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Diversity in EEG: Why is it important?

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Electroencephalography (EEG)-based brain-computer interfaces (BCIs) are increasingly deployed across clinical and consumer contexts, yet the research foundations underpinning these systems reflect a profound lack of demographic diversity. Hardware limitations, particularly the inability of standard EEG electrode systems to achieve reliable scalp contact across curly, kinky, and afro-textured hair types, represent a concrete and under acknowledged barrier to inclusive data collection. We present findings from a mixed-methods survey of 31 EEG researchers and practitioners, finding that 74% reported hardware-related challenges with diverse hair types, with difficulties clustering at cap placement and preparation. Qualitative themes revealed patterns of signal degradation, extended setup burden, explicit participant exclusion, downstream data loss, and a systemic researcher knowledge gap. Existing hardware solutions only partially address this problem. We argue that electrode redesign capable of achieving reliable scalp contact across all hair types is a prerequisite for BCI systems that work equitably for all.

INTRODUCTION

Brain-computer interfaces (BCIs) represent a transformative technology that enables users to control external devices by decoding neural activity, bypassing the need for muscular involvement [1, 2]. Electroencephalography (EEG)-based BCIs have been widely adopted across applications ranging from motor rehabilitation for stroke and spinal cord injury patients to communication aids for individuals with locked-in syndrome [3], and increasingly into domains serving healthy users such as education, entertainment, and occupational settings [4]. As BCI technology matures and its market expands globally, a critical question emerges: for whom are these systems actually being developed and validated? A growing body of evidence from the broader neuroscience literature reveals that the research foundations upon which BCI systems are built suffer from a profound lack of diversity, a problem that threatens to undermine the efficacy, safety, and equitable deployment of BCI technologies for large segments of the global population.

The diversity crisis in neuroscience is well documented [5, 6]. The overwhelming majority of neuroscience research has been conducted with participants drawn from Western, Educated, Industrialised, Rich, and Democratic (WEIRD) societies [6, 7], with studies finding that 96% of cognitive psychology participants came from Western industrialised countries and 90% of neuroimaging studies were conducted in Western nations [8]. Even more troublingly, most studies fail to report basic demographic information about their participants: fewer than 4% of articles in leading cognitive neuroscience journals reported the race and ethnicity of their samples, with not a single EEG study in that review reporting racial demographics [9]. Where demographic data are reported such as the UK Biobank, the world's largest neuroimaging database, comprises approximately 95% white participants [10, 11], and a review of 20 global neuroscience clinical trials found that 85.6% of the participants were white [12]. An examination of the major publicly available BCI datasets that drive the current algorithm development reinforces this concern.

Existing motor imagery datasets, while representing important scientific contributions, consistently reflect a narrow pattern of participant recruitment. For instance, the OpenBMI dataset [1] includes 54 subjects drawn exclusively from Korea University, and a multi-day motor imagery dataset [2] comprises 62 healthy, right-handed university students aged 17–30 recruited from the World Robot Conference Contest in China. Similarly, a five-session motor imagery (MI) dataset [13] was recorded from 25 subjects at Shanghai University. The cross-dataset variability study by Xu et al. [14] further illustrates this trend by aggregating eight MI datasets, all obtained under controlled, single-site laboratory conditions. The multi-centre P300 study by Flores et al. [15], the BCI competitions [16], and the EEG foundation challenge by Aristimunha et al. [17] made explicit progress by combining datasets from different countries and hardware configurations. Across these efforts, participants are overwhelmingly drawn from single institutions within single countries, and while some datasets represent geographic diversity beyond Western contexts, none report racial, ethnic, or hair-type characteristics. This absence of demographic reporting makes it impossible to evaluate the representativeness of these datasets, reinforcing

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a broader pattern in the neuroscience literature in which homogeneity is not documented but also not challenged.

The consequences of this demographic homogeneity for BCI performance are substantial and multifaceted. At the most fundamental level, neural structure and function vary meaningfully across populations: race/ethnicity and socioeconomic status contribute to individual differences in episodic memory, attention, and emotion [5]. Cultural factors shape brain development, influencing everything from economic security and nutrition to daily routines, with documented differences in neural function across cultures for theory of mind, emotion regulation, and face perception [18]. Herbert et al. [4] highlight that language, a factor characterised by enormous global diversity, with over 6,500 languages spoken worldwide, is almost entirely unaddressed in BCI research, with most implementations restricted to a single language, primarily English. Given that bilingual individuals exhibit different functional brain organisation compared to monolinguals, including differences in cognitive functions directly relevant to BCI performance such as attention, memory, and imagery, the current monolingual and monocultural approach to BCI development represents a significant limitation [4].

Documented differences between racial and ethnic groups have been demonstrated in neuroscience. EEG studies have found that Black participants show decreased power in delta and beta bands during sleep, independent of socioeconomic factors [19]. While direct evidence in BCI contexts is limited, documented population-level differences in EEG characteristics suggest that assuming universal neural signatures across ethnicities is unwarranted. Lim et al. [20] have documented that Black/African American individuals are twice as likely, and Hispanic/Latino individuals 1.5 times as likely, to develop Alzheimer's disease compared to non-Hispanic white individuals. Critically, this is not merely a difference in prevalence, Black/African American and non-Hispanic white individuals exhibit opposite patterns of Default Mode Network resting-state connectivity in Alzheimer's disease, potentially demonstrating race-specific disease trajectories [21]. BCI-based diagnostic tools trained predominantly on white participants may therefore not only underperform but actively mischaracterise disease states in Black patients, precisely the population bearing the greatest disease burden.

Beyond specific clinical populations, demographic differences in neural characteristics have broader implications for BCI algorithms. Inter-subject variability is already recognised as one of the most significant challenges in the BCI field, independent of demographic diversity. Maswanganyi et al. [22] demonstrated that merging EEG signals acquired from different subjects resulted in significant declines in intention detection rate, with accuracy drops of up to 21% across sessions. Lee et al. [1] found that a lack of BCI response affected 53.7% of users in motor imagery paradigms, with large performance variations between both subjects and sessions. Shen et al. [23] showed that EEG variability poses a great challenge to affective BCI frameworks, with inter-subject emotion commonality reaching only 30–40% even under optimised conditions. If this variability is already problematic within demographically homogeneous samples, the challenge will be considerably amplified as BCI systems are deployed to genuinely diverse populations whose neural data may differ systematically from the training distributions.

The implications compound further as BCI research increasingly relies on transfer learning and deep learning approaches to overcome inter-subject variability. Xu et al. [14] demonstrated that deep learning models trained on one dataset are unable to generalise well to other datasets, with models becoming highly specialised to their training dataset structure. Xu et al. [24] further showed that cross-dataset variability, arising from differences in equipment, electrode configurations, and recording environments, significantly reduces the transfer performance of deep learning models. Han et al. [25] developed graph neural network frameworks specifically to address the challenge of heterogeneous electrode configurations across datasets, demonstrating that even technical differences between recording setups create substantial barriers to model generalisation. Critically, these studies identify both physiological variability (between subjects) and environmental variability (between recording setups) as sources of distribution shift [14]. When the training data underlying these algorithms systematically excludes certain populations, the models will not merely fail to generalise, they will embed and amplify existing biases. As Kam et al. [26] warn, AI models trained on unrepresentative data will inherit and amplify existing biases, a concern that extends directly to the machine learning classifiers at the heart of modern BCI systems.

The under-representation of diverse participants in EEG research is not incidental, it is structurally embedded in the hardware upon which data collection depends. Non-invasive BCI systems rely fundamentally on EEG signal acquisition, yet EEG electrode and cap hardware is not designed to work with the full range of human hair types [27]. Traditional electrode systems allow only approximately one centimetre of space between electrode and scalp, meaning that thick, voluminous, curly, and coily hair types (more common among individuals with African or Caribbean heritage) cannot be accommodated as shown in Figure 1 [7, 27, 28]. This phenotypic bias in instrumentation results in black participants being excluded from EEG research at substantially higher rates, with a review of 81 EEG papers finding that only five included Black participants and none confirmed whether their data survived quality checks [7]. When participants with thick or curly hair are successfully fitted, they face longer and more burdensome data collection sessions and higher rates of data exclusion during post-processing [27]. These systematic hardware barriers mean that the neural signatures, decoding algorithms, and normative baselines that underpin BCI systems have been derived

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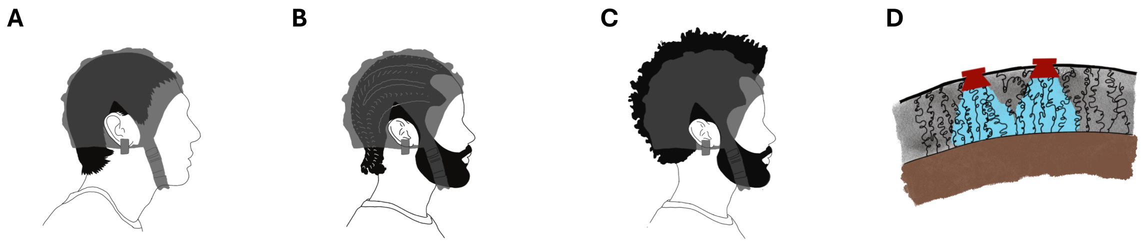

Figure 1: Image A is an example of an EEG cap fitting on a user with straight and thin hair, allowing minimal gel to obtain a signal. Image B demonstrates placing a cap on curly hair in a protective style, creating further distance from the scalp leading to bridging and excess gel as shown by image D. Image C is an example of curly and long hair, which would lead to the cap not fitting over the users head, leading to discomfort and further distance from the electrode and the scalp.

from an unrepresentative subset of the global population.

In this paper, we asked EEG researchers for their perspective on this phenotypic bias, if it impacts their research, and what they believe the solution is to better understand this systematic barrier. Further, we discuss previous solutions which address this hair bias and the pitfalls faced by these prototypes. Finally, we conclude with recommendations for the field of BCI to improve diversity in datasets, in turn improving outcomes for ethnicities that are often neglected in academic studies.

MATERIALS AND METHODS

A mixed-methods survey was designed to characterise the prevalence and nature of EEG hardware challenges encountered when recording from participants with curly, kinky, or afro-textured hair. The survey was distributed via LinkedIn, Discord, and WhatsApp within communities of EEG researchers and practitioners, and was open to individuals with any level of experience conducting or participating in EEG research. As the surveys were fully anonymous on non-sensitive topics, this study was considered minimal risk by UCL ethics and did not require ethical approval. A total of 31 respondents completed the survey, though not all respondents answered every question; response counts are reported per item where relevant. The survey comprised both closed-response items (yielding quantitative data on challenge prevalence, stage of occurrence, and appetite for solutions) and open-ended questions (capturing specific challenges, perceived causes, downstream research impacts, and suggested solutions). Qualitative responses were synthesised thematically to identify dominant patterns across the sample.

We acknowledge several limitations: the sample is self-selected and modest in size, respondents were not asked to report their own demographic characteristics or geographic location, and recruitment through research-adjacent online communities may over-represent individuals already sensitised to diversity concerns in EEG research. The survey findings should therefore be interpreted as practitioner-level qualitative evidence that complements the published literature, rather than as a representative epidemiological estimate of challenge prevalence across the field.

RESULTS

Respondent Profile: Respondents represented a broad range of EEG research contexts, including BCI paradigms (motor imagery, SSVEP, P300, speech decoding), clinical applications (stroke rehabilitation, neurodegenerative disease), and cognitive and developmental neuroscience. This breadth indicates that the hardware challenges described below are not confined to a single subfield but are distributed across the landscape of EEG research.

Prevelance of Hardware Challenges: Of the 31 respondents, 23 (74%) reported having experienced challenges when using EEG systems with participants who have curly, kinky, or afro-textured hair. This rate is consistent with the systematic exclusion patterns documented in the published literature and suggests that hardware-related barriers are a routine, rather than exceptional, feature of EEG data collection practice.

Stage of Challenge: Among those who reported challenges, difficulties were most frequently encountered during cap placement (n=24), preparation (n=19), recording (n=15), and post-session physical cleaning (n=6). The fact that challenges cluster at cap placement and preparation before any neural data has been collected underscores that the barrier is primarily one of hardware design rather than signal processing.

EEG Systems in Use: Respondents reported using a range of commercial EEG systems, with g.tec the most commonly used (n=9), followed by BioSemi (n=7), Brain Products (n=3), NeuroScan (n=3), EGI/Philips (n=2), and a further six respondents specifying other systems including Clarity and custom setups. The distribution of challenge reports across multiple major hardware platforms reinforces that the problem is not specific to any single manufacturer but reflects an industry-wide design norm.

Nature and Consequence of Hardware Challenges: Qualitative responses converged on five interrelated themes. The most consistently reported challenge was signal quality degradation. Respondents described persistently high impedances, elevated noise, and unreliable scalp contact arising from hair volume and density preventing electrodes from reaching the scalp. Several noted that standard remediation strategies - additional conduc-

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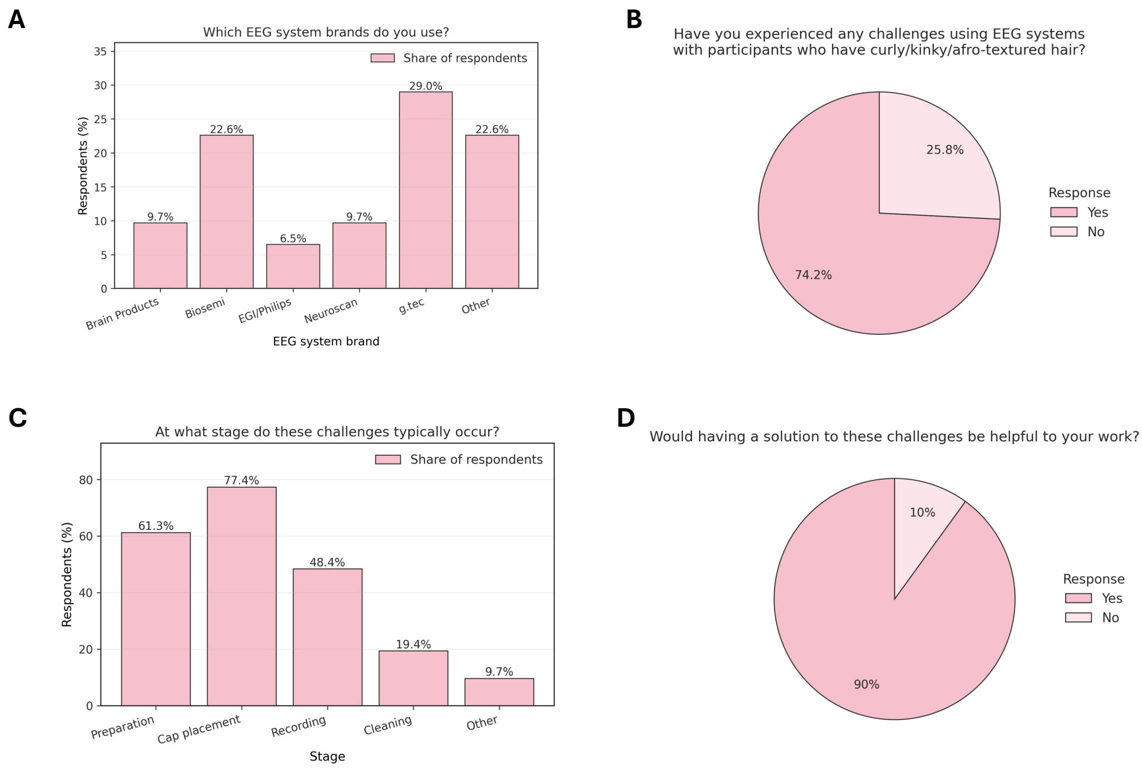

Figure 2: Bar and pie charts highlighting the quantatative results on (A) Users EEG system brand, (B) If users have experienced difficulties with participants hair types/styles, (C) At what stage were there difficulty with hair types/styles, and (D) Would a solution to these challenges be helpful

tive gel and repeated re-gelling - were less effective with curly hair than with straight hair, and one respondent noted that classification performance was markedly poorer for participants with curly or kinky hair compared to the rest of their sample.

The second theme was extended and burdensome setup. Respondents described substantially longer preparation times, with one noting an additional 30–40 minutes of capping time that still did not achieve full contact, and another describing a session in which scalp abrasion during electrode placement resulted in minor bleeding. Gel application was frequently characterised as difficult, with conductive gel failing to penetrate dense hair reliably and drying faster in thicker/curlier hair textures. Post-session gel removal was also identified as a significant burden for participants, with one respondent noting that gel residue persisted in their hair for days after the session.

Third, respondents described patterns of explicit participant exclusion. Several reported that protective hairstyles (braids, cornrows, locs) constituted de facto exclusion criteria in their labs, and that even participants with loose kinky hair required workarounds that were not always successful. One respondent noted they had never had a Black participant return for a follow-up session, pointing to the compounding effect of poor participant experience on longitudinal research and dataset diversity.

Fourth, the downstream consequence was data loss and analytical compromise: noisy data was discarded, preprocessing pipelines required stricter thresholds, and in some cases entire participant datasets were excluded post-hoc. These losses are commonly attributed to hardware in published methods sections, rendering the demographic skew in resulting datasets invisible.

Finally, respondents identified a researcher knowledge gap as a structural contributor to the problem. Multiple respondents noted that they had received no training in how to handle kinky and curly hair types, and one characterised systematic exclusion as a norm echoed by colleagues across institutions worldwide. This suggests that even where workarounds exist, they are not being disseminated effectively within the field.

Appetite for Hardware Solutions: Of the 30 respondents who answered the final closed question, 27 (90%) indicated that having a solution to these hardware challenges would be helpful to their work. Suggested approaches included hair-penetrating or pin-based electrodes, longer electrode stems to reach through dense hair, more flexible and stretchable cap designs, and electrode systems designed to function independently of hair type. The convergence of respondents on electrode redesign, rather than protocol modifications or participant preparation, as the preferred solution reinforces the framing of this problem as an engineering challenge requiring novel hardware solutions.

DISCUSSION

From our findings, as shown from Figure 2, we can

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acknowledge the 74% of researchers mentioning challenges with EEG setup for thick and curly hair mimics the exclusion patterns documented in the literature [7, 27]. The fact that the majority of challenges are faced during the cap placement and preparation highlights that non-inclusive EEG hardware is the leading factor for participant removal as opposed to participant or protocol problems. The qualitative responses of the survey demonstrated themes of high noise and impedance during recordings, leading to extended setup times. Once the data processing starts, researchers often identified data loss or artefacts, leading to removal of participants from the dataset. It was also mentioned that labs often listed hairstyles predominately used by Black demographics in their exclusion criteria.

The compounding exclusion pipeline in EEG research creates a cascade effect. Limitations in EEG hardware lead to participant exclusion or data removal. This in turn creates homogenous datasets for machine learning training and due to this bias in training data would lead to underperformance in the very populations excluded from their development. As there is clear evidence that physiological variability is a source of distribution shift and accuracy reduction in classifiers [14, 22] a systematic exclusion of specific ethnicities will lead to a lack of robustness and generalisability in BCI applications. This highlights that exclusion at the hardware stage does not remain isolated but propagates downstream and impacts all methods which use BCI datasets.

Even though this issue is still faced in both neuroscience and BCI research, meaningful progress has been made in literature. The Sevo electrode [29] is one example where the electrodes utilise braided hair as an anchor to maintain scalp contact. While Sevo electrodes are the most cited solution for interfacing with thick and curly hair, their reliance on braided styles introduces extended setup times and perpetrate the practitioner knowledge gap with diverse hair types. As a result, the implementation of these electrodes in academia does not fully address researcher's needs for an ideal solution: a system that functions for all hair types and styles, matches wet electrode impedance, and requires no hair preparation or modification.

The diversity deficit in BCI research is not merely an abstract concern about scientific rigour, it is an immediate and escalating barrier to the equitable deployment of a technology that has the potential to transform the lives of millions. BCI systems are moving beyond laboratory prototypes into clinical rehabilitation, assistive communication, smart home control, education, and entertainment [3, 4]. As these systems transition from controlled research settings to real-world deployment, they will encounter the full diversity of human populations: diversity in neural characteristics shaped by genetics, culture, and lived experience [5, 18], diversity in the languages users speak and the cultural frameworks through which they process information [4], and diversity in the physical characteristics that determine whether current EEG hardware can reliably acquire their brain signals at all [7, 27, 30].

If BCI technology replicates patterns of exclusion similar to the field of neuroscience, it risks not only producing inequitable outcomes but further deepening the distrust that already limits participation of under-represented groups in neuroscience research. Conversely, addressing diversity in BCI represents a uniquely actionable opportunity. Unlike many systemic barriers, the technical limitations of EEG hardware represent a clear engineering problem: developing electrodes that achieve reliable scalp contact across all hair types, without requiring participants to alter their hairstyles. Solving this would remove one of the most tangible sources of exclusion [7, 27, 30]. Coupled with systematic demographic reporting, diverse dataset development, and culturally informed BCI design, such innovations could establish an inclusive foundation for BCI systems that work reliably for all users.

This paper highlights the urgent need for BCI researchers to confront the diversity deficit in their field, whilst also analysing survey results that demonstrate the systematic barriers present in EEG hardware. By drawing on the extensive evidence of exclusion documented in broader neuroscience and translating these findings to the specific context of BCI applications, we argue that diversity is not a peripheral concern but a central challenge that will determine whether BCI technology fulfils its transformative potential for all of humanity.

CONCLUSION

The findings presented here confirm that EEG hardware limitations are a routine and systemic barrier to inclusive BCI research, not an edge case. The 74% challenge rate reported by practitioners, concentrated at the point of hardware-participant interaction, demonstrates that exclusion begins before a single neural signal is recorded. This exclusion propagates downstream: into homogeneous datasets, into algorithms that cannot generalise to the populations they are intended to serve, and ultimately into clinical and consumer BCI systems that will underperform for those with the greatest unmet neurological need. Existing electrode solutions represent meaningful but incomplete progress, and the field has not yet produced hardware that functions reliably across all hair types and styles while maintaining wet electrode signal quality. As BCI systems transition from laboratory settings to global deployment, the window to address this structural bias is narrowing. Electrode innovation is not a peripheral concern, it is a prerequisite for equitable BCI.

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