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Title

An EEG dataset for structured auditory sequence processing with Morse code sounds

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Abstract

Auditory processing of structured sound sequences requires information to be integrated across time while preserving sequence content and order, allowing different properties of the same auditory input to guide different behavioral decisions. Yet openly available human EEG resources remain limited for studying explicitly structured auditory sequences processed under different decision rules within the same participants. Here we present MorseEEG-ATP, a two-task EEG dataset from 32 Morse-naïve adults who listened to the same set of 78 single-character Morse-code sounds while performing dot-count and first–last matching tasks. The dataset combines shared auditory input with distinct decision rules, enabling investigation of sequence-level temporal and structural variation, task-associated EEG and behavioral features, and cross-task correspondence and generalization. It includes continuous BIDS-organized EEG, trial-level behavioral and event records, auditory stimuli and metadata, baseline-preprocessed derivatives, and analysis code. Technical validation demonstrates consistent behavioral task engagement, characterizes EEG preprocessing yield, identifies consistent stimulus-marker-locked EEG responses, and provides exploratory evidence of EEG spectral variation associated with individual differences in task performance.

Background & Summary

Auditory temporal structure processing depends not only on the acoustic properties of individual sounds but also on how those sounds are organized and integrated over time[1]. Effective processing of auditory sequences requires retaining the content and order of preceding elements after the sounds have passed[2,3]. A central question is how such retained sequence is encoded, maintained, and flexibly used to guide different behavioral decisions. With its millisecond-scale temporal resolution, EEG is well suited to tracking how such information is encoded and maintained as an auditory sequence unfolds.

Addressing this question requires datasets that allow sequence composition and order to be precisely controlled while task demands are systematically varied. Publicly available neurophysiological datasets have substantially broadened the range of auditory questions that can be investigated. At the level of controlled auditory discrimination, recent EEG resources have examined goal-directed discrimination and attentional reorientation using pure tones, frequency-modulated sweeps, and speech syllables in the presence of naturalistic distractors[4]. At the level of

discrete speech representation and decoding, EEG datasets have included isolated consonants and vowels, coarticulated phoneme combinations, real words, and pseudowords, supporting analyses across different phonetic and lexical contexts[5]. At the level of continuous and speech-in-noise processing, MEG-SCANS includes audiobook listening and noisy-sentence perception, together with short chirps for signal-quality assessment, and supports temporally resolved analyses of neural responses to speech[6]. Together, these resources cover a broad range of auditory processing, from controlled discrimination and discrete speech representation to continuous and speech-in-noise listening.

However, these datasets are less suited to isolating how a predefined sequence structure is represented and how the same sequence is processed under different decision rules. Their primary dimension of variation is stimulus complexity or ecological validity, rather than the precise control of sequence composition and order combined with an independent manipulation of task rule. As a result, they do not allow stimulus-driven sequence representations to be separated from task-dependent use of those representations. Within this landscape, open-access human EEG datasets centered on explicitly structured auditory sequences remain comparatively scarce, particularly those in which sequence composition and order are precisely controlled and the same stimuli are processed under different decision rules.

Morse code (MC) is particularly well suited to such a design because each character consists of a predefined sequence of short and long elements with a known composition and order[7]. Moreover, for MC-naïve participants, these structured sequences can be processed without relying on established lexical or semantic knowledge of the corresponding characters. Previous neurophysiological and neuroimaging work has examined training-related ERP changes in auditory processing following MC training[8], the transition from perceptual to lexico-semantic processing[9], and the temporal dynamics of trained MC decoding[10]. Although MC has been used in previous EEG and MEG studies, we are not aware of any other openly available human EEG dataset specifically providing recordings of auditory MC sequence processing with task-rule manipulation. The present dataset was therefore designed to fill this gap and to support research on the encoding, maintenance, and task-dependent use of temporally structured auditory sequences.

To address this gap, we present MorseEEG-ATP, an auditory EEG dataset in which MC-naïve participants listened to the same set of single-character MC sequences under two different task rules. In both tasks, participants were not required to identify the corresponding English letters or to perform complete MC decoding. Instead, the tasks required participants to extract different properties of the same sequence, such as the number of short elements or the relationship between the first and final elements. By presenting the same auditory sequences under different decision rules, the dataset supports within-participant comparisons of task-associated EEG and behavioral responses, although task-related differences cannot be disentangled from fixed task-order effects. MorseEEG-ATP therefore provides a resource for investigating how temporally structured auditory sequences are encoded, maintained, and flexibly used under different decision rules.

MorseEEG-ATP offers value at the stimulus, task, and data levels. At the stimulus level, the explicit element composition, order, and temporal structure of MC provide a reproducible framework for studying structured auditory sequences whose organization can be precisely described and controlled. At the task level, the same participants processed the same stimulus set under two different decision rules, enabling within-participant comparisons of behavioral and EEG features that are shared across tasks or vary with task demands, as well as analyses of cross-task correspondence and generalization. At the data level, MorseEEG-ATP provides the auditory stimuli

and associated metadata, trial-level behavioral and event records, continuous EEG organized according to BIDS conventions[11,12], baseline-preprocessed EEG derivatives, and the corresponding preprocessing and analysis code. These complementary data levels allow users either to implement preprocessing pipelines tailored to specific research questions from the continuous EEG recordings or to reproduce and extend reference analyses using the released derivatives and scripts. Overall, MorseEEG-ATP provides a standardized, openly reusable resource for investigating structured auditory-sequence processing and for developing, comparing, and evaluating analytical methods for auditory EEG.

Methods

Ethics and participants

We recruited 32 healthy adult volunteers (14 females; mean age 21.9 ± 1.5 years). Thirty participants were right-handed, and two were left-handed. All participants reported normal hearing. All were university students and had no prior experience in learning or using MC, to minimize potential confounding effects of prior training on task performance. Participants reported no recent use of psychoactive medications and no personal or family history of psychiatric or neurological disorders. Written informed consent was obtained from all participants after they had been fully informed about the experimental procedures and before participating about the experimental procedures. The study was conducted in accordance with the Declaration of Helsinki[13] and was approved by the Ethics Committee of the University of Electronic Science and Technology of China (Approval No.: 106412023030125880).

Experimental design and paradigm

This study employed a within-participant, two-task EEG design using MC sounds corresponding to the 26 English letters. Successful task performance required participants to discriminate the duration category of individual tone elements and use different aspects of the resulting sequence information. The dot-count task emphasized discrimination and accumulation of short elements as the sequence unfolded, whereas the first–last matching task required participants to encode and temporarily retain the duration category of the first element for comparison with the final element.

All participants completed both tasks. The tasks used the same set of 78 MC audio files, block structure, and basic single-trial timing, but differed in their instructions, decision rules, response prompts, and response-key mappings. Participants always completed the dot-count task first and the first–last matching task second, with a 10-min rest interval between tasks; task order was neither randomized nor counterbalanced. Stimulus construction, task rules, and the detailed experimental procedure are described below.

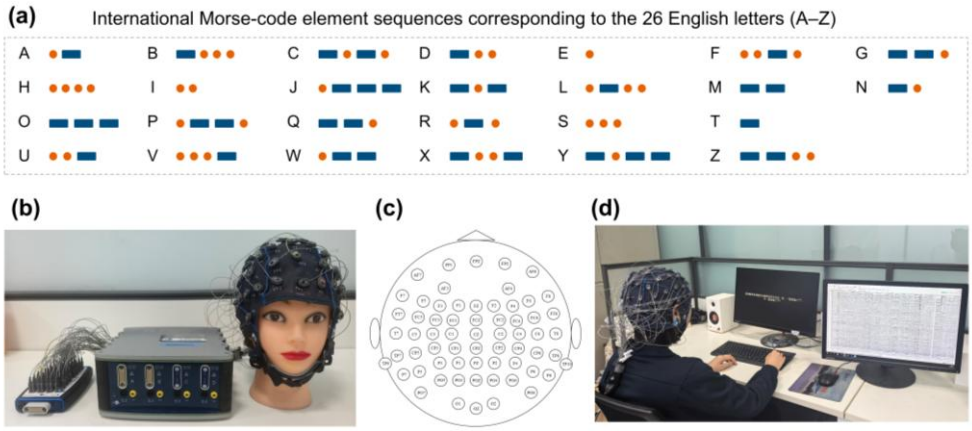


Fig. 1 Experimental materials and EEG recording setup. (a) International Morse-code element sequences corresponding to the 26 English letters (A–Z). (b) EEG acquisition system and active-electrode cap. (c) Electrode layout of the 62 scalp EEG channels. (d) Experimental environment used for the auditory EEG tasks.

Stimuli. The stimulus set comprised single-character Morse-code (MC) audio stimuli corresponding to the 26 English letters shown in Fig. 1a. Each stimulus consisted of one to four short and long tone elements arranged according to the International MC representation of the corresponding letter.[7] The stimuli were generated using in-house MC training software with a tone frequency of 1100 Hz. The software output was recorded and segmented according to the onset and offset boundaries of individual characters to produce the MP3 files used in the experiment. No gain adjustment, noise reduction, spectral modification, fade-in/fade-out, onset/offset ramp, or other audio post-processing was applied after segmentation.

The final stimulus set comprised 78 MP3 files, with one version of each of the 26 English letters under each of three software-defined conditions labeled 15, 30, and 40 characters per minute (CPM). All audio files were preserved in the format used during EEG acquisition, with a sampling rate of 48 kHz and a bit rate of 128 kbps. The correspondence among audio files, stimulus labels, event codes, and relative file paths is provided in *stimulus_label_mapping.tsv*.

Nominal presentation-rate conditions. The 15-, 30-, and 40-CPM labels were inherited from the stimulus-generation software and were retained for audio-file naming, block organization, and event-code mapping. Because MC characters differ in the number and arrangement of short and long elements, actual audio-file durations vary across characters and conditions. Accordingly, the CPM values are treated as nominal software-defined condition labels rather than as uniformly scaled acoustic rates.

Tasks. The specific task rules were as follows.

Dot-count task (Exp1). On each trial, participants heard the MC sound corresponding to one English letter and reported the number of short elements by pressing a numeric key from 0 to 4. Successful performance required discrimination of each element as short or long and online accumulation of the number of short elements within the sequence. Participants were not required to report the complete element order or identify the corresponding English letter.

First–last matching task (Exp2). On each trial, participants heard the MC sound corresponding to one English letter and judged whether the first and final elements belonged to the same duration category (both short or both long). Participants pressed numeric key 1 for a match and 0 for a mismatch. Successful performance required encoding and temporarily retaining the duration category of the first element until the final element was presented for

comparison.

The letter E contains a single short element, whereas the letter T contains a single long element. For these two single-element characters, the correct response was 1 in both cases. These trials did not involve comparison between two distinct element positions. E and T were nevertheless retained as part of the complete A–Z stimulus set and were identified as single-element trials in the event metadata.

Experimental procedure

The two tasks followed the same overall experimental procedure, as illustrated in Fig. 2. Before each task, Chinese-language instructions were presented on the screen to explain the experimental procedure, the current task requirements, and the response-key mapping. Participants then completed practice trials under the nominal 15 CPM condition, followed by three formal blocks in the fixed order of 15, 30, and 40 CPM as described above.

Each task included 10 practice trials under the nominal 15 CPM condition to familiarize participants with the MC sounds, trial procedure, task rule, and response-key mapping. Playback volume was also adjusted during practice according to each participant's subjective perception of sound clarity and comfort. A 10-s rest period followed the practice trials. Practice trials were not included in the released formal behavioral data or baseline-preprocessed EEG derivatives.

Each formal block contained 52 trials, comprising two presentations of each of the 26 English letters, with trial order randomized within the block. Each participant therefore completed two formal trials for each task-by-letter-by-nominal-CPM combination. Each task contained 156 formal trials, yielding 312 formal trials across the two tasks. Consecutive formal blocks were separated by a 300-s rest period.

Each trial comprised four successive stages: fixation, auditory-stimulus presentation, response, and an intertrial interval. A white fixation cross was first presented at the center of a black screen for 300 ms. A MC sound corresponding to a single English letter was then presented while the fixation cross remained visible. Stimulus duration was determined by the actual duration of the corresponding MP3 file. Participants were instructed to listen to the complete sound, minimize head and body movements during sound presentation, and withhold their response until E-Prime had completed playback of the corresponding audio file.

After the software-defined completion of audio playback, the task-specific response prompt shown in Fig. 2 was presented, and a response window of up to 3000 ms began. Keypresses outside the permitted range were not treated as valid responses, and the program continued to wait for a valid keypress. The response stage ended when the first valid keypress was detected or when the 3000-ms response window elapsed. A trial was recorded as an omission if no valid response was made within this interval. No trial-by-trial correctness feedback was provided. The response stage was followed by a black-screen intertrial interval that varied randomly from 1000 to 3000 ms.

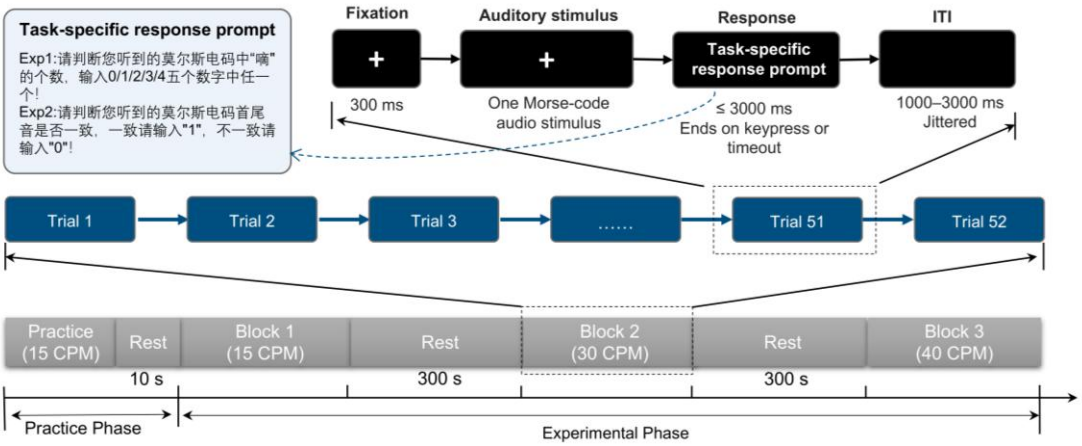


Fig. 2 Experimental procedure and single-trial structure. Each task included 10 practice trials under the nominal 15 CPM condition, followed by three formal blocks presented in the fixed order of 15, 30, and 40 CPM. Each formal block contained 52 randomized trials (26 letters × 2 presentations). A trial consisted of a 300-ms fixation period, presentation of one Morse-code audio stimulus, a response period of up to 3000 ms, and a jittered intertrial interval of 1000–3000 ms. The fixation cross remained visible during sound presentation, and the task-specific response prompt appeared after E-Prime completed audio playback.

Implementation and event markers

The experimental paradigm was programmed and administered using E-Prime 3.0. All MP3 stimuli were generated before the experiment and presented directly through the E-Prime SoundOut object during task performance. No online sound synthesis, time stretching, or rate conversion was performed during the experiment.

A stimulus event code was assigned to each letter-by-nominal-CPM combination. Event codes 1–26 corresponded sequentially to letters A–Z under the nominal 15 CPM condition, codes 27–52 corresponded sequentially to letters A–Z under the nominal 30 CPM condition, and codes 53–78 corresponded sequentially to letters A–Z under the nominal 40 CPM condition. Both tasks used the same event-code range of 1–78, and task identity was distinguished by the BIDS task entity (dotcount or firstlast) in the corresponding recording. When E-Prime initiated the SoundOut object, the stimulus event code was written to the EEG recording through the g.tec trigger input interface and was reset to zero before the next sound presentation.

The stimulus event codes marked only the software-defined initiation of playback of the complete MP3 file. The corresponding trial-condition and behavioral information was recorded in the E-Prime logs and is provided in the released BIDS *_events.tsv and *_beh.tsv files.

Behavioral data recording

E-Prime recorded stimulus file, stimulus event code, audio-file duration, target response, participant keypress, and behavioral timing information for each formal trial. In the released behavioral tables, the field Resposetime—with the field name retained as spelled in the released dataset—represents the interval from the software-defined completion of playback of the corresponding audio file and the simultaneous onset of the response prompt to the participant's first valid keypress, expressed in milliseconds.

The variable stimutoRT_time represents the total interval from the software-defined initiation of the SoundOut object to the participant's first valid keypress and was calculated as

the sum of the audio-file duration and the post-prompt response time: stimutoRT_time = audio-file duration + Resposetime.

Thus, stimutoRT_time includes both the duration of audio-file playback and the response time following presentation of the response prompt. Because audio-file duration varies across letters and nominal CPM conditions, stimutoRT_time should not be treated directly as a conventional reaction-time measure for comparisons across stimuli. In contrast, Resposetime is referenced to the onset of the response prompt.

If a participant did not make a valid keypress within the 3000 ms response window, the participant-response field was left blank, Resposetime was assigned a value of 3000 ms, and stimutoRT_time was recorded as the sum of the corresponding audio-file duration and the 3000-ms response window. The trial was then marked as an omission. For omission trials, the value of 3000 ms in Resposetime represents the programmed timeout rather than an observed response latency. The released behavioral data contain only formal experimental trials and exclude practice trials.

Key parameters of the experimental design, trial timing, response procedure, and event-marker implementation are summarized in Table 1.

Parameter	Setting
Stimulus set	78 MP3 files: 26 English letters × 3 nominal CPM conditions (15, 30, and 40 CPM)
Tasks and order	Dot-count followed by first–last matching; fixed order with a 10-min inter-task rest
Practice	10 trials per task at nominal 15 CPM; followed by a 10-s rest
Formal-block structure	3 blocks per task in fixed 15→30→40 CPM order; 52 trials per block; 300-s rests between blocks
Formal trials	156 per task; 312 per participant across both tasks
Response mapping	Dot-count: numeric keys 0–4; first–last matching: 1 = match, 0 = mismatch
Single-trial timing	300-ms fixation → audio presentation for the actual MP3 duration → response window ≤3000 ms → 1000–3000-ms jittered ITI
Omission and feedback	Omission if no valid response occurred within 3000 ms; no trial-by-trial correctness feedback
Event markers	Codes 1–78 encoded letter × nominal CPM condition and marked software-defined initiation of the E-Prime SoundOut object

Table 1. Key experimental design, trial timing, and event-marker parameters.

EEG Data Acquisition

EEG data were recorded in a quiet and comfortable laboratory environment. Participants were seated directly in front of the monitor and were instructed to remain attentive, listen carefully to each auditory stimulus, and respond according to the task instructions (Fig. 1d). During sound presentation, participants were asked to minimize blinking, head movements, and body movements to reduce related artifacts.

Auditory stimuli were presented in a free-field configuration through a pair of EDIFIER MR3BT active loudspeakers. The loudspeakers were connected to the experimental computer through a wired audio connection and positioned symmetrically on the left and right sides of the monitor. The distance between the two loudspeakers was approximately 70 cm, and the distance from each loudspeaker to the participant's midline listening position was also

approximately 70 cm, forming an approximately equilateral triangular listening arrangement. The acoustic centers of the loudspeakers were positioned approximately at the participant's chest level.

Playback volume was adjusted individually during the practice phase according to each participant's subjective perception of sound clarity and comfort. Once determined, the volume setting remained unchanged across both tasks and all formal blocks for that participant. Sound-pressure level was not measured or calibrated at the participant's listening position; therefore, absolute presentation levels may have differed across participants.

EEG signals were acquired using a 64-input-channel g.HIamp active-electrode system manufactured by g.tec medical engineering GmbH, Austria, and recorded using g.Recorder version 5.16.00 (Fig. 1b). Electrode placement followed an extended international 10–20 layout (Fig. 1c). Electrode impedance was maintained below 5 kΩ before data acquisition. No dedicated electrooculography channels were recorded.

The recording configuration comprised 62 scalp EEG channels. Input channel 63 was connected to the right earlobe and served as the recording reference, input channel 64 was not used, and AFz served as the ground electrode. Channel names, channel types, data units, and electrode coordinates are documented in the accompanying dataset metadata. EEG was sampled at 600 Hz. During acquisition, an online hardware band-pass filter of 0.1–100 Hz and an online hardware notch filter of 48–52 Hz were applied, with the latter used to attenuate power-line interference. Both filters were implemented by the EEG acquisition system during recording. Stimulus event codes generated by E-Prime were transmitted to the EEG acquisition system through the g.tec trigger input interface.

EEG Data Preparation and Preprocessing

To support both flexible data reuse and reproducible reference analyses, the dataset was released at two processing levels: continuous EEG data converted and organized according to EEG-BIDS conventions, and baseline-preprocessed derivatives. The continuous BIDS data allow users to implement preprocessing procedures tailored to their specific research questions, whereas the baseline-preprocessed derivatives provide a reproducible example workflow and reusable reference outputs.

Continuous BIDS Data Preparation and Format Conversion

The original EEG recordings were exported from g.Recorder in HDF5 format. To improve accessibility and compatibility with commonly used EEG analysis software, the continuous recordings were subsequently converted to BrainVision format, comprising .vhdr, .vmrk, and .eeg files, and organized according to BIDS version 1.10.1 and the EEG-BIDS conventions. The conversion preserved the original sampling rate, stimulus event codes, and channel order. Apart from file-format conversion and BIDS metadata organization, no additional offline filtering, rereferencing, epoching, unusable-channel replacement, artifact correction, or trial rejection was applied to the continuous BIDS data. The term "continuous BIDS data" therefore refers to the continuous recordings obtained from the original proprietary HDF5 files through format conversion and BIDS organization.

Associated files, including *_eeg.json, *_channels.tsv, *_events.tsv, and *_beh.tsv, document EEG acquisition parameters, channel information, software event markers, trial conditions, behavioral responses, and behavioral timing information. These files enable users

to select alternative reference schemes, filter settings, epoch definitions, and artifact-management procedures according to their specific research aims.

Real-time signal inspection during data acquisition identified three recordings containing one channel without a usable EEG signal: PO4 in sub-13, PO4 in sub-14, and TP8 in sub-15. The originally acquired signals from these channels were retained unchanged in the continuous BIDS data.

Baseline preprocessing

In addition to the continuous BIDS data, baseline-preprocessed derivatives were generated using MATLAB R2022b and EEGLAB v2024.0[14]. These derivatives were intended to provide a reproducible example preprocessing workflow and reusable reference outputs. Users may modify the released code according to their specific research aims and reprocess the continuous BIDS data. The baseline preprocessing pipeline comprised unusable-channel replacement, average rereferencing, continuous-data filtering, trial epoching, baseline correction, and trial rejection, performed in this order.

Unusable-channel replacement. Before average rereferencing and filtering, the three previously identified unusable channels were replaced using local averages of predefined neighboring channels. For sub-13 and sub-14, PO4 was replaced at each time sample by the arithmetic mean of P4, PO8, and POz. For sub-15, TP8 was replaced by the arithmetic mean of T8, C6, CP6, and P8. This procedure used predefined local channel averages rather than spherical-spline interpolation or automated bad-channel reconstruction. Channel replacement was applied only to the baseline-preprocessed derivatives, whereas the originally acquired signals were retained in the continuous BIDS data.

Average rereferencing. Following unusable-channel replacement, the 62 scalp EEG channels were rereferenced to their average. At each time sample, the mean voltage across the 62 scalp channels was calculated and subtracted from each channel.

Data filtering. Following average rereferencing, the continuous EEG data were band-pass filtered from 1 to 40 Hz using the EEGLAB eegfilt function. The sampling rate was 600 Hz, and the filter order specified in the preprocessing script was 100. The released code preserves the function call and parameters used to generate the baseline-preprocessed derivatives.

Trial epoching. Trial epochs were defined relative to the E-Prime SoundOut event markers in the BIDS event files. Each marker was defined as event time zero for the corresponding trial, $t = 0$. The marker represented the software-defined initiation of MP3 playback rather than an independently measured physical acoustic onset. No correction was applied for leading intervals within the audio files or for unmeasured delays in the complete playback chain.

For trials containing a valid response, the final stored epoch began at the first sample after $t = 0$ and ended at the sample corresponding to the trial-specific stimutoRT_time. The variable stimutoRT_time represented the interval from software-defined event time zero to the participant's valid keypress. For omission trials, Resposetime was assigned a value of 3000 ms, and stimutoRT_time was calculated as the duration of the corresponding audio file plus the 3000-ms response window. Accordingly, omission-trial epochs included the complete audio-file playback period and the full subsequent 3000-ms response window. All formal trials, including omission trials, were initially epoched and entered into the subsequent amplitude-threshold-based quality-control procedure; practice trials were not included in baseline preprocessing.

Baseline correction. The 200-ms interval preceding event time zero was used for baseline correction. For each trial and channel, the mean amplitude from −0.2 to 0 s relative to $t = 0$ was calculated and subtracted from all post-event samples in the corresponding trial. Pre-event samples were used only for baseline estimation and were not retained in the final trial matrices. Consequently, each stored trial matrix began at the first sample after $t = 0$.

Trial rejection. Following baseline correction, a trial was excluded if the absolute amplitude of any scalp EEG channel exceeded 200 μV at any sample within the epoch. This criterion was used primarily to remove large-amplitude transients, substantial movement artifacts, and severe electrode disturbances while retaining data for further user-defined processing. The baseline preprocessing did not include independent component analysis, EOG regression, or automated bad-channel detection, and no explicit removal of ocular- or muscle-artifact components was performed. Users requiring more stringent or analysis-specific artifact management should begin with the continuous BIDS data and modify the released code according to their research requirements.

The baseline-preprocessed derivatives were saved in MATLAB .mat format, with one derivative file provided for each participant and task. Only trials that passed the amplitude-threshold-based quality-control procedure were retained. These files were intended as example baseline-preprocessed outputs and should not be regarded as fully artifact-corrected, analysis-ready data. Users requiring alternative reference schemes, filter settings, epoch definitions, or artifact-management procedures should regenerate the derivatives from the continuous BIDS data.

Data Records

Dataset access and organization

The MorseEEG-ATP dataset is openly available from OpenNeuro under accession ds007655[15]. The data version corresponding to this manuscript is version 1.0.2:https://openneuro.org/datasets/ds007655/versions/1.0.2. The dataset is organized according to BIDS version 1.10.1 and the EEG-BIDS conventions and contains two tasks, identified as dotcount and firstlast. The dataset-level directory contains dataset_description.json, README, participants.tsv, and participants.json, which provide dataset- and participant-level metadata. The files task-dotcount_events.json and task-firstlast_events.json describe the fields and coded values used in the event files for the two tasks.

The stimuli/ directory contains an audio/ subdirectory, a README file, and stimulus_label_mapping.tsv. The audio/ subdirectory contains the 78 MP3 files used in the experiment. The file stimulus_label_mapping.tsv documents the correspondence among the stimulus event code (StimTrigger), stimulus label (Stimulus), total audio-file duration (cuetime), and relative audio-file path (stim_file). The field cuetime represents the total duration of the corresponding audio file in milliseconds.

The code/ directory contains documentation and MATLAB scripts for HDF5-to-BrainVision/EEG-BIDS conversion, behavioral analysis, baseline EEG preprocessing, stimulus-marker-locked event-related response analysis, PSD feature extraction and statistical analysis, and leave-one-subject-out classification. The released scripts include step0_hdf5_to_bids.m, step1_behavior_analysis.m, step2_preprocess.m, step3_extract_PSD.m, step4_ERP_analysis.m, step5_PSD_ranksum_FDR.m, and step6_PSD_LOSO_classification.py, together with the HDF5 conversion script, associated

helper functions, the electrode-location file, and documentation. The overall directory structure is shown in Fig. 3.

Participant-Level Behavioral and Continuous EEG Data

Data from each participant are stored in the corresponding sub-XX/ directory, which contains separate beh/ and eeg/ subdirectories. The sub-XX/beh/ directory contains two trial-level behavioral files, sub-XX_task-dotcount_beh.tsv and sub-XX_task-firstlast_beh.tsv. Each file records behavioral responses, response outcomes, and behavioral timing information for the formal trials of the corresponding task. Practice trials are not included in the released behavioral files.

The sub-XX/eeg/ directory contains the continuous EEG recordings and associated metadata for the two tasks. Each continuous recording is stored in BrainVision format and comprises a .vhdr header file, an .eeg continuous-signal file, and a .vmrk event-marker file. Each recording is also accompanied by *_eeg.json, *_channels.tsv, and *_events.tsv files, which document EEG acquisition parameters, channel information, and trial-level stimulus events and condition annotations, respectively. These files constitute the continuous BIDS data described above and underwent no additional offline signal processing beyond format conversion and BIDS organization.

Baseline-preprocessed derivative data

The baseline-preprocessed derivative data are stored in derivatives/preprocessed/. This directory contains a derivative-level dataset_description.json file and one MATLAB .mat file for each participant and task, such as sub-01_task-dotcount_desc-preproc_eeg.mat and sub-01_task-firstlast_desc-preproc_eeg.mat.

Each .mat file contains a variable named sub_preData, organized as a two-level cell-array structure by block and trial. The three top-level cells correspond to the three nominal presentation-rate blocks: cell 1 represents the nominal 15-CPM block, in which event codes 1–26 were used; cell 2 represents the nominal 30-CPM block, in which event codes 27–52 were used; and cell 3 represents the nominal 40-CPM block, in which event codes 53–78 were used. The top-level cell identifies the nominal CPM block and the event-code range used within that block; however, the individual retained trial matrices do not contain separate event codes or original trial indices.

Each top-level cell contains the trial epochs retained after amplitude-threshold-based quality control for the corresponding block. Each trial is stored as a two-dimensional [channels × samples] matrix with 62 rows corresponding to the scalp EEG channels; signal amplitudes are expressed in μV.

Trial-matrix duration varies because the endpoint of each epoch was defined by either the participant's valid keypress or expiration of the response window. The E-Prime SoundOut event was defined as event time zero ($t = 0$). For trials with a valid response, the matrix extends from the first sample after ($t = 0$) to the sample corresponding to the valid keypress. For omission trials, the matrix includes the corresponding audio-file playback period and the full subsequent 3000-ms response window. The interval from −0.2 to 0 s was used only for baseline correction and is not included in the stored matrices.

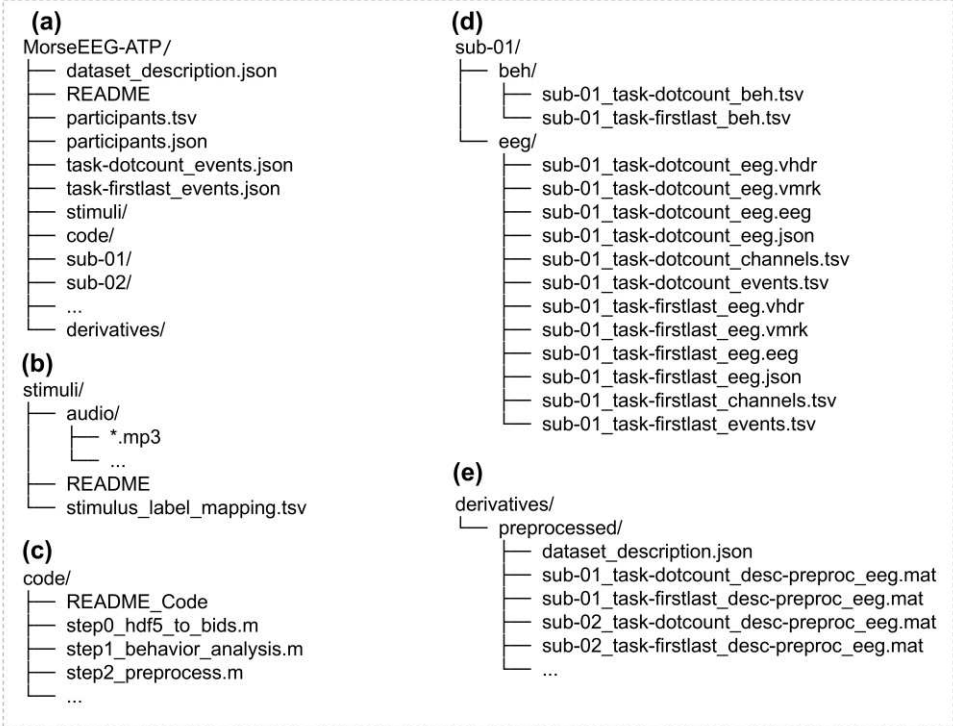


Fig. 3 The folder structure of the MorseEEG-ATP dataset. (a) Dataset-level directory structure and metadata files. (b) Auditory stimulus files and the stimulus-label mapping table. (c) Documentation and selected MATLAB scripts for behavioral and EEG analyses. (d) Example participant-level behavioral files, continuous EEG recordings, and associated metadata. (e) Baseline-preprocessed derivative files.

Technical Validation

The technical validity of the MorseEEG-ATP dataset was evaluated from four complementary perspectives: behavioral performance, EEG data quality and preprocessing yield, stimulus-marker-locked event-related responses, and task-performance-related EEG variation. Together, these analyses assess whether participants remained effectively engaged during data acquisition, whether the released EEG recordings and baseline-preprocessed derivatives contain sufficient usable data, whether reproducible event-related EEG responses are present, and whether the dataset contains measurable EEG variation associated with inter-individual differences in task performance.

Behavioral validation

Behavioral performance was examined as part of the technical validation of the EEG dataset to assess whether participants followed the task requirements and maintained adequate task engagement during data acquisition. Across participants, mean accuracy was 77.6% in Exp1 (dot-count) and 84.1% in Exp2 (first–last match), exceeding the corresponding uniform response-option chance levels of 20% and 50%, respectively. Mean participant-level response time was 1251.2 ms in Exp1 and 1162.8 ms in Exp2. For these summaries, response time was calculated across all 156 formal trials in each task; trials without a valid response retained the programmed 3000-ms response-window limit in the calculation. This timeout value therefore represents the upper limit of the response window rather than an observed response latency.

Behavioral distributions were broadly comparable across the three experimental blocks (Fig. 4a,

b). Neither accuracy nor response time showed an obvious monotonic deterioration from Block 1 to Block 3 in either experiment, indicating that the behavioral data did not exhibit clear progressive performance loss over the course of the recording session. Because block order was fixed, however, these block-wise summaries are intended as descriptive measures of within-session performance rather than as estimates of presentation-rate effects.

Task engagement was further characterized by the frequency of omission trials. In Exp1, 150 of 4,992 formal trials were omissions (3.00%), corresponding to 4.69 ± 8.44 trials per participant (range, 0–42) and participant-level omission rates ranging from 0% to 26.92%. In Exp2, 90 of 4,992 trials were omissions (1.80%), corresponding to 2.81 ± 5.57 trials per participant (range, 0–28) and omission rates ranging from 0% to 17.95%. Omissions were therefore retained explicitly as a separate measure of response completeness, in addition to their contribution to the participant-level response-time summary.

To assess whether the dataset preserves stable inter-individual behavioral variation across tasks, cross-task correspondence was quantified using Pearson correlation, Spearman correlation, and ICC (Fig. 4c, d). Accuracy showed strong cross-task correspondence (Pearson's r=0.91, Spearman's ρ=0.82, both p<0.001), with an ICC (C, 1) of 0.79. Response time showed similarly strong correspondence across tasks (Pearson's r=0.85, Spearman's ρ=0.82, both p<0.001), with an ICC(C,1) of 0.82. Thus, although absolute performance differed between Exp1 and Exp2, participants who performed relatively well in one task tended to show similarly favorable performance in the other.

Together, the above-chance accuracy, low overall omission rates, broadly stable block-wise behavioral distributions, and cross-task preservation of inter-individual differences support the behavioral validity of the recordings for subsequent dataset-level analyses. The observed correspondence is interpreted specifically as consistency of task performance within the present auditory temporal-pattern discrimination paradigm and should not be taken as an independent measure of general auditory ability or short-term memory capacity.

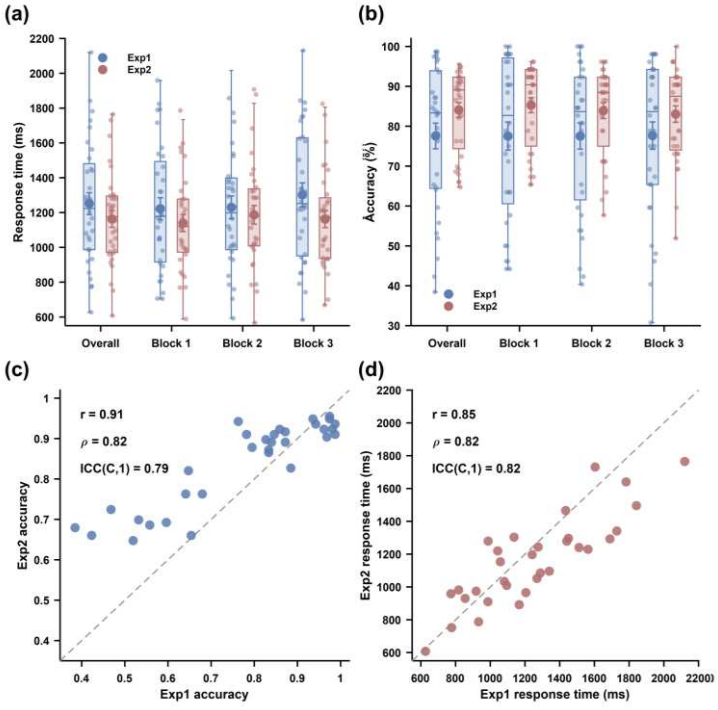


Fig. 4 Behavioral performance and cross-task consistency across the two auditory discrimination

tasks. (a) Participant-level response-time distributions for Exp1 (dot-count) and Exp2 (first–last match), shown overall and separately for Blocks 1–3. Response time was calculated across all formal trials, with omission trials retaining the programmed 3000-ms response-window limit. (b) Participant-level accuracy distributions under the same conditions. In A and B, individual dots represent participants, boxplots summarize participant-level distributions, and filled circles with error bars indicate the mean ± SEM. (c) Cross-task correspondence in participant-level accuracy. (d) Cross-task correspondence in participant-level response time. Each point in C and D represents one participant (N=32); dashed lines indicate equality between Exp1 and Exp2. Insets report Pearson's r, Spearman's ρ, and ICC(C,1).

EEG data quality and preprocessing yield

EEG data quality was evaluated at both the continuous-recording level and the level of the baseline-preprocessed derivatives. Inspection identified one unusable channel in three recordings: PO4 in sub-13 and sub-14 and TP8 in sub-15. The originally acquired signals were retained unchanged in the continuous BIDS data. In the baseline-preprocessed derivatives, PO4 was replaced by the arithmetic mean of P4, POz, and PO8, whereas TP8 was replaced by the arithmetic mean of C6, T8, CP6, and P8.

Following baseline preprocessing, 3,731 of 4,992 formal trials were retained in Exp1 (74.74%), whereas 4,225 of 4,992 trials were retained in Exp2 (84.64%). Across both tasks, 7,956 of 9,984 trials were retained, corresponding to an overall retention rate of 79.69% (Table 2). Participant-level retention varied substantially, with mean rates of 74.74 ± 23.19% in Exp1 and 84.64 ± 20.37% in Exp2, ranging from 21.15% to 100.00% and from 7.69% to 100.00%, respectively. Retention statistics for the three nominal CPM blocks are also summarized in Table 2. Participant- and block-level retention statistics for all 32 participants are provided in Supplementary Table 1. Because nominal CPM condition and block order were not independently varied, these block-level values are reported descriptively and should not be interpreted as isolated effects of presentation rate.

These statistics characterize the output of the baseline preprocessing pipeline rather than missing data in the original recordings. The continuous BIDS data remain available for alternative preprocessing, whereas the provided derivatives serve as reproducible baseline-preprocessed reference data.

Task	Formal trials	Retained trials, n/N (%)	Participant-level retention, mean ± SD (range)	15 CPM, n/N (%)	30 CPM, n/N (%)	40 CPM, n/N (%)
Exp1	4,992	3,731/4,992 (74.74%)	74.74 ± 23.19% (21.15–100.00%)	1,107/1,664 (66.53%)	1,282/1,664 (77.04%)	1,342/1,664 (80.65%)
Exp2	4,992	4,225/4,992 (84.64%)	84.64 ± 20.37% (7.69–100.00%)	1,395/1,664 (83.83%)	1,384/1,664 (83.17%)	1,446/1,664 (86.90%)
Overall	9,984	7,956/9,984 (79.69%)	—	—	—	—

Table 2. Summary of trial retention in the baseline-preprocessed EEG derivatives. Values represent trials retained after the baseline preprocessing quality-control procedure. Each participant contributed 156 formal trials per task, with 52 trials in each nominal CPM block. Participant-level values summarize retention percentages across the 32 participants. Block-level values are descriptive because nominal CPM and block order were not independently varied.

Stimulus-marker-locked event-related responses

To evaluate the suitability of MorseEEG-ATP for event-related EEG analyses, we examined whether reproducible stimulus-marker-locked responses could be identified in both experiments.

Only trials retained after the baseline preprocessing quality-control procedure were included. Retained trials were first averaged within each participant, and the resulting participant-level waveforms were then averaged across participants to obtain grand-average responses for Exp1 and Exp2.

Event-related responses were time-locked to the software event marker associated with initiation of playback of the complete MC character in E-Prime. Accordingly, the responses represent character-level event-related activity and were not separately time-locked to the onset of individual short or long elements within each character. The latency between the E-Prime event marker and the physical acoustic onset at the loudspeaker was not independently measured. All latency values reported below should therefore be interpreted relative to the recorded software event marker rather than to a calibrated acoustic onset.

Both experiments showed a reproducible sequence of stimulus-marker-locked deflections (Fig. 5). Scalp topographies averaged over 150–250 ms showed a prominent fronto-central negative distribution in both Exp1 and Exp2 (Fig. 5a, c). Guided descriptively by this spatial pattern, Fz was selected for waveform visualization, where a pronounced negative deflection was evident at approximately 200 ms after the software event marker. Scalp topographies averaged over 250–300 ms showed a subsequent centrally distributed positive pattern in both experiments (Fig. 5b, d). Cz was therefore selected for visualization of the corresponding waveform, which showed a clear positive deflection following the earlier negative response. Electrode selection was thus topography-guided and descriptive rather than prespecified.

Participant-level waveforms at Fz and Cz were additionally examined to assess whether the grand-average pattern reflected broadly distributed responses across the sample rather than being attributable to a small number of participants (Supplementary Fig. 1). Similar negative–positive temporal structure was observable across participants, together with substantial inter-individual variability in response amplitude and waveform morphology.

These results demonstrate that MorseEEG-ATP contains reproducible stimulus-marker-locked EEG activity at both the group and participant levels and support its use for event-related analyses. Because physical acoustic onset was not independently time-calibrated, the observed deflections are described here according to their polarity, spatial distribution, and latency relative to the software event marker rather than being assigned to canonical ERP components on the basis of absolute latency alone.

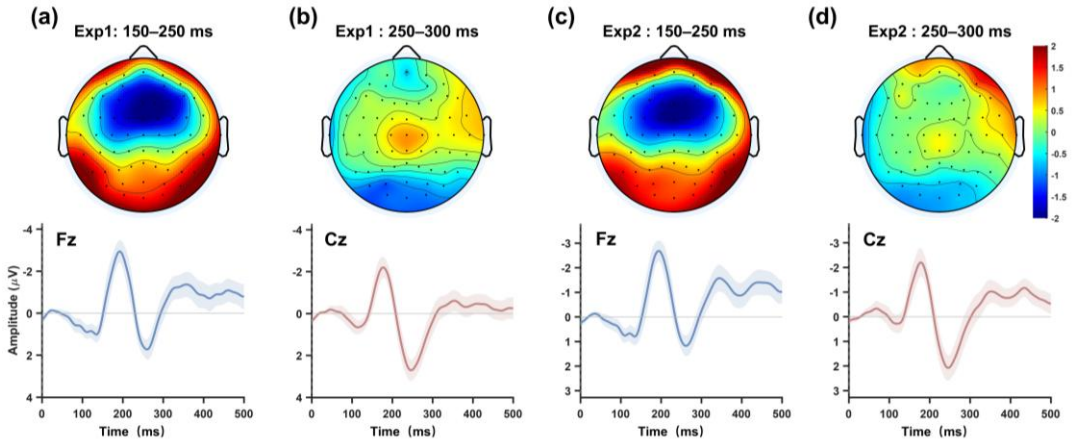


Fig. 5 Stimulus-marker-locked event-related EEG responses in Exp1 and Exp2. (a, c) Scalp topographies averaged over 150–250 ms after the software event marker and the corresponding grand-average waveforms at Fz for Exp1 (dot-count) and Exp2 (first–last match), respectively, showing a

fronto-central negative deflection. (b, d) Scalp topographies averaged over 250–300 ms and the corresponding grand-average waveforms at Cz, showing a subsequent centrally distributed positive deflection. Shaded areas indicate point-wise 95% confidence intervals of the grand-average waveform across participants. Only trials retained after baseline preprocessing quality control were included. Responses were time-locked to the E-Prime software marker associated with initiation of playback of the complete Morse-code character. Because the latency between this software marker and physical acoustic onset at the loudspeaker was not independently measured, all reported latencies are referenced to the software event marker.

Exploratory validation of task-performance-related EEG variation

To further validate the utility of MorseEEG-ATP for investigating inter-individual differences, we examined whether behavioral task performance could be quantified consistently and whether the resulting participant stratification was associated with systematic EEG variation. Task performance was summarized from accuracy and response time averaged across Exp1 and Exp2. Consistent with the behavioral analyses described above, response time was calculated across all formal trials, with omission trials retaining the programmed 3000-ms response-window limit. Response speed was defined as 3000-RT, such that larger values indicated faster responding. Accuracy and response speed were normalized across the 32 participants by dividing each measure by its corresponding across-participant sum. The fused task-performance score for participant *i* was defined as

$$S_i = W_{\mathrm{ACC}} ACC_i^{\mathrm{norm}} + (1 - W_{\mathrm{ACC}}) RS_i^{norm}$$

where i denotes the participant of interest, j indexes all 32 participants, $RS_i = 3000 - RT_i$ $RS_i = 3000 - RT_i$, $ACC_i^{\mathrm{norm}} = ACC_i / \sum_j ACC_j$, and $RS_i^{\mathrm{norm}} = RS_i / \sum_j RS_j$.

To examine the relative weighting of accuracy and response speed, candidate values of W_{ACC} from 0.5 to 1.0 in increments of 0.1 were evaluated (Fig. 6a-c). For each weight, participants were re-ranked and divided into equally sized higher-performing (“Strong”) and lower-performing (“Weak”) groups (n=16 each). Group separation in accuracy and the response-time advantage of the Strong group were standardized across candidate weights and summed to obtain a descriptive behavioral balance score. This score reached its maximum at W_{ACC} = 0.8, corresponding to weights of 0.8 for accuracy and 0.2 for response speed, and this weighting was therefore retained for subsequent analyses. Because the weighting was derived from the present dataset, the resulting stratification is treated as an exploratory measure of task performance rather than as a standardized measure of general auditory ability.

To evaluate whether MorseEEG-ATP contains measurable EEG variation associated with task-performance differences, spectral power was compared between the behaviorally defined groups. PSD was estimated using the Welch method[16] for the Delta, Theta, Alpha, Beta, and Gamma bands. For each participant, PSD features were first averaged within each task and then across Exp1 and Exp2, yielding one participant-level representation for group comparison. Channel-wise differences between the Strong and Weak groups were assessed using Wilcoxon rank-sum tests followed by Benjamini–Hochberg false-discovery-rate correction[17] across the 62 channels within each frequency band (q<0.05). Alpha was the only tested band with channels surviving correction: significant differences were observed at 39 of 62 channels, and all showed higher Alpha-band power in the Strong group than in the Weak group. The significant channels were spatially widespread, extending from frontal and fronto-central regions through central

and parietal sites to posterior regions (Fig. 6d). No channels survived FDR correction in the Delta, Theta, Beta, or Gamma bands. These results indicate a systematic association between the behaviorally derived task-performance stratification and Alpha-band spectral variation in the present dataset.

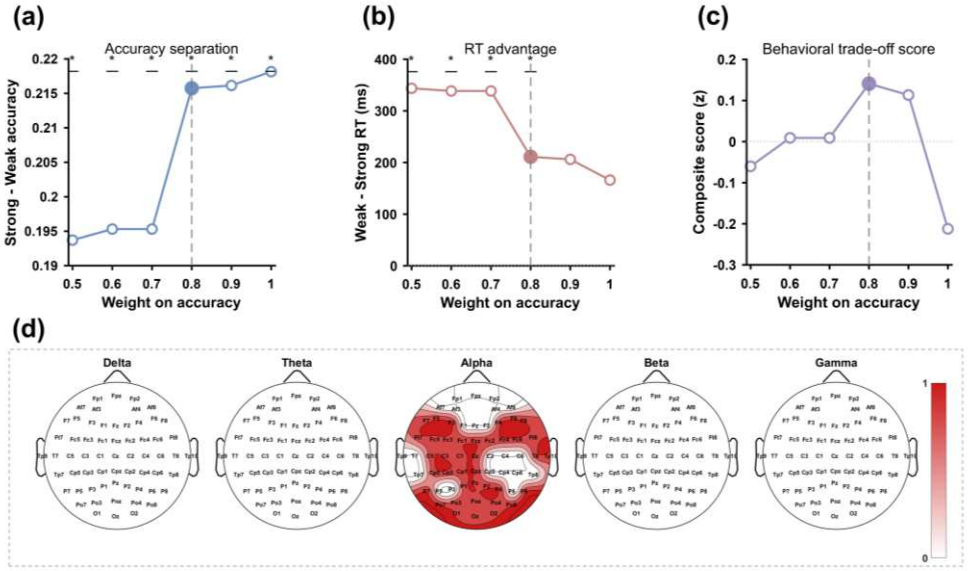


Fig. 6 Behavioral task-performance stratification and associated PSD differences. (a) Accuracy separation between the Strong and Weak groups across candidate accuracy weights (W_{ACC}). (b) Response-time advantage of the Strong group, calculated as Weak minus Strong RT. (c) Behavioral balance score combining standardized accuracy separation and RT advantage. The filled marker and vertical dashed line indicate the selected weighting (W_{ACC}=0.8); asterisks denote uncorrected between-group comparisons with p<0.05. (d) Topographic distribution of channels showing significant Strong–Weak differences in Delta-, Theta-, Alpha-, Beta-, and Gamma-band PSD after channel-wise Wilcoxon rank-sum tests and Benjamini–Hochberg FDR correction (q<0.05). Red regions indicate channels surviving FDR correction and do not represent the magnitude of the PSD difference.

To avoid subject-level data leakage and evaluate generalization to unseen participants[18],we performed leave-one-subject-out (LOSO) classification using Alpha-band PSD and four baseline classifiers: support vector machine (SVM)[19], random forest (RF)[20], multilayer perceptron trained using back-propagation (MLP)[21], and a one-dimensional residual network adapted from the ResNet architecture (ResNet1D)[22]. The Strong and Weak groups were encoded as class 1 and class 0, respectively. Trial-level probabilities for the Strong class were averaged within each held-out participant to obtain a subject-level P(strong). Figure 7 summarizes classification performance and the distribution of subject-level probabilities, with results for the other frequency bands provided in Supplementary Fig. 2. Together, the spectral and classification analyses provide an exploratory technical-validation benchmark showing that MorseEEG-ATP can support investigations of relationships between EEG features and inter-individual variation in task performance.

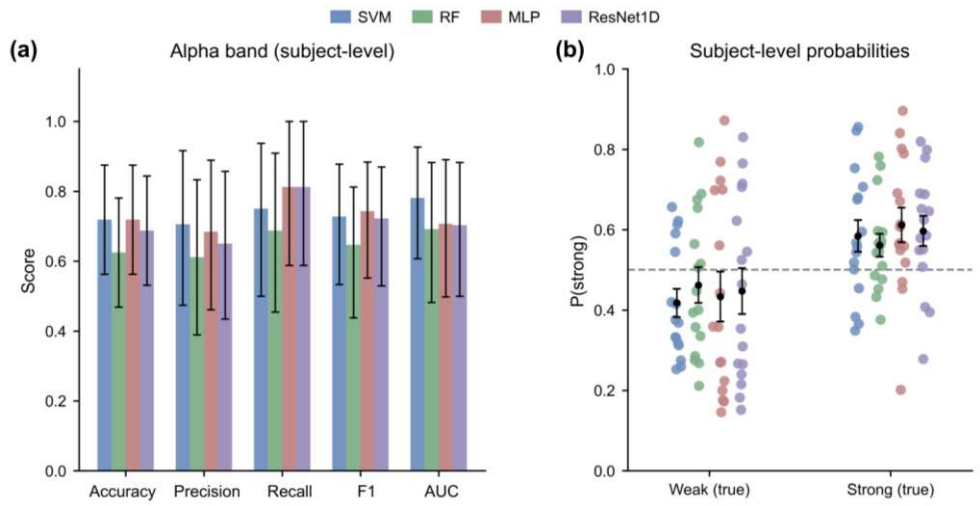


Fig. 7 Cross-participant classification of behaviorally defined task-performance groups using Alpha-band PSD. (a) Subject-level performance of four baseline classifiers (SVM, RF, MLP, and ResNet1D) under leave-one-subject-out cross-validation, summarized using accuracy, precision, recall, F1 score, and AUC. Error bars indicate 95% bootstrap confidence intervals across the 32 participants. (b) Distribution of subject-level probabilities assigned to the Strong class, grouped according to the true behavioral labels (Weak vs. Strong). Colored dots represent individual participants, and black dots with error bars indicate group mean ± SEM. The horizontal dashed line denotes the 0.5 classification threshold.

Usage Notes

The 15-, 30-, and 40-CPM labels denote software-defined nominal presentation-rate conditions. Because task order and nominal-CPM block order were fixed rather than randomized or counterbalanced, comparisons across tasks or blocks may also reflect practice, fatigue, or time-on-task effects, and block-level differences cannot be attributed uniquely to nominal CPM. Each participant contributed two formal trials for each task × letter × nominal-CPM combination; analyses at the level of individual letters or similarly narrow stimulus subsets should therefore take the limited number of trials per cell into account. In the first–last matching task, E and T were single-element characters and did not involve comparison between distinct first and final positions. These trials may be excluded or modeled separately in analyses specifically targeting retention and comparison across multiple element positions.

EEG event time zero (t = 0) corresponds to the software-defined initiation of the E-Prime SoundOut object rather than an independently measured physical acoustic onset. End-to-end latency in the audio playback chain was not measured; analyses requiring precise absolute response latency should therefore take this timing limitation into account. Playback volume was adjusted individually during practice according to perceived clarity and comfort and was then held constant across formal recordings for that participant. Sound-pressure level was not calibrated at the listening position, so absolute presentation level may have varied across participants.

The baseline-preprocessed derivatives provide reproducible reference outputs but are not intended to represent fully artifact-corrected EEG data. The preprocessing pipeline does not include ICA, EOG regression, or explicit correction of ocular and muscle artifacts. In addition, the existing .mat derivative files do not contain a separate trial index directly linking each retained trial matrix to the corresponding row in the event and behavioral files. Users requiring alternative preprocessing, more stringent artifact correction, or exact trial-level correspondence among EEG,

event, and behavioral records should reconstruct the required derivatives from the continuous BIDS data using or adapting the released code.

Data Availability Statement

The continuous BIDS EEG data, trial-level event and behavioral records, auditory stimulus files and associated metadata, dataset-level metadata, and baseline-preprocessed derivatives of MorseEEG-ATP are openly available from OpenNeuro under accession ds007655. The data version corresponding to this manuscript is version 1.0.2[15]: https://openneuro.org/datasets/ds007655/versions/1.0.2

Code Availability Statement

The MATLAB code used for HDF5-to-BrainVision/EEG-BIDS conversion, behavioral analysis, baseline EEG preprocessing, stimulus-marker-locked event-related response analysis, PSD feature extraction and statistical analysis, and leave-one-subject-out classification is available in the code/ directory of the OpenNeuro dataset ds007655, version 1.0.2 [15]. Processing was implemented using MATLAB R2022b, EEGLAB v2024.0, and the required MATLAB toolboxes. The released code includes step0_hdf5_to_bids.m, step1_behavior_analysis.m, step2_preprocess.m, step3_extract_PSD.m, step4_ERP_analysis.m, step5_PSD_ranksum_FDR.m, and step6_PSD_LOSO_classification.py, together with the electrode-location file and documentation.

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Author contributions

B.Y., Y.Z. conceived of the idea and supervised the research. Z.H., Y.Z., S.Z., C.P., L.T., K.G., Y.G., B.L. contributed to discussion, experimental design, execution, and manuscript structure. Z.H., C.P. visualizes the experimental results. Z.H., Y.Z. wrote the manuscript.

Competing interests

The authors declare no competing interests.

Supplementary Information

The online version contains supplementary material, including Supplementary Table 1 and Supplementary Figs. 1–2.

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Supplementary Files

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