channel and one vertical channel. Impedances were kept below 10 kΩ. Signals were digitized at a sampling rate of 1000 Hz.

Following Dmochowski *et al.* (2012), preprocessing of EEG data was performed using custom MATLAB (R2016b, MathWorks, Natick, MA, USA) scripts with EEGLAB toolbox (version 14.1.0, Delorme & Makeig, 2004). Data were filtered at a 1 Hz high-pass and a 50 Hz notch, and down-sampled to 250 Hz. As we focused on the EEG activity during course clip watching, data were segmented from the beginning to the end of each video. Eye-movement artifacts were corrected using a regression-based approach (Elbert, Lutzenberger, Rockstroh, & Birbaumer, 1985; Gratton, Coles, & Donchin, 1983): (*i*) approximating the amplitude relation between EOG channels and each EEG channel and (*ii*) then subtracting the estimated proportion of the EOG from the EEG. The regression-based

correction was separately performed on the entire data block corresponding to each video. Two EOGs and two mastoid channels were then omitted, leaving 60 channels in the following analyses. Bad channels were automatically rejected for exceeding mean channel power by five standard deviations. Outlier samples in each kept channel were rejected for their magnitudes exceeding the mean of that channel by more than five standard deviations. Data within -40 to +40 ms (20 sampling points) relative to each identified artefactual outlier were additionally rejected and all replaced by zeros. The preprocessed EEG data entered into subsequent analyses.

2.5 Inter-subject correlation (ISC)

The analysis of inter-subject correlation (ISC, Dmochowski *et al.*, 2012, 2014; see more details in www.parralab.org/isc/) was computed to quantify the neural similarity while subjects were watching the same naturalistic stimuli. It aims to find components (here, linear combinations of electrodes) capturing maximal correlation across all subjects. The concept of maximizing correlations resembled that in canonical correlation analysis (Hotelling, 1936), with a constraint being that the same projection vectors were employed for all the datasets.

ISC analysis was done individually for each course clip. It included three steps. First, correlated components were captured across all subjects' neural datasets (subjects × electrodes × time-points) by solving an eigenvalue problem similar to the principle component analysis (PCA, Parra and Sajda, 2003). Second, three strongest correlated components (i.e. C1, C2, and C3) were retained while other smaller ones were ignored (Dmochowski *et al.*, 2012, 2014; Ki *et al.* 2016). Spatial distributions of the C1, C2 and C3, informing the approximate locations of the underlying neuronal sources, were visualized (Parra *et al.*, 2005; Haufe *et al.*, 2014). Finally, for each subject, component-wise (i.e.,

projected EEG data) correlations were computed between this subject and each of all remaining subjects, and then averaged. The ISC was then obtained as the sum of the correlation coefficients over C1, C2 and C3.

(Insert **Fig. 2** here)

2.6 Statistical analyses

Following previous EEG-ISC studies (Dmochowski *et al*., 2012; Ki *et al.*, 2016), we used phase-randomization technique to determine chance-level ISC of each course clip (Theiler *et al.*, 1992). To do so, Fast Fourier Transformation was first used to extract the original phases and amplitudes of pre-processed EEG data. Then, randomly generated phases were added to the original phases. With unchanged original amplitudes, inverse Fast Fourier Transformation was then used to reconstruct phase-randomized surrogate EEG data. By this step, the phase-randomized EEG surrogate data were not supposed to correlate across subjects. For each course clip, significance level was determined by comparing ISC of the original data to the mean ISC of 1000 phase-randomized surrogate data sets. The resulting p values for fifteen course clips were then corrected using false discovery rate (FDR) procedure (Benjamini & Yekutieli, 1995).

We calculated the motivational effectiveness of course clips by averaging the learning desire rankings across subjects. Fifteen course clips were then classified into three categories with different degrees of motivational effectiveness, high (average rankings from 11 to 15) vs. medium (6–10) vs. low (1–5); two clips (i.e., No. 3 and No. 12) were classified into the high effective category, two (i.e., No. 10 and No. 13) into the low effective category, and eleven (i.e., the remaining) into the medium effective category. Such a classification was validated by an additional group of independent raters. Prior to the EEG experiment, using

the identical experimental procedures except for the EEG collection, behavioural data were pre-collected from an independent group of twenty-five subjects (six males, mean age 21 years, range 19–25 years, 1 left-handed). The independent raters classified exactly the same two clips into the high effective category, exactly the same two into the low effective category and exactly the same remaining eleven into the medium effective category as the EEG group did. To validate the use of group-averaged rankings for classification, we measured the variability of learning desire rankings for course clips across subjects (including EEG subjects and independent raters) using intra-class correlation (ICC). The ICC reached 0.93, suggesting that the variability of the group-averaged rankings for course clips across subjects were fairly low (Koo & Li, 2016).

With the aforementioned classification of course clips, we then conducted one-way repeated measures ANOVAs to relating motivational effectiveness (high vs. medium vs. low) with ISC values (i.e. ISC and sub-components). Specifically, for each subject, ISC values of each effective category were first averaged across course clips in that category and then compared using repeated measures ANOVAs, with motivational effectiveness (high vs. medium vs. low) as a within-subject variable. For *post hoc* pairwise comparisons, we used paired *t*-tests with FDR correction.

We further conducted a Pearson correlation analysis between ISC difference (high vs. low) and learning desire difference (high vs. low). Difference values (i.e. ISC difference and learning desire difference) were calculated by subtracting values of the low effective category (after averaging values across two involved course clips) from values of the high effective category (after averaging values across two involved course clips). To note, considering ISC varies due to individual differences (Petroni *et al*., 2018), we chose to use the difference values rather than values of either low or high effective category. ISC of the low effective

category, served as an active baseline, was subtracted to control for individual differences. Here we focused on learning desire rankings decided after all the viewings of course clips rather than learning desire ratings of "do you want to learn the course?" collected after each course clip viewing since they were highly correlated with each other ($r(15) = 0.97$, $p < 0.001$) and the former were less biased to limited information. Given the evidence linking sub-components of ISC (i.e. C1, C2, and C3) to separate cognitive functions (Dmochowski *et al*., 2014; Cohen & Parra, 2016), parallel correlation analyses were also separately performed between sub-component ISCs difference (high vs. low) and learning desire difference (high vs. low).

Previous studies have found that human brain is optimized to make the fastest decision at a specified accuracy after successively integrating external perceptional inputs (Bogacz *et al*., 2006; de Gardelle & Summerfield, 2011; Gold & Shadlen, 2007; Tsetsos *et al*., 2012). How early brain responses predict subsequent behaviors has been computed by identifying the earliest time-point, at which time-cumulative brain activity was significantly correlated with subsequent behaviors (Jiang *et al*., 2015; Liu *et al*., 2019; Zheng *et al*., 2018). Accordingly, we explored how early ISC predicted learning desire by identifying the earliest time-point, at which time-cumulative ISC difference (high vs. low) was correlated with subsequent learning desire difference (high vs. low). Specifically, time course correlation analyses between time-cumulative ISC difference and subsequent learning desire difference were repeatedly performed from 0.1 s to 133 s (the shortest duration among the four course clips involved in low and high effective categories) with time increment of 0.1 s. The time-cumulative ISC at a certain cumulative time (*ct*) was computed by the time points from 1 to *ct* * 250 (sampling rate). The subsequent learning desire difference used in the time course correlation analyses was same as that used in the aforementioned full time correlation

analysis. The resulting *p*-values, at the same size of repeated times for correlation analyses, were then corrected using FDR methods. Accordingly, if there existed a certain time point, after which *p*-values of the correlations between the time-cumulative ISC difference and learning desire difference started and maintained to survive the FDR correction, such a time point would be labelled as the starting time point that ISC could successfully predict learning desire. Time increments with 0.5 s, 1 s, 2 s, 5 s, and 10 s also returned similar results. In addition, parallel time course correlation analyses were performed for sub-component ISCs (C1, C2 and C3), separately.

Moreover, we attempted to provide neurophysiological suggestions for why some naturalistic educational materials elicited high learning desire. To do so, for individual subjects, we focused on reason ratings (i.e. "value" and "interest") and ISC of their own Top 2 course clips with highest rankings. "Value" and "interest" ratings were averaged across individual-level Top 2 course clips and compared using a paired *t*-test. Next, we conducted Spearman correlation analyses between reason ratings (i.e. "interest" and "value") and ISC, which was also averaged across individual-level Top 2 course clips for each subject.

2.7 Code Accessibility

The code described in the paper is freely available online at https://github.com/YiZhuECNU/EEG-ISC.git. The code is available as Extended Data1. It can be performed using MATLAB (version 2016b) in a Windows 10 system.

3. Results

3.1 The significant ISCs for course clips

As expected, each of 15 video-evoked ISCs (i.e. averaged ISC across all the subjects) significantly exceeded its corresponding chance-level ISC determined by phase-randomized surrogated data (*ps* < 0.001, FDR corrected), indicating that course clips induced significant learner-wise similar neural activities.

(Insert **Fig. 3** here)

3.2 ISC of high vs. medium vs. low effective course clips

We next sought to identify whether ISC varied by motivational effectiveness. A one-way repeated measures ANOVA comparing ISC across motivational effectiveness (high vs. medium vs. low) factor, on ISC was conducted. Results revealed a significant main effect, $F(2, 28) = 8.36$, $p = 0.001$, $\eta_p^2 = 0.37$. Follow-up pair-wise comparisons showed that ISC was significantly larger for the medium effective category ($M \pm SD$, 0.09 ± 0.02), $t(14) = 3.18$, corrected $p < 0.05$, Cohen's $d = 0.68$, and for the high effective category (0.10 ± 0.02), $t(14) = 3.25$, corrected $p < 0.05$, Cohen's $d = 0.86$, than that for the low effective category (0.08 ± 0.02) (**Fig. 4A**).

Similar analyses on sub-component ISCs (C1, C2 and C3) consistently showed the main effect of motivational effectiveness, *Fs* > 6.78, *ps* < 0.004, $\eta_p^2 > 0.33$. Follow-up pair-wise comparisons showed results as follows: for C1, ISC of the high effective category was larger than that of the medium effective category, $t(14) = 3.98$, $p < 0.01$, Cohen's $d = 0.58$, and that of the low effective category, $t(14) = 3.03$, $p < 0.05$, Cohen's $d = 0.59$; for C2, ISC of the medium effective category was significantly larger than that of the low effective category, $t(14) = 4.00$, $p < 0.01$, Cohen's $d = 0.98$; for C3, the respective ISC of the medium and high effective categories was larger, $t(14) = 6.28$, $p < 0.001$, Cohen's $d = 1.01$, and tended to be

larger than that of the low effective category, $t(14) = 2.58$, $p < 0.1$, Cohen's $d = 0.89$ (**Fig. 4B lower panel**).

Representative spatial projections of three correlation-maximizing components on the scalp showed that the first component was symmetric and marked approximately in the frontal and occipital lobes, the second component was approximately in the bilateral frontotemporal lobes and the third component was marked widely in the parietal cortex (**Fig. 4B upper panel**). Such scalp projections resulted from viewing course videos were in accordance with those previously found for other audiovisual stimuli (e.g. Dmochowski *et al.*, 2012, 2014).

(Insert **Fig. 4** here)

3.3 ISC as a predictor of course-learning desire

We then tested whether ISC predicted subjects' course-learning desire. ISC difference (high vs. low) was significantly correlated with learning desire difference (high vs. low), $r(15) = 0.74$, $p = 0.002$ (**Fig. 5A**). Parallel correlation analyses for sub-component ISCs found that the sub-component ISCs difference (high vs. low) were independently correlated with the learning desire difference (high vs. low): C1, $r(15) = 0.66$, $p = 0.007$; C2, $r(15) = 0.58$, $p = 0.02$; C3, $r(15) = 0.47$, $p = 0.08$ (**Fig. 5C**).

To identify how early ISC predicted learning desire, time course correlation analyses were repeatedly conducted with 0.1-second time increment from 0.1 s to 133 s between time-cumulative ISC difference (high vs. low) and subsequent learning desire difference (high vs. low). We found that at 100.6 s after the video onset, the time cumulative ISC difference (high vs. low) started to become a significant predictor of subsequent learning desire difference (high vs. low) ($p < 0.05$, FDR corrected, **Fig. 5B**). Later on, correlations

retained constantly significant till the video ended. Parallel time course correlation analyses were conducted for each sub-component ISC. Results revealed a key role of C1 (but not C2 and C3) in the prediction (starting at 85.5 s, **Fig. 5D**).

(Insert **Fig. 5** here)

3.4 The association between ISC and "interest"/"value"

In an attempt to provide neurophysiological suggestions for why some course clips are effective to evoke learning desire, we tested whether ISC was associated with "value" and/or "interest". Behaviorally, ratings of "interest" ($M \pm SD$, 3.67 ± 0.36) was highest among all the reasons and significantly exceeded ratings of "value" (3.27 ± 0.62), $t(14) = 2.45$, $p = 0.03$, Cohen's $d = 0.79$ (**Fig. 6A**). Moreover, ISC for individual-level Top 2 course clips was significantly correlated with ratings of "interest" ($r(15) = 0.77$, $p = 0.0008$, **Fig. 6B**), but not "value" ($r(15) = 0.32$, $p = 0.25$, **Fig. 6C**).

(Insert **Fig. 6** here)

4. Discussion

Here we employed EEG-derived ISC approach to capture the degree of shared brain responses to naturalistic educational materials. Results revealed that (*i*) online course videos prompted similar neural activity across learners; (*ii*) the neural similarity was enhanced by the motivational effectiveness of course clips for evoking learning desire; (*iii*) the neural similarity was predictive of course-learning desire (even before finishing the viewing of the entire video); (*iv*) the neural similarity was associated with "interest-based" (rather than "value-based") learning desire. These results were discussed successively as follows.

First, using EEG, we recorded learners' general patterns of neuronal activity at the time scale during the watching of online course videos. We found that all fifteen course clips,

regardless of their motivational effectiveness for evoking learning desire, elicited significant neural similarity across learners. This result aligns well with pervious findings that brains of different individuals tend to act in unison during the natural watching (Dmochowski *et al.*, 2012, 2014; Hasson, *et al.*, 2004; Ki *et al.*, 2016). Thus, inter-subject correlation (ISC) across multiple brains tends to provide a sensitive and quantifiable measure of the continuous neural responses to naturalistic stimuli. Critically, this measure makes it feasible for conventional laboratory paradigms to move beyond the rigid trial-based structure where discrete stimuli are repetitively presented.

Second, although all course clips prompted similar neural processing across learners, we found significantly larger ISC for high (vs. medium, vs. low) effective course clips. It seems that course clips, which engage learners' brains more collectively, are more effective to evoke course-learning desire. This finding is consistent with prior studies demonstrating larger ISC during strong (vs. weak) powerful political speeches (Schmälzle *et al.*, 2015), and more (vs. less) effective anti-alcohol public service announcements (Imhof *et al.*, 2017). ISC has also been found to predict the preferential effectiveness of advertisements in an EEG study (Dmochowski *et al.*, 2014). However, here we failed to demonstrate that ISC scaled monotonically with the motivational effectiveness of course clips. To note, the duration of advertisements used in Dmochowski *et al.* (2014) is identical (i.e. 30 s), while the duration of course clips used in our study is not (i.e. 57–215 s). We suspected that the longer watching of materials might damage the sustained attention or vigilance (Nuechterlein, Parasuraman, & Jiang, 1983; Sarter, Givens, & Bruno, 2001), thence modulating ISC (Cohen *et al.*, 2018; Iotzov *et al.*, 2017; Ki *et al.*, 2016).

Third, course-learning desire could be predicted by the neural similarity. Moreover, time course analyses showed that ISC was predictive of subsequent course-learning desire after

about 80-s watching of videos. The first maximally correlated component (C1) played a key role in such a prediction. Representative scalp projection of the C1 exhibited a symmetric pattern marked in the frontal and occipital electrodes. Such a component captures the neural activity possibly reflecting the visual processing (Dmochowski *et al.*, 2012, 2014), suggesting that the visual property of educational materials is crucial for promoting learning desire. This finding is in accordance with previous studies showing that visual properties, such as saliency, influence the final decision (Milosavljevic, Navalpakkam, Koch, & Rangel, 2012; Towal, Mormann, & Koch, 2013). The second component (C2) in the bilateral frontotemporal lobes, was possibly recruited in the auditory processing (Hickok & Poeppel, 2007). Besides, C1 and C2 might also capture supramodal responses (Cohen & Parra, 2016). The third component (C3) was marked widely in the parietal cortex, which might be associated with attentional modulation to audio-visual stimuli (Nardo, Santangelo, & Macaluso, 2011; Shomstein & Yantis, 2006). The global scalp patterns observed in current study aligned with those found in a previous fMRI study, where spatial dimension of the observed EEG-derived neural similarity was probed by regressing BOLD activation time series onto the neural similarity scores (Domochowski *et al*., 2014). In a final detail, approximate 80-s video watching was sufficient to predict the course-learning desire. This finding bolsters the optimization of brain to make the fastest decision at a specified accuracy after successively integrating external perceptional inputs (Bogacz, Brown, Moehlis, Holmes, & Cohen, 2006; de Gardelle & Summerfield, 2011; Gold & Shadlen, 2007; Tsetsos, Chater, & Usher, 2012).

Fourth, we provided neurophysiological suggestions for why some course clips were effective to evoke learning desire by testing the association between ISC and “value”/ “interest”. For course clips ranked with higher learning desire by individuals, (*i*) “interest”

was reported to be a more important reason for further course study, and (*ii*) neural similarity during the processing of those videos was associated with self-reported "interest" rather than "value". These findings support "interest-based" learning desire hypothesis – learners' interest effectively promote learning desire (Ainley *et al.*, 2002; Harackiewicz *et al.*, 2002; Hidi & Renninger, 2006; Krapp, 2002). Given the evidence that ISC is strongly modulated by attention (Cohen *et al.*, 2018; Iotzov *et al.*, 2017; Ki *et al.*, 2016) and the potential association between attention and interest (Shirey, 1992), we suspected that attention might play a role in the relationship between ISC and "interest-based" learning desire. As an important note, although "value-based" learning desire hypothesis did not gain the supporting results in current study, we could not assuredly draw a conclusion that "value" played no role in promoting learning desire. It might be the case that our ISC measure was not so sensitive to the "value-based" online learning. Future independent replications are needed to provide more evidence.

Several limitations of this work, along with future directions, deserve noting. First, scalp projections of correlated components are not valid to exactly locate brain sources due to the inherently limited spatial resolution of EEG. Therefore, future studies should consider adopting source analyses (e.g. standardized low-resolution brain electromagnetic tomography, Pascual-Marqui, 2002) with high-resolution EEG, as well as fMRI/MEG with satisfactory spatial resolution (e.g. Domochowski *et al*., 2014). Second, *post hoc* power analyses with *G*Power* (Erdfelder, Faul, & Buchner, 1996) indicated that a sample size of approximately 13 would be sufficient to obtain statistical power at the recommended 0.8 level (Cohen, 1998) with Cohen's $d = 0.86$ reported in the result that ISC was larger for high (vs. low) effective course clips. However, our sample size ($N = 15$) was far from adequate to examine how individuals' factors (e.g. goal orientation, Elliot & Mcgregor, 2001) influenced

the neural responses to educational messages in a top-down manner, calling for future studies. Finally, "value" and "interest" were viewed independently in the present study, since the correlation conducted on individual subjects between "value" and "interest" ratings for their own high effective course clips was not significant ($r(15) = 0.26$, $p = 0.34$). However, "value" and "interest" have been found to interact with each other and have interplay effects on competence belief, success expectancy, and learning performance (Fryer & Ainley, 2018; Hidi & Renninger, 2006; Nuutila *et al.*, 2018). Future studies might test the interplay of "value" and "interest" in other contexts of online learning, e.g., courses with (1) high value + high interest, (2) high value + low interest, (3) low value + high interest, and (4) low value + low interest, and the power of ISC measure to differentiate between them.

To sum up, the current results indicate that naturalistic educational materials with greater motivational effectiveness enhanced neural similarity across learners. Such enhanced neural similarity is predictive of learning desire, which is based on "interest". From a "collective-brain" perspective, the use of EEG-derived ISC approach holds the potential to evaluate the motivational effectiveness of naturalistic educational materials. Our study paves the way to investigate learners' motivation at a neurophysiological level in the context of online learning. It also holds relevance for instructional designs to aid learning interest deficit.

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Table 1. Summary of course clips

No.	Course title	Topic	Duration (s)	URL-ending *	Online Enrollment *M*	Online Enrollment *Rank*
1.	Psychological Health of College Students	Psychology	100	NEU-1001930012#/info	2991	5
2.	Taoist Wisdom	Philosophy	81	XJTU-1001522001#/info	3528	2
3.	Chinese Poetry Art	Literature	149	SCU-21006#/info	4937	1
4.	Silk Culture and Products	Art	129	SUDA-1001754250#/info	160	15
5.	Managerial Communication	Management	133	NUEPU-292001#/info	2168	6
6.	Economic Geography and Vicissitude of Enterprises	Economics	67	ZNUEDU-1001615011#/info	848	10
7.	Culture of Mathematics	Math	123	NANKAI-312001#/info	3350	4
8.	Applied Optics	Physics	57	BIT-1001606003#/info	1481	9
9.	Medicinal Chemistry	Chemistry	121	CPU-1001570004#/info	1831	7
10.	Engineering Materials and Manufacturing	Engineering	133	SDU-306001#/info	776	12
11.	Cytobiology	Biology	132	SCU-46011#/info	1511	8
12.	First Aid General Knowledge	Medical Science	170	WHU-85001#/info	3368	3
13.	Space Humanities and Arts	Interdiscipline	215	NUAA-1001764004#/info	836	11
14.	Medical Ethics	Interdiscipline	170	XJTU-47022#/info	382	13
15.	Fantastic Bionics	Interdiscipline	129	JLU-32007#/info	187	14

Note. Online Enrollment (person-time/session) was recorded by the date of 2017/03/26.

*URL beginning with http://www.icourse163.org/course/

Figure Captions

Fig. 1. Schematic illustration of the experimental procedure. (**A**) Experimental setup. (**B**) Events and time flows in a trial. (**C**) Subjects ranked courses based on their learning desire form 1 (highest) to 15 (lowest). Note that in the following analyses, rankings were reversely coded.

Fig. 2. Overview of the three-step ISC analysis. Neural responses are recorded on D electrodes from N subjects during the time (0–T s) of stimuli presentation. First, a few (first three in this study) maximally correlated components are extracted. Second, the spatial distribution of each component is visualized. Third, for each subject, ISC is measured as the sum of the averaged correlation coefficients between that subject and remaining subjects over the first three components. Ed = Electrode d. Sn = Subject n. Ci = Component i.

Fig. 3. Video evoked vs. chance level ISC of each course clip. ISC evoked by each course clip significantly exceeded its chance level. Each dot represents one subject. Error bars indicate standard errors. $^{***}p < 0.001$, FDR corrected.

Fig. 4. ISC of high vs. medium vs. low effective course clips. (**A**) ISCs of high and medium effective clips were respectively larger than that of low ones. (**B**) Upper panel: One representative illustration (i.e. the highest effective course clip) of the scalp projections of the first three maximally correlated components (i.e. C1, C2, & C3). Color indicates how strongly the component activity correlated with the EEG signals recorded on different electrodes across the scalp. Lower panel: sub-component ISCs were also enhanced when the motivational effectiveness of course clips increased. Each dot represents one subject. Error

bars indicate standard errors. $^{\#}p < 0.1$, $^{*}p < 0.05$, $^{**}p < 0.01$, $^{***}p < 0.001$, FDR corrected.

Fig. 5. ISC predicted course-learning desire. (**A**) Pearson correlation indicated ISC difference (high vs. low) positively associated with the subject's learning desire difference (high vs. low) ($r(15) = 0.74$, $p = 0.002$). (**B**) ISC difference became a significant correlate of learning desire difference after about 100-second watching. The vertical red line with an asterisk indicates the earliest time (100.6 s), at which such a correlation reached the significance. The horizontal dashed line indicates correlation coefficient ($r(15) = 0.64$, $p < 0.05$, FDR corrected). (**C**) Pearson correlations indicated sub-component ISCs difference independently associated with the subject's learning desire difference. (**D**) For C1, the vertical purple line with an asterisk indicates the earliest time (85.5 s), at which correlation reached the significance. The horizontal dashed line indicates correlation coefficient ($r(15) = 0.60$, $p < 0.05$, FDR corrected). C2 or C3 showed no such early prediction effect. Each dot represents one subject. $^{\#}p < 0.1$, $^{*}p < 0.05$, $^{**}p < 0.01$.

Fig. 6. ISC was associated with "interest" rather than "value". (**A**) Ratings of "interest" significantly exceeded those of "value". (**B**) For individual-level high effective course clips, the Spearman correlation indicated that ISC positively associated with the ratings of "value" ($r(15) = 0.77$, $p = 0.0008$), (**C**) but not with ratings of "interest" ($r(15) = 0.32$, $p = 0.25$). Each dot represents one subject. Error bars indicate standard errors. $^{*}p < 0.05$, $^{***}p < 0.001$.

Extended Data 1

This is the MATLAB code to compute EEG-derived inter-subject correlation (ISC) using correlated component analysis, specified for EEG data collected from the NeuroScan system. You will need EEGLAB (version 14.1.0) and Curry7 format EEG data to run Step1_preprocess_demo.m.

You will need following files to run Step2_ISC_demo.m:

1. runisc.m (EEG-ISC specific code)
2. topoplot.m (stand-alone version of EEGLAB's popular display function)
3. Neuroscan64.loc (Neuroscan location file for topoplot)
4. notBoxPlot.m (stand-alone version of Rob Campbell's scatter plot)
5. Data file (e.g. v12. mat, EEG data with 60 electrodes from 15 subjects while watching the course clip No.12, time-points × channels × subjects)

Fig. 1

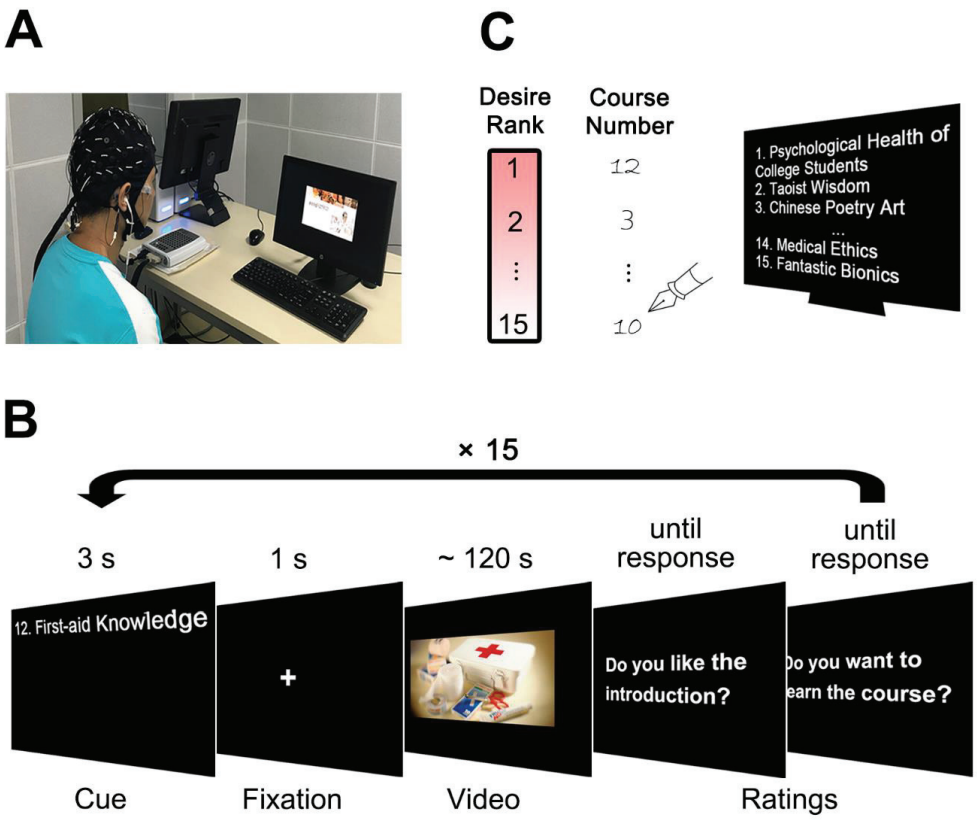
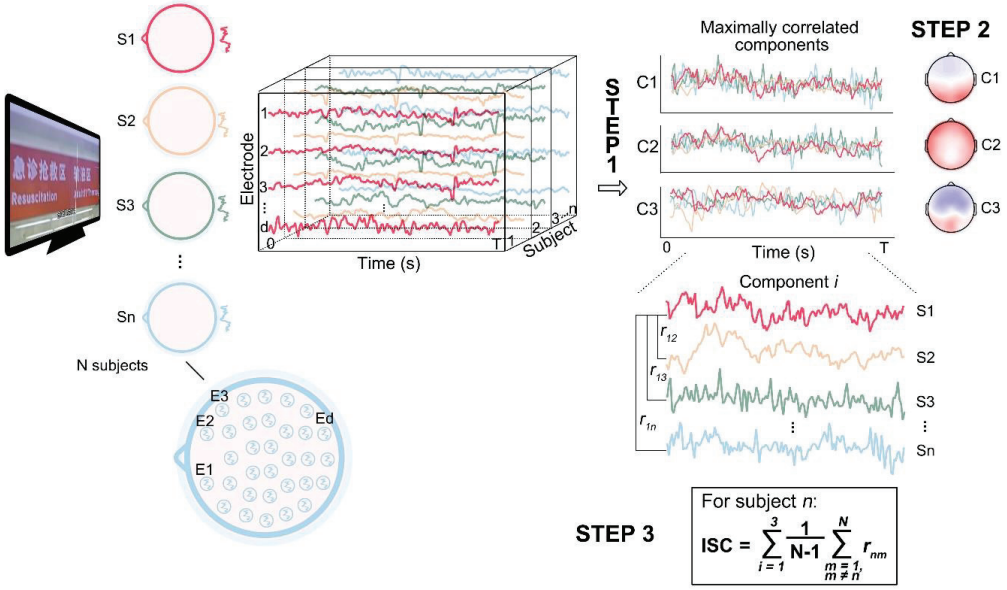
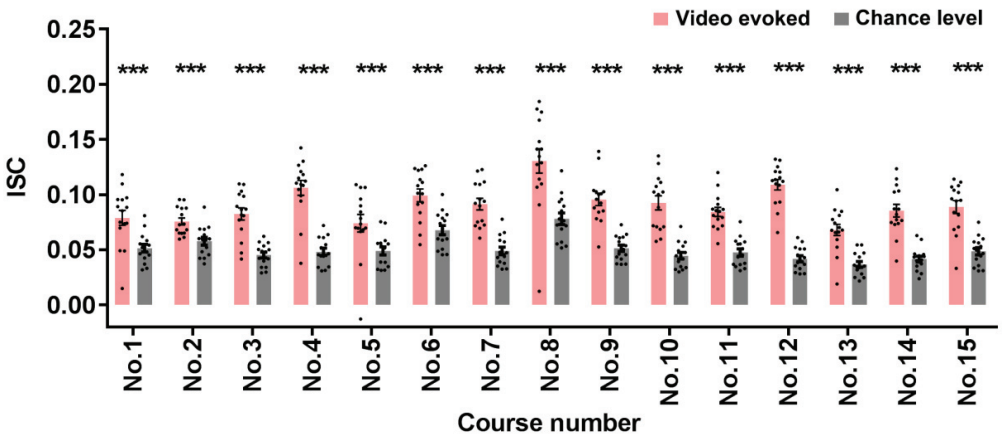


Fig. 2



740 **Fig. 3**



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743 **Fig. 4**

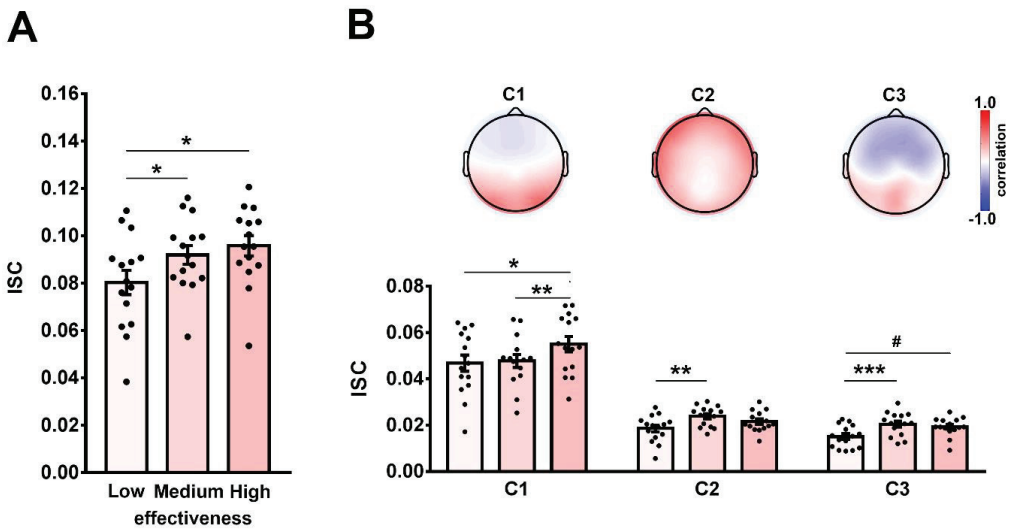

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Fig. 5

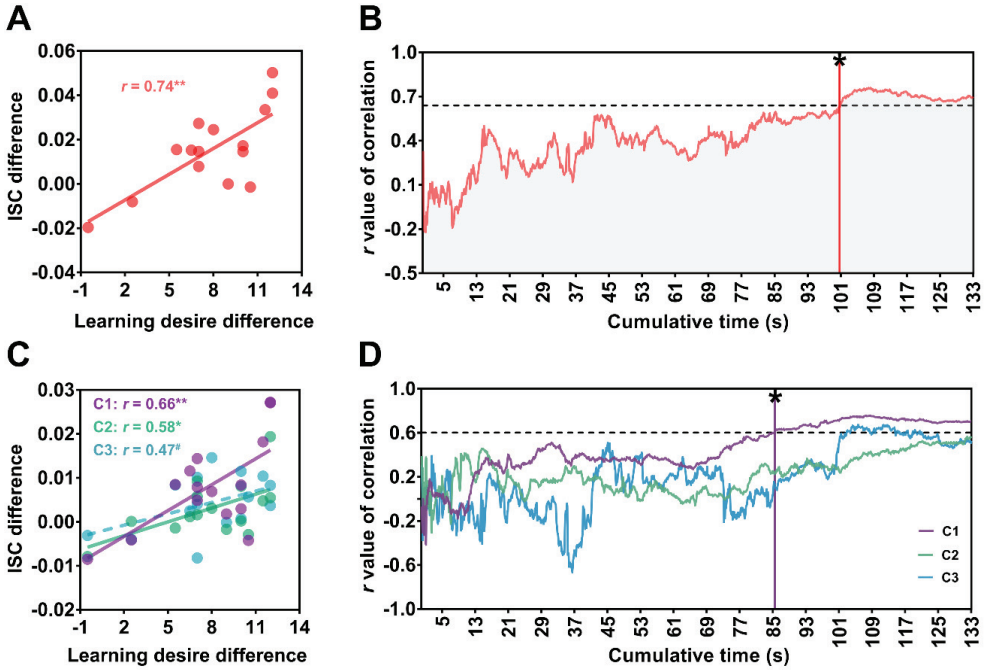

Fig. 6