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Data Article

An open-access EEG dataset from indigenous African populations for schizophrenia research

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ABSTRACT

Machine-learning pipelines for schizophrenia demand large, ethnically diverse electroencephalography (EEG) corpora, yet African populations remain under-represented in the public domain. The African Schizophrenia EEG Dataset (ASZED-153) helps close this gap with 153 raw, 16-channel recordings from 76 clinically characterized patients and 77 matched controls recruited in south-western Nigeria (mean age ≈ 39 years). Signals were acquired at two hospital units using Contec KT-2400 (200 Hz) and BrainMaster Discovery24-E (256 Hz) systems under harmonized protocols, retaining only the devices' default filter settings.

Each session contains four paradigms—eyes-closed resting state, arithmetic working-memory, auditory oddball to elicit mismatch negativity, and a 40 Hz auditory steady-state response—so oscillatory, ERP and cognitive-load markers can be compared within the same individuals. Recordings are released unchanged in European Data Format, accompanied by structured .gnr sidecars detailing clinical scores, device settings and protocol metadata, enabling transparent end-to-end pipelines

Data are organized in a version-controlled tree with a public key-map, allowing new African centers to append recordings without breaking existing scripts and paving the way

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for federated growth beyond Nigeria. By uniting ancestral diversity, multi-task paradigms and minimal preprocessing, ASZED-153 will allow researchers audit ancestry-linked performance drift in existing classifiers, probe biomarkers that may be masked in Euro-Asian cohorts, benchmark algorithms across hardware heterogeneity, and prototype reproducible, open science workflows.
ASZED-153 is openly available via Zenodo under a CC-BY licence, and contributions to future releases are welcomed. We anticipate that this resource will accelerate the development of fair, generalizable and clinically useful EEG-based tools for schizophrenia worldwide.

Specifications table

Subject	Psychiatry and Mental Health
Specific subject area	Computational Diagnosis of Schizophrenia.
Type of data	EEG signal – .edf Node, Subset, Subject, Session Metadata – .gnr Descriptive Statistics – .csv Versions, Nodes, Subsets Description – .kmp, .txt
Data collection	Data was collected using Contec-KT2400 (at 200Hz) and BrainMaster Discovery24-E (at 256Hz) EEG systems at 16 electrode sites. Two protocol variants: P1.1 (rest/cognitive/MMN) and P1.2 (adding 40Hz-ASSR) were delivered via a custom-built software, developed using C#. Eligibility required legal age, informed consent, no drug abuse history, and for controls, no family history of mental disorders. Clinical assessment used MINI, PANSS, WHODAS tools. MMN protocol used 1KHz standard (100ms) with duration/frequency deviants; ASSR used 40Hz stimulation. Data stored in EDF format with standardized metadata.
Data source location	Institution: Obafemi Awolowo University Teaching Hospital College (OAUTHC) City/Town/Region: Ile-Iffe, Osun State Country: Nigeria Institution: Wesley Guild Medical Outpost City/Town/Region: Ilesa, Osun State Country: Nigeria
Data accessibility	Repository name: African Schizophrenia EEG Dataset Data identification number: 10.5281/zenodo.14178398 Direct URL to data: https://zenodo.org/records/14178398
Related research article	none

1. Value of the Data

- Closes a critical gap in open SZ-EEG resources: Fewer than 2 % of schizophrenia EEG recordings currently available for research include African-descent participants [1–3]. By contributing data from indigenous Nigerians, ASZED-153 lets investigators immediately stress-test models trained on Euro-Asian data and quantify ancestry-related performance drift. Future versions of the dataset will feature data from other parts of the African continent.
- Supports multi-angle biomarker discovery inside one coherent cohort: Each participant completed resting state, arithmetic-load, mismatch-negativity (MMN) and 40 Hz auditory steady-state response (ASSR) protocols under identical recording conditions. Researchers can therefore relate oscillatory power, event-related potentials and cognitive-load dynamics without the confounds that plague meta-analyses stitched from separate studies. The design encour-

ages subtype or trajectory work—e.g., isolating patients who fail both MMN and ASSR versus those who fail only one—without hunting for additional data.
- Promotes rigorous, reproducible AI development: Signals are released raw in EDF, with only the on-device band-pass applied, and accompanied by a structured .gnr sidecar containing device specs, electrode impedances, drug status and PANSS scores. Starting from an untouched waveform lets teams publish transparent preprocessing pipelines and benchmark them head-to-head instead of relying on opaque, pre-cleaned signals. This follows bias mitigation recommendations [3].
- Ready continent-wide expansion: The repository follows a strict node → subset → subject → session hierarchy with a public JSON key-map of sites, cap models and protocol tweaks. Any African lab can drop future data into the tree without breaking existing data or scripts, enabling federated growth and incremental releases (e.g., ASZED-500, ASZED-1000). That lowers the technical barrier for multi-site collaborations and for crowdsourcing annotation tasks such as automatic artefact labelling.
- Enables robustness checks across real-world hardware heterogeneity: Recordings were made on both Contec KT-2400 (200 Hz) and BrainMaster Discovery24-E (256 Hz) systems, covering the most common clinic-grade devices available in West and Southern Africa. Method developers can explicitly test how sampling rate, amplifier noise floor and impedance tolerance influence feature stability.

2. Background

Schizophrenia (SZ) diagnosis still hinges on overt psychosis and subjective clinical judgement [4], a situation complicated by heterogeneous symptom clusters [5,6]. To achieve earlier and more objective detection, researchers increasingly deploy machine-learning analyses of electroencephalography (EEG), whose low cost and millisecond resolution make it more accessible and scalable than other neuroimaging modalities [7–9]. Deep-learning classifiers already differentiate schizophrenia (SZ) from controls with encouraging accuracy [10], particularly when combined with feature engineering techniques that adequately capture the underlying non-linear dynamics such as those based on Lyapunov-exponent analysis [11,12]. Furthermore, decades of work have mapped frequency and event-related potential anomalies in SZ [13–15]. Yet almost all public SZ-EEG datasets originate in Europe, North America or East Asia [16–19], while audits of psychophysiology databases and even EEG cap design confirm that people of African descent remain drastically under-represented [1,2,20–23].

This under-representation is not just an equity problem, but one with likely clinical implications. Ancestry shapes brain signals. For example, low-voltage-alpha resting EEG, which can mask oscillatory biomarkers, has been shown to be two- to three-fold more prevalent in African-American young adults than in European cohorts [3], and delta/alpha power ratios that separated SZ from bipolar disorder in a South-African sample were non-discriminative in earlier non-African studies [24]. Because African genomes harbor the greatest human genetic diversity, they are likely to encode electrophysiological variants still invisible in current datasets [1]. Collecting and sharing high-quality EEG from indigenous African participants is therefore essential both to build diagnostic models that generalize globally and to discover novel SZ biomarkers. The African Schizophrenia EEG Dataset (ASZED) directly addresses this gap by providing the first expandable, pan-African resource.

3. Data Description

Given the significance of addressing the under-representation of African populations in schizophrenia EEG studies, ASZED was intentionally structured for continuous expansion. Version naming conventions explicitly reflect the number of subjects included, such as ASZED-153

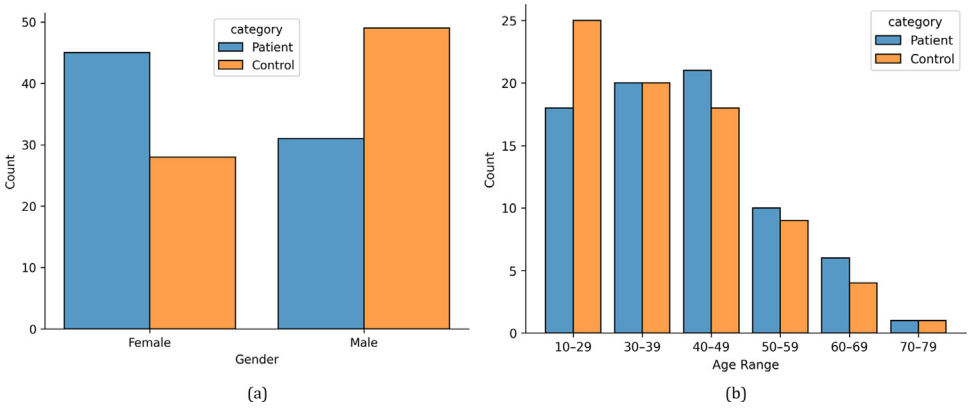

Fig. 1. Distribution of Participant Demographics. (a) Gender distribution across study groups and (b) Age distribution of the cohort.

for the initial dataset comprising 153 participants. While the current dataset originates solely from Southwest Nigeria, future updates will incorporate recordings from across the African continent. Researchers from other regions are encouraged to contribute additional data, leveraging this infrastructure to foster collaborative growth.

ASZED-153 consists of EEG recordings from 76 patients (Age: 40 ± 12; 45 Females, 31 Males) diagnosed with schizophrenia through Mini International Schizophrenia Interview (MINI), Positive and Negative Symptoms Scale (PANSS), and World Health Organization Disability Assessment Schedule (WHODAS) clinical instruments. It also consists of 77 controls (Age: 38 ± 13; 28 Females, 49 Males). Fig. 1 shows the gender and age distribution of participants. The dataset sources for both patient and controls from southwest Nigeria, making use of active cases in the mental health units of Obafemi Awolowo University Teaching Hospital Complex (OAUTHC) as patients, while selecting hospital workers without family history mental disorder as healthy controls. More details about the acquisition are presented in the Experimental Design section, while the rest of this section will focus on the structure of the dataset.

The European Data Format (.EDF) has been adopted for saving all EEG recordings. This choice of an open format was made with future expansion and interoperability in mind. Data in the dataset are stored in a tree directory structure as shown in Fig. 2. The primary motivation for this structure, and why this section will articulate it in some detail, is the imperative for future expansion of the dataset. This structure would make it possible to treat future contributions to the dataset as part of a cohesive whole even if there are differences in protocols, annotation schemes, and recording devices across multiple sites.

The ASZED database, illustrated in the hierarchical diagram (Fig. 2), is organized as a collection of major version folders. Within these, node folders represent data collection sites. Each node contains subset folders, where recordings share the same device, acquisition protocol, and annotation scheme. Both major and minor version changes occur at the same level in the tree, with node folders being subdirectories of minor version folders, as depicted in the leftmost branch of Fig. 2. Generic (.GNR) and text (.TXT) files at different levels provide structured metadata:

- TXT files of major version and node folder: major folder contain a TXT file describing the recording sites of nodes within the major version. Node folders also contain a TXT file describing the EEG recording device for each subset folder within the node.
- Subject folder .GNR files: Contain non-identifying demographic information and inherited parent-folder metadata.
- Session folder .GNR files: Detail recording durations in minutes and inherited protocol information.

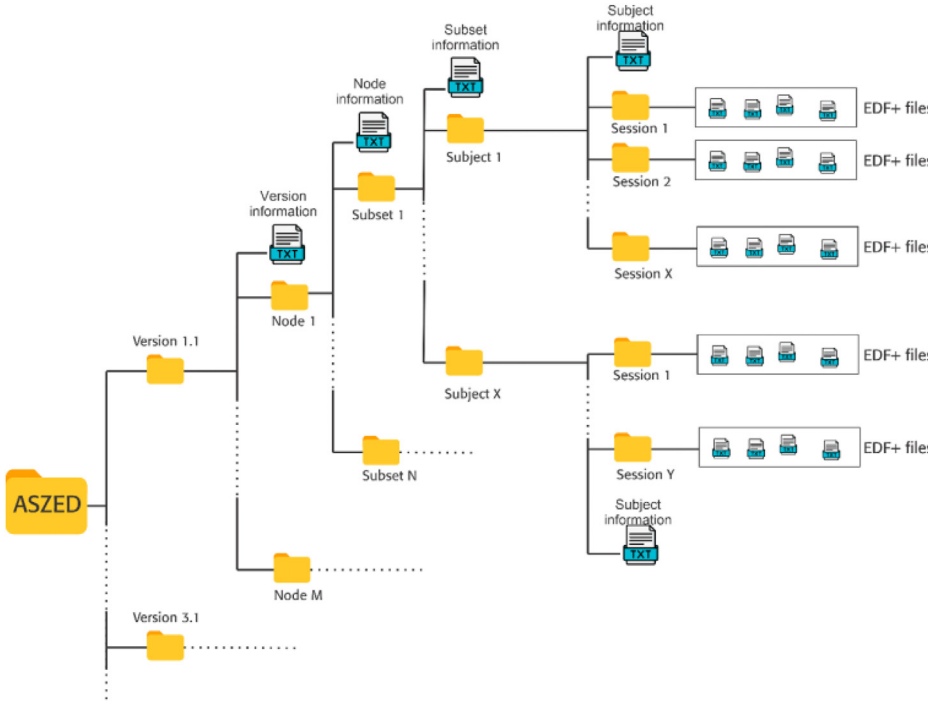

Fig. 2. ASZED database structure.

The root directory of the database, on the same level as the ASZED folder as shown in Fig. 2, contains a Keymap (.KMP) file mapping. This ensures each recording site (node) and recording device (subset) have a unique identifier. The content of the keymap file is listed below:

- Node numbers mapped to collection sites
- EEG device identifier
- Protocol numbers mapped to descriptions
- Annotation scheme numbers mapped to descriptions

The root directory contains a spreadsheet of non-identifying demographic information for its participants. Version numbers can be based on the folder structure or subject count. Using the folder structure, version numbers follow the format A.B.C.D, indicating:

A: Major version number
B: Minor version number
C: Node number
D: Subset folder number

Subsequent versions replicate data from the most recent version and add new data appropriately following the database structure. For example, "version_1.3" will initially contain the exact contents of "version_1.2", then add new node, subset, subject or session folders as defined by the metadata of newly acquired data.

Given the plan to keep increasing the dataset, the full name of various versions of the dataset will include the number of total subjects as a suffix. For example, the current version is AZSED-153 which consists of version_1.1. Subsequent versions containing version_1.1 and more will be referred to according to the total number of subjects in such versions. Users may refer to structured versions or full (subject count) versions depending on the specific data subsets they are using. ASZED-153 is available on Zenodo [25].

4. Experimental Design, Materials and Methods

4.1. Participants for ASZED-153

Prior to participation, all candidates underwent screening to ensure compliance with inclusion and exclusion criteria. Participants were required to be of legal age with capacity to provide informed consent. For patients with severe symptoms, participation required the presence of a legal guardian who could confirm age, medical history, and provide legal consent. Individuals with a history of drug abuse were excluded from participation. All subjects underwent clinical evaluation using three standardized instruments: the Mini International Schizophrenia Interview (MINI), Positive and Negative Symptoms Scale (PANSS), and World Health Organization Disability Assessment Schedule (WHODAS). For healthy controls, an additional exclusion criterion was any family history of mental disorders. To ensure optimal EEG recording quality, participants were instructed not to apply hair products within 24 hours of their scheduled recording session.

Data collection took place across two sites: Obafemi Awolowo University Teaching Hospital College (Ile-Ife) and its medical outpost Wesley Guild Unit (Ilesa) in Osun State, recruiting 153 participants (77 controls, 76 patients). All experimental procedures received approval from the Obafemi Awolowo University Teaching Hospital College Ethics Committee.

4.2. Recording devices, electrode sites and cohorts

EEG recordings utilized two systems: the Contec-KT2400 operating at 200 Hz with integrated notch filtering for power line noise, and the BrainMaster Discovery24-E sampling at 256 Hz. Data collection occurred in two cohorts, corresponding to the two recording systems. Both systems used identical electrode placements following the standard 10–20 system at sixteen sites: Fp1, Fp2, F3, F4, F7, F8, C3, C4, Cz, T3, T4, T5, T6, P3, P4, and Pz.

Minimal preprocessing was carried out on the data before saving them, in order to keep them as pristine as possible, so they can accommodate the widest range of future applications by researchers. Data acquired with the Contec-KT2400 applied hardware configured 50 Hz notch filter and a bandpass filter of 0–100 Hz, while data acquired with the BrainMaster Discovery24-E are saved without any filtering while ensuring data-quality through z-scores during acquisition. No further processing has been done on the data. Future researchers are, therefore, free to carry out any additional preprocessing that is suitable for their particular needs. This includes, for example, resampling to bring the data from both devices in ASZED-153 to the same effective sampling rate. Moreso, the file organization system also acts to ensure that data from different devices are placed in different folders, so thoughts and methods on reconciling the two recordings could be more open-ended.

4.3. Experimental procedure

Data acquisition was managed through GENERIS, a custom-developed software platform available upon request. GENERIS implemented the acquisition protocols, managed annotation schemes, controlled EEG recording devices, and stored data in EDF format. The software enabled precise control over recording phase durations and synchronized stimulus presentation with EEG recording. GENERIS is not being publicly released but will be made available on request to all future intending contributions to the ASZED dataset.

Two acquisition protocols were implemented, as detailed in Table 1. Protocol P1.1 comprised four phases: two resting states (simulated sleep), a cognitive (arithmetic) task, and an auditory oddball task. Protocol P1.2 extended this with an additional 40 Hz auditory steady-state response (ASSR) phase. Participants attention was managed through a random video partici-

Table 1
Data acquisition protocols.

Phase	Protocol P1.1	Protocol P1.2
1	Rest 1	Rest
2	Arithmetic task	Fixed Auditory Stimulus
3	Rest 2	Arithmetic Task
4	Auditory Oddball Task	Rest 2
5	Nil	Auditory Oddball Task

Table 2
Cue and instruction delivery methods.

Phase	Protocol 1.1	Protocol 1.2
1	Verbal & Visual Instructions	Verbal & Visual Instructions
2	Synchronization scheme one	Verbal Instructions
3	Verbal & Visual Instructions	Synchronization scheme two
4	Verbal & Visual Instructions	Verbal & Visual Instructions
5	nil	Verbal & Visual Instructions

pants were required to watch while acquisition, cues and stimuli presentation went on; the random video was not required during cognitive tasks which employed both visual and auditory cues.

During arithmetic task, participants associated numbers with letters and performed calculations based on these associations within sentences. Cognitive task lasted between 10 s and 60 s based on participant ability. Two annotation schemes were implemented for the arithmetic task recordings, designated as ats_1.1 and ats_1.2. The first scheme either provided no specific task annotations or marked the start of the first subtask or end of the entire task phase, while the second documented the beginning and end of each subtask. Table 2 outlines the cue and instruction delivery methods for each protocol phase. All verbal instructions were pre-recorded and delivered through the same headset used for auditory stimuli.

The auditory oddball task elicited mismatch negativity (MMN) through random presentation of deviant tones (1KHz, 250 ms duration deviant; 3KHz, 100 ms frequency deviant) within a stream of standard tones (1KHz, 100 ms), maintaining an 80:10:10 ratio of standard to deviant tones. Auditory oddball task lasted for 7 s to 60 s. The auditory oddball task was selected to probe selective attention, a function of sensory memory often impaired or dissociated in schizophrenics.

The ASSR phase presented a 40 Hz repetitive tone which lasted for 1 s while participants listened to an unrelated audio clip to maintain attention. ASSR phase lasted for 7 s with ASSR stimulation presented twice. The 40 Hz stimulation eliciting ASSR was selected to probe perceptual awareness which is associated with hallucinations.

Recording sessions typically continued through all protocol phases, with participants taking mandatory non-recorded 10-minute breaks between sessions. Additional rest periods were provided as needed, with subsequent phases beginning only after participant readiness was confirmed. Resting state recordings lasted for 5 s to 10 s after ensuring patients went into a state of simulated sleep.

4.4. EEG dataset

All EEG data are preserved in their raw form and stored in EDF format without preprocessing; this is done to allow for independent analysis by users of the dataset. To maintain participant confidentiality, all identifying information has been removed from the EDF files while preserving essential recording parameters and event markers.

Limitations

- A key limitation of this study is the geographical scope of the **initial data cohort**. All participants were recruited from two affiliated medical centers located within a single region of southwestern Nigeria (OAUTHC, Ile-Ife and the Wesley Guild Medical Outpost, Ilesa). Consequently, the current sample primarily reflects the genetic and environmental diversity of this specific region. As the dataset expands with contributions from other African nodes, its diversity is expected to increase, which will enhance the broader generalizability of future findings.

Technical aspects to note:

- Data collection utilized two EEG systems (200 Hz and 256 Hz sampling rates) without resampling to match data; subset folders differentiate data collected with different recording device or acquisition parameters.
- Initial versions implemented different annotation schemes for cognitive tasks.
- The dataset size (153 participants) represents the first phase of an ongoing data collection effort, with plans for expanded geographic coverage and increased participant numbers ongoing as at time of publication of this article.

Ethics Statement

All EEG recording of participants was carried out in accordance with the Declaration of Helsinki. All participants volunteered, read and signed written informed consent. In case of participants with impairments, legal guardians read and signed written informed consent. The data collection process was approved by the Obafemi Awolowo University Teaching Hospital College Ethics Committee.

Data Availability

ASZED - The African Schizophrenia EEG Dataset (Original data) (Zenodo).

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Declaration of Competing Interests

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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