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An EEG dataset of information impairment susceptibility during emotional audiovisual viewing

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Contributions

Zisheng Kang: Conceptualization; Methodology; Data curation; Investigation; Formal analysis; Software; Visualization; Writing – original draft; Writing – review & editing.
Junpeng Zhang: Supervision; Funding acquisition.
Lifang Yang: Writing – review & editing.

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Abstract

Electroencephalography (EEG) is a non-invasive, millisecond-resolution measure of brain activity widely used in emotion and cognition research. However, public EEG resources rarely pair standardized behavioral screening with neurophysiology, limiting work on individual vulnerability to information-related psychological impairment. We release the Information Impairment Susceptibility EEG Dataset (IIS-EEG): 33-channel EEG recorded at 1000 Hz from 12 healthy adult men selected via an extreme-group strategy from a larger questionnaire cohort. EEG was collected in one session during passive viewing of emotion-eliciting audiovisual clips under positive, neutral, and negative conditions, then segmented offline into condition-specific continuous recordings. Data are minimally preprocessed (no ICA cleaning), stored in FIF, and organized in EEG-BIDS; all files are de-identified and questionnaire responses are not shared. As a technical validation, leakage-free subject-wise decoding (2-s windows) showed EEGNet reached 0.685 – 0.720 subject-level BACC, exceeding a log-bandpower + balanced logistic regression baseline

0.505 – 0.575. IIS-EEG supports emotion EEG analyses, susceptibility research, and method benchmarking.

Background & Summary

The rapid growth of digital media and information technologies has reshaped how individuals perceive, evaluate, and respond to information[1,2]. While abundant information can facilitate learning and decision-making, exposure to injurious information may also produce harmful psychological consequences[3]. In military and related applied psychology contexts, information impairment is commonly described as a disruption of the recipient's psychological structure triggered by injurious information, which can in turn lead to cognitive bias, emotional dysregulation, diminished volition, and, in severe cases, personality distortion[4]. This definition highlights information impairment as more than a transient emotional reaction: it reflects a susceptibility-driven imbalance that manifests across cognition, affect, and behavior and differs markedly between individuals[5-7]. To date, individual differences in information impairment susceptibility have been assessed primarily through self-report questionnaires[8,9]. Although such instruments provide efficient and scalable screening, they offer limited insight into the neurophysiological processes that accompany or predispose these vulnerability profiles. We therefore hypothesized that individuals with different levels of information injury susceptibility would exhibit distinct emotion-related neural dynamics, which should be observable in electrophysiological measures during affective stimulation. As a result, the neural correlates of information impairment susceptibility remain insufficiently characterized, and publicly available neurophysiological resources that connect standardized questionnaire-based susceptibility measures with electrophysiological recordings are still scarce.

Electroencephalography[10-14] (EEG) provides a non-invasive method with millisecond temporal resolution for studying neural activity related to emotional and cognitive processing. EEG has been widely used in affective neuroscience to examine transient emotional reactivity[15-20], sustained affective states, and individual differences in emotion regulation under controlled laboratory conditions. Emotion-eliciting video paradigms, which present naturalistic audiovisual stimuli, are commonly used to induce sustained emotional states while preserving ecological validity[21,22]. Despite the extensive application of EEG in emotion research, existing open datasets seldom combine emotion-evoked EEG recordings with questionnaire-defined vulnerability traits, particularly those framed around susceptibility to information impairment.

To help address this gap, we present the Information impairment Susceptibility EEG Dataset (IIS-EEG), a curated dataset designed to support research on neurophysiological correlates of individual differences in information impairment susceptibility. An overview of the dataset generation and organization pipeline is provided in Fig. 1. IIS-EEG contains EEG recordings from 12 healthy adult male participants selected from a larger questionnaire cohort using an extreme-group strategy based on scores from a standardized information impairment scale. EEG data were collected in a single experimental session during passive viewing of

emotion-eliciting audiovisual clips under positive, neutral, and negative conditions. The continuous recordings were subsequently segmented offline into condition-specific datasets corresponding to each emotional category.

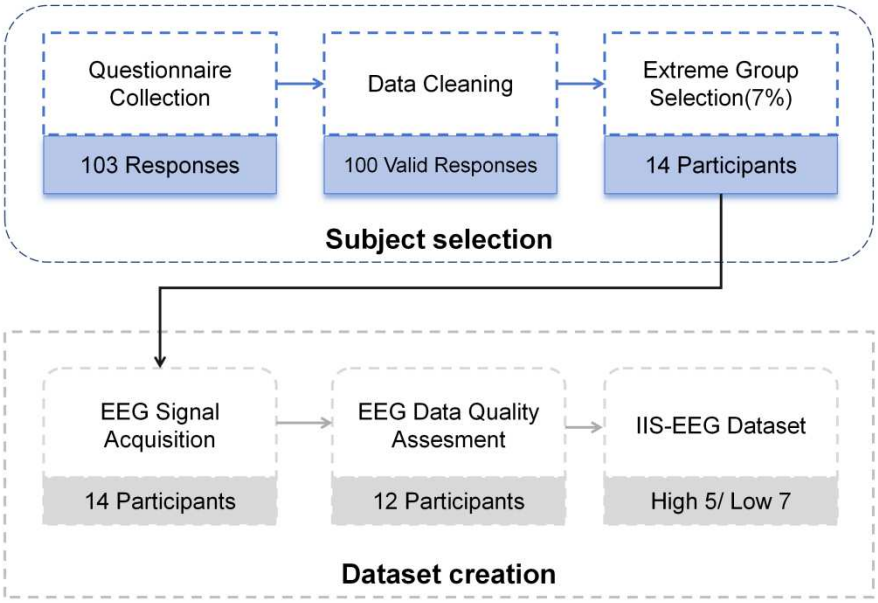


Figure 1: Overview of the dataset generation pipeline

All EEG recordings were acquired using a standardized protocol and organized in accordance with the Brain Imaging Data Structure[23] (BIDS) recommendations for EEG. The released dataset provides minimally preprocessed, condition-segmented EEG recordings stored in FIF format, together with essential metadata to facilitate reuse. Importantly, no automated artifact correction or ICA-based component removal was applied, enabling users to implement alternative preprocessing pipelines suited to their specific analysis objectives. The emotional video stimuli are not redistributed with the dataset; however, they originate from a publicly available standardized emotional film database and can be obtained independently to support replication or extension studies.

IIS-EEG is intended as a reusable resource for a range of applications, including emotion-related EEG analyses, research on individual differences, and the development or benchmarking of signal-processing and machine-learning methods. Potential use cases include identifying neural signatures associated with sustained emotional stimulation, characterizing trait-related variability in EEG dynamics, and conducting methodological validation using condition-segmented EEG data.

Methods

Participants

A total of 103 participants completed the questionnaire assessment. An extreme-group recruitment strategy was then applied, and individuals whose scores fell within the top and bottom 7% of the questionnaire score distribution were invited for EEG recording. Fourteen volunteers meeting these criteria participated in the EEG experiment. After data quality inspection and predefined exclusion procedures, EEG recordings from 12 participants were retained and included in the released dataset (high susceptibility group: n = 5; low susceptibility group: n = 7).

All participants were healthy adult male undergraduate students, aged 20–23 years (mean ± SD: 21.0 ± 1.21 years), and right-handed. Participants reported normal or corrected-to-normal vision and no history of neurological disorders. Exclusion criteria included a self-reported history of psychiatric disorders, current use of medications known to affect central nervous system functioning, and any other condition likely to interfere with EEG recording quality or experimental compliance. Participation was voluntary and compensated, and participants were informed that they could withdraw at any time without penalty.

To reduce potential confounding factors, participants were instructed to obtain sufficient sleep prior to the experiment and to abstain from alcohol consumption. All recordings were conducted in fixed morning time slots in a quiet, comfortable environment with controlled lighting. Of the 14 participants who underwent EEG recording, data from two participants were excluded during post-acquisition quality control. One dataset was excluded due to irrecoverable file corruption, and the other was excluded due to poor signal quality together with recording interruption. Only datasets meeting the predefined quality criteria were retained for public release. To protect participant privacy, all EEG data were fully anonymized prior to sharing. Each participant was assigned a unique identifier ("sub-01" to "sub-12"), and no personally identifiable information was retained in any distributed files. The released dataset contains only de-identified EEG recordings and associated metadata, and is designed to minimize the risk of re-identification.

The study protocol was approved by the Medical Ethics Committee of Sichuan University (Approval No. KS20250216) prior to data collection. Written informed consent for participation and public sharing of anonymized EEG data was obtained from all participants before the experiment. All procedures complied with standard ethical principles for human-subject research, and participant privacy and confidentiality were protected throughout. All participants received a detailed explanation of the experimental procedures, potential risks, and the data sharing plan before participation. Written informed consent was obtained from all participants, including explicit consent for anonymized EEG data to be shared publicly for academic research purposes. All procedures followed standard ethical principles for human subject research, and participant rights, privacy, and confidentiality were protected throughout.

Questionnaire

Individual susceptibility to information-related psychological impact was assessed using the Personal Information Impairment Scale[9] (PIIS), a standardized self-report questionnaire

originally developed for military populations. PIIS was not created specifically for the present dataset; rather, it is a previously published instrument with reported psychometric properties, designed to quantify vulnerability to information-induced cognitive–affective and behavioral impairment. The scale was developed and validated in a large military sample and has shown acceptable reliability and validity in prior studies[25].

PIIS is grounded in the information impairment framework and conceptualizes information-related psychological impact as a multidimensional construct spanning attitude, emotion, and behavior domains. The finalized scale contains 14 items distributed across these three dimensions. Items are rated on a five-point Likert scale (1–5), with higher scores indicating greater information impairment. A subset of items is reverse-scored following the original scoring scheme. In the present study, only the PIIS total score was used for participant screening and grouping. The questionnaire was administered online and completed anonymously. During the questionnaire phase, 103 responses were collected. To support data quality, predefined exclusion criteria were applied, including removal of responses with implausibly short completion times (<10 s), which were treated as likely inattentive or invalid. Only responses meeting the quality criteria were retained for subsequent processing.

Questionnaire scores were used exclusively to define susceptibility labels and to guide participant recruitment for EEG acquisition. Specifically, an extreme-group strategy was applied to the empirical distribution of PIIS total scores: individuals in the upper and lower 7% were identified as candidates for EEG recording. Participants were recruited solely from these high- and low-score groups to increase contrast in susceptibility and reduce ambiguity in group assignment; intermediate-score respondents were not included in the EEG phase. Questionnaire item-level data are not included in the released EEG dataset. PIIS was used only to derive susceptibility labels for recruitment and grouping, whereas the public release contains de-identified EEG recordings and associated metadata without individual questionnaire responses. This design reduces privacy risk while maintaining the utility of the dataset for studying neurophysiological correlates of individual differences in information impairment susceptibility.

Experimental Paradigm

The experimental paradigm was designed to elicit sustained emotional states using naturalistic audiovisual stimuli. Emotion-evoking video clips were presented under three affective conditions: positive, neutral, and negative. All clips were selected from a publicly available standardized emotional film database developed for Asian cultural contexts (“A New Standardized Emotional Film Database for Asian Culture”)[24]. The original audiovisual content of each stimulus was preserved; only temporal segmentation was applied when needed to match the intended clip duration. Each participant completed a single experimental session in which 20 clips were presented in total. The positive condition comprised eight positive clips, the negative condition comprised eight negative clips, and the neutral condition comprised four neutral clips. Individual clips lasted approximately 1 – 3 min. The stimulus set, clip counts, and presentation order were identical across participants.

The emotional conditions were presented in a fixed sequence, with positive stimuli first, followed by neutral stimuli, and negative stimuli last. Within each condition, clip order was also fixed. This ordering was chosen to promote relatively gradual affective shifts and to reduce abrupt transitions between opposing emotional valences that could increase carry-over effects. The overall structure of the paradigm is illustrated in Fig. 2. Before the session began, participants were asked to sit comfortably and to adjust the audio volume to a comfortable level using the provided earphones. During stimulus presentation, participants passively watched the clips without performing an explicit task or providing behavioral responses. They were instructed to minimize head movement, excessive blinking, and other body movements to reduce motion-related EEG artifacts. No behavioral ratings or post-stimulus reports were collected in this protocol.

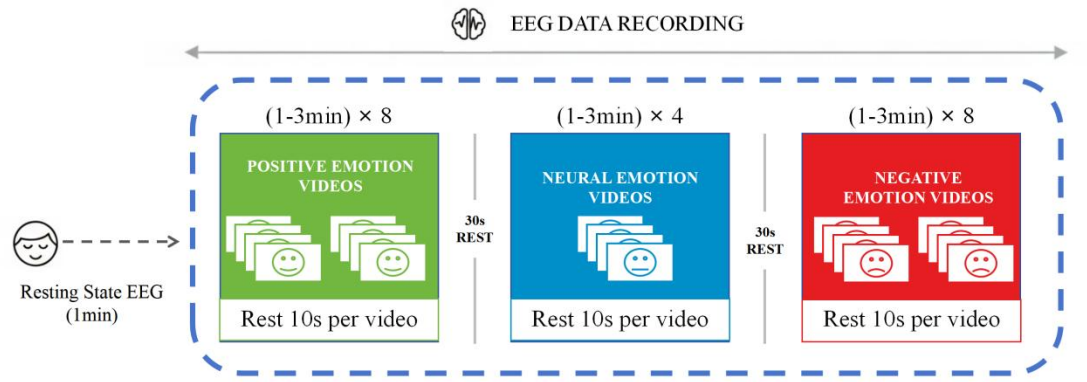


Figure 2: Experimental environment and EEG electrode configuration

To reduce fatigue and potential emotional carry-over, rest intervals were embedded throughout the session. A 10 s rest period was inserted between consecutive clips, during which a textual rest instruction was displayed on the screen. In addition, a longer 30 s rest period was provided between emotional conditions, accompanied by an on-screen cue indicating the rest phase. These intervals allowed participants to relax and reorient before the next stimulus segment. EEG was recorded continuously throughout the session, including all stimulus and rest periods. For data release, the continuous recordings were segmented offline by emotional condition to yield three condition-specific EEG datasets (positive, neutral, and negative). The released dataset does not provide trial-level annotations for individual clips, and the shared data are organized at the condition level.

Stimuli were presented on a 27-inch Dell monitor (2560 × 1440 pixels). Audio was delivered via noise-cancelling earphones (AirPods Pro 2) to standardize auditory presentation and reduce environmental noise. The paradigm was implemented in PsychoPy[26], which controlled stimulus timing and sequencing. The released dataset contains de-identified EEG recordings and associated metadata only; the video stimuli are not redistributed. However, the original materials are publicly available through the referenced film database and can be obtained independently for replication or extension studies.

Data Acquisition

EEG data were acquired using a Neurogin SR1 EEG acquisition system with Ag/AgCl wet electrodes. Signals were recorded from 33 channels positioned according to the international 10 – 20 system[27], including bilateral mastoid electrodes (M1 and M2). All recordings were sampled at 1000 Hz. The acquisition setup and electrode configuration are illustrated in Fig. 3. During recording, the hardware applied an online bandpass filter of 0.01 – 200 Hz. No online



(a) (b)

Figure 3: Experimental paradigm for emotion-eliciting EEG acquisition

notch filter was used, and no additional online processing was applied.

Before electrode placement, standard scalp preparation was performed, including skin cleaning and mild abrasion when necessary, to reduce contact impedance. Electrode impedances were measured and adjusted prior to recording and were maintained below $5\ k\Omega$ for all channels throughout the experiment. Participants were seated in a semi-reclined posture in a quiet laboratory room during EEG acquisition, and EEG was recorded continuously for the entire session. Before stimulus presentation, a 1-min eyes-closed resting-state recording was collected to characterize baseline physiological activity.

During the experiment, the acquisition system recorded stimulus-related annotations. These annotations are not included in the public release. For data sharing, the continuous recordings were segmented offline by emotional condition to generate condition-specific EEG data corresponding to positive, neutral, and negative viewing periods. All EEG recordings were stored in FIF format. The released dataset includes the condition-segmented EEG data and associated metadata only. The original continuous recordings with the full set of acquisition annotations are retained by the authors and may be made available upon reasonable request.

Data Pre-processing

Offline preprocessing was performed in MNE-Python[28]. All steps were applied using the same pipeline across participants and emotional conditions, and no ICA-based cleaning was performed at any stage. For datasets with recovered stimulus annotations, the continuous recordings were first inspected to identify stimulus segments based on annotation codes. Emotional stimulus blocks were then extracted according to predefined markers, and only segments corresponding to the target emotional condition were retained. Segments from the

same condition were concatenated to form a continuous, condition-specific EEG recording for each participant.

Before signal processing, channel names were standardized using a predefined renaming scheme to match conventional EEG nomenclature. Electrode locations were assigned using a standard 10 – 20 montage. When channel position information was unavailable for specific channels, the montage assignment was applied to the remaining channels without discarding data. Re-referencing was performed using linked mastoids (M1/M2) when available; otherwise, an average reference was applied. Recordings were resampled to 250 Hz to reduce data volume and computational cost while retaining the temporal resolution required for common EEG analyses. Power-line interference was attenuated using a 50 Hz notch filter, followed by a 1 – 40 Hz band-pass filter to reduce slow drifts and high-frequency noise while preserving frequency components typically analyzed in cortical EEG.

Non-EEG physiological channels were treated separately. When present, ECG channels were identified via channel-type metadata and excluded from the EEG preprocessing stream. Because ICA-based artifact correction was not applied, no automatic removal of ocular, cardiac, or muscle-related components was performed. This choice preserves signal characteristics and allows users to implement artifact handling strategies appropriate to their specific research objectives.All preprocessing was conducted uniformly across participants. The released preprocessed data therefore consist of condition-segmented EEG recordings that underwent channel standardization, montage assignment, re-referencing, resampling, notch filtering, and band-pass filtering, but no additional artifact rejection or component-based cleaning. Preprocessed recordings were saved in FIF format and organized as derivative data for public release.

Data Records

The Information impairment Susceptibility EEG Dataset (IIS-EEG) will be released through an online repository 10.5281/zenodo.18396886. All distributed files are fully anonymized and contain no personally identifiable information. The dataset is organized to follow the BIDS EEG specification. At the dataset root, we provide dataset_description.json, participants.tsv, participants.json, and a README file. EEG data are organized by subject (sub-01 to sub-12) under sub-XX/eeg/. An overview of the dataset organization is shown in Fig. 4.

Only derivative-level EEG data are released. For each subject, we provide condition-segmented continuous recordings corresponding to the positive, neutral, and negative stimulus conditions. Data are stored in FIF format and accompanied by standard BIDS sidecar metadata. Recording parameters are documented in the corresponding _eeg.json files, and channel-level information is provided in channels.tsv. File names encode the subject identifier and emotional condition, together with a label indicating preprocessing scope. Specifically, clean_noica denotes minimally preprocessed data without ICA-based artifact correction. The label raw is used in file names to indicate that the shared data remain

continuous condition-level segments; it does not refer to the original unshared acquisition files.

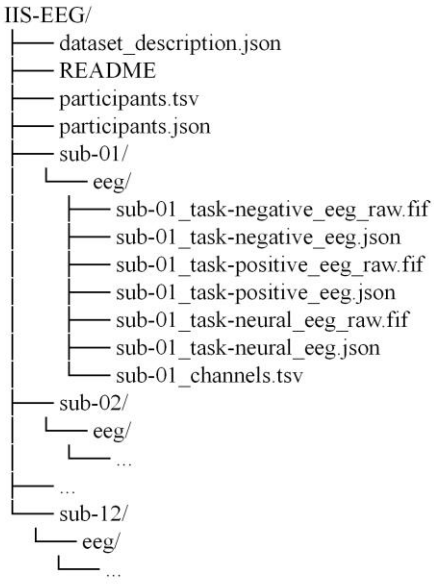


Figure 4: BIDS organization of the IIS-EEG dataset

No events.tsv files are included because the released recordings are condition-level segments extracted offline rather than event-locked trials with clip-level timing. The emotional video stimuli are not redistributed with the dataset. However, they originate from a publicly available standardized Asian emotional film database and can be obtained independently for replication or extension studies.

Technical validation

We evaluated the usability of the stimulus-state EEG segments for downstream decoding by performing binary classification to distinguish individuals with high versus low information-impairment susceptibility (12 subjects; low = 7, high = 5). To avoid information leakage induced by windowing, we adopted a strictly subject-wise evaluation protocol using a fixed split file defining 50 repeated splits (test_size = 0.2), such that all windows from a given subject were assigned exclusively to either the training or test set within each split. Any data-dependent transformations were fitted using training data only and then applied to the held-out test data.

Each sample corresponded to a 2-second EEG window (500 samples after downsampling; 33 channels). Performance was computed at both window level (pooling all test windows within a split) and subject level (averaging predicted probabilities across windows for each test subject and thresholding at 0.5). Two representative baselines were used: an interpretable classical pipeline log-relative bandpower[29] + balanced logistic regression[30] and a compact

deep-learning baseline EEGNet[31]. Table 1 summarizes the key settings required to interpret the validation protocol.

We evaluated both baselines separately under neutral, positive, and negative emotional stimulus conditions using the same leakage-free subject-wise fixed splits (50 repeats). Performance is reported as mean ± standard deviation across splits at both window level and subject level.The comparative performance trends are further visualized in Fig 5 and 6. Fig 5 shows the window-level balanced accuracy (BACC) for each emotional condition, while Fig 6 summarizes the subject-level BACC obtained by aggregating window predictions within each test participant. Consistent with Tables 2 and 3, EEGNet outperforms the classical bandpower baseline across conditions at both evaluation levels.

Table 1. Data splitting strategy and baseline configuration used for technical validation.

Model	Data Splitting Strategy	Optimizer	Learning Rate	Batch Size	Epochs	Classifier / Feature Settings
EEGNet	Subject-wise fixed splits, 50 repeats (test_size = 0.2); subject-exclusive train/test	Adam	0.001	64	500	Cross-entropy loss; subject-level voting by mean P(high) (threshold = 0.5)
Bandpower + LogReg	Subject-wise fixed splits, 50 repeats (test_size = 0.2); scaler fitted on train only	–	–	–	–	Log-relative bandpower (Welch PSD), bands: delta/theta/alpha/beta/gamma (1–45 Hz); log10; Logistic Regression (L2, liblinear, C=1.0, class_weight=balanced); train cap 300

Table 2. Performance of the Bandpower + Logistic Regression (balanced) baseline (mean ± std across 50 fixed subject-wise splits).

Condition	Window-level ACC	Window-level BACC	Subject-level ACC	Subject-level BACC
Neutral	0.5361 ± 0.1012	0.5175 ± 0.1151	0.6000 ± 0.2694	0.5750 ± 0.2956
Positive	0.5191 ± 0.1008	0.5034 ± 0.1069	0.5667 ± 0.3177	0.5400 ± 0.3326
Negative	0.5313 ± 0.1026	0.5240 ± 0.0997	0.5133 ± 0.2353	0.5050 ± 0.2648

Table 3. Performance of the EEGNet baseline (mean ± std across 50 fixed subject-wise splits).

Condition	Window-level ACC	Window-level BACC	Subject-level ACC	Subject-level BACC
Neutral	0.6015 ± 0.0979	0.5960 ± 0.0961	0.7200 ± 0.2168	0.7200 ± 0.2295
Positive	0.5835 ± 0.1286	0.6031 ± 0.1248	0.6400 ± 0.2413	0.6850 ± 0.2248
Negative	0.5952 ± 0.0901	0.5911 ± 0.0967	0.6867 ± 0.1953	0.6850 ± 0.2071

Across all conditions, EEGNet consistently outperformed the classical bandpower baseline under the same leakage-free subject-wise protocol. Because susceptibility is defined at the participant level, subject-level voting provides the most relevant evaluation target: EEGNet achieved subject-level BACC values around 0.685–0.720 (Table 3), whereas the bandpower baseline ranged from approximately 0.505 to 0.575 (Table 2). The bandpower + logistic regression pipeline serves as an interpretable lower-bound baseline and yields near-chance performance in some conditions, consistent with the difficulty of decoding trait-like susceptibility from short-window spectral summaries under strict cross-subject generalization. The relatively large standard deviations, particularly at subject level, are expected given the limited cohort size and the small number of held-out subjects per split; therefore, these baselines should be interpreted as a conservative technical validation of dataset usability rather than an optimized benchmark.

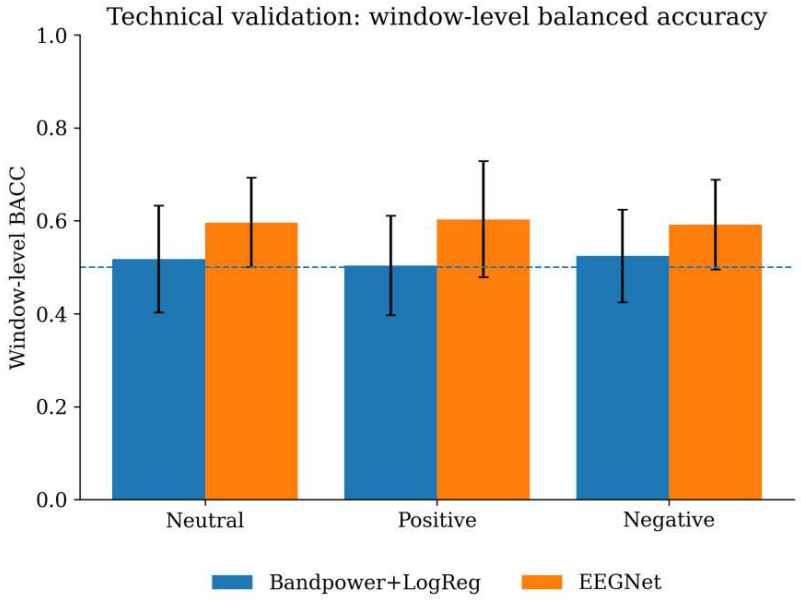


Figure 5: Window-level BACC comparison (EEGNet vs Bandpower+LogReg across conditions)

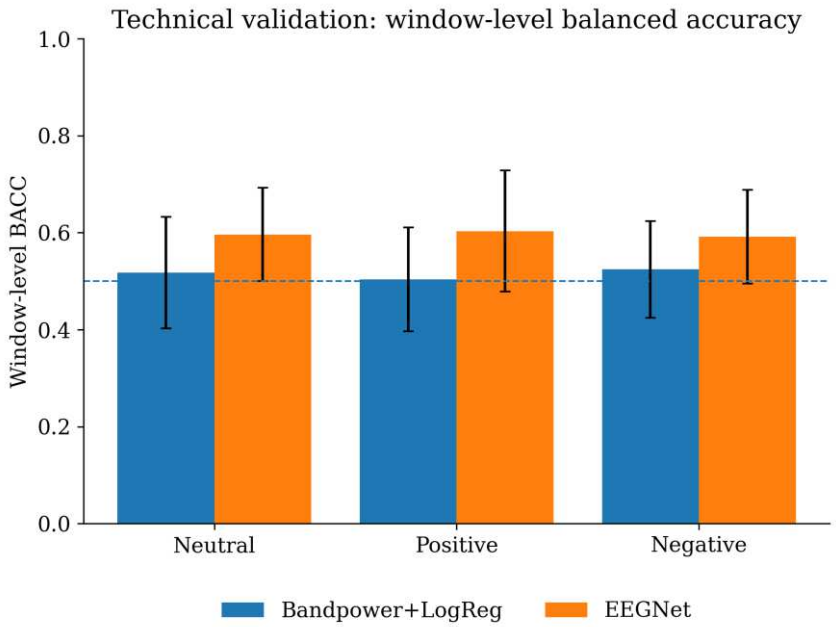


Figure 6: Subject-level BACC comparison (EEGNet vs Bandpower+LogReg across conditions)

Usage Notes

This dataset is intended to support statistical analyses, feature extraction, and machine-learning studies investigating neurophysiological correlates of individual susceptibility to information impairment. The released EEG recordings can be used as inputs to custom preprocessing and analysis pipelines, while the minimally preprocessed derivative data provide a practical starting point for baseline decoding and classification experiments.

Researchers may also use IIS-EEG for methodological benchmarking across conventional machine-learning models and deep-learning approaches. Where permitted by local ethics and data-governance requirements, the dataset can be extended by integrating EEG with questionnaire-derived susceptibility labels and additional psychological assessments collected by the user, which may improve predictive performance and support richer analyses of individual differences.

Data availability

The Information impairment Susceptibility EEG Dataset (IIS-EEG) is publicly available at 10.5281/zenodo.18396886. The release contains condition-segmented stimulus-state EEG recordings and associated metadata for 12 participants, including subject-level susceptibility labels and basic demographic information. Data are organized in accordance with the BIDS EEG specification and include the standard BIDS metadata files at the dataset root, together with per-subject EEG recordings and channel metadata as described in the Data Records section.

Users are requested to cite this Data Descriptor when using IIS-EEG. The dataset has been de-identified prior to release and contains no personally identifiable information. Use of the dataset is governed by the license specified in the repository (CC BY 4.0).

Code availability

The code used to generate the released dataset is available at https://github.com/lemonadecapsule/IIS-EEG-PreProcessing.git. The repository contains scripts for offline preprocessing and dataset construction, including channel-name standardization, montage assignment, re-referencing, resampling, notch and band-pass filtering, condition-level segmentation, and export to FIF files with BIDS-compatible metadata. Code is provided under the MIT License. The model-training code used for technical validation is not distributed; the validation protocol and key settings are described in the Technical Validation section and summarized in Table 1.

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Competing Interests

The authors declare no competing interests.