Activity-induced gene expression in the human brain

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Key findings

- Electrical stimulation of the human cortex allows the identification of an activity-dependent gene expression signature.

- Neurons and microglia in the human brain exhibit distinct transcriptional signatures following electrical stimulation.

- Single nuclear chromatin accessibility studies reveal cell-type-specific epigenomic changes and specific transcription factor motifs in microglia.

Abstract

Activity-induced gene expression underlies synaptic plasticity and brain function. Here, using molecular sequencing techniques, we define activity-dependent transcriptomic and epigenomic changes at the tissue and single-cell level in the human brain following direct electrical stimulation of the anterior temporal lobe in patients undergoing neurosurgery. Genes related to transcriptional regulation and microglia-specific cytokine activity displayed the greatest induction pattern, revealing a precise molecular signature of neuronal activation in the human brain.

Main

Activity-induced gene expression underlies the ability of the brain to learn and adapt to environmental stimuli. Dynamic changes in transcriptomic patterns are essential for cognition[1-3], affective processing[4], addiction[5], and the initiation of behaviors[6,7]. However, these experiments have been mostly conducted in rodents[8,9] and human induced pluripotent stem cells[10], and it remains unknown how closely they reflect actual processes in the living human brain. Studies of activity-dependent gene expression in humans *in vivo* are lacking due to the availability and accessibility of tissue that can be acutely manipulated. Direct current electrical stimulation is used in the field of epilepsy surgery and could provide a major avenue to address this important challenge. Stimulation of the amygdala in epileptic patients enhances declarative memory[11], and closed-loop stimulation of the lateral temporal cortex rescues intervals of poor memory encoding[12]. Moreover, electrical stimulation is an effective, therapeutic tool to improve memory[12] and depression[13]. Here, we applied direct electrical stimulation of the anterior temporal lobe of patients undergoing neurosurgery to examine activity-dependent changes in gene expression and chromatin accessibility in the human brain for the first time.

We recruited 8 adult neurosurgical patients undergoing surgical resection of seizure foci following clinical monitoring to treat epilepsy. The patients underwent an anterior temporal lobectomy, during which samples were resected from the neocortex and processed immediately after removal. The participants were evenly distributed between two experimental paradigms. For the first group (stimulated paradigm, n=4 subjects), a

sample was at baseline and then an adjacent region of cortex was stimulated using

bipolar electrical stimulation (50 Hz). Thirty minutes later, a sample was taken from the

stimulated region **(Fig. 1a; Extended Data Fig. 1, Supplementary Table 1)** In the

second group (unstimulated paradigm, n=4 subjects), a sample was taken at baseline

and then 30 min later a second sample was taken without stimulation **(Fig. 1b;**

Extended Data Fig. 1). Tissue was subjected to whole-transcriptome RNA sequencing

(RNA-seq) to identify activity-induced genes following electrical stimulation. RNA-seq

analysis from the stimulated and baseline samples revealed 124 significantly

differentially expressed genes induced by electrical stimulation, with 112 up-regulated

and 12 down-regulated **(Fig. 1c**; FDR<0.05, log2fold change>0.2; **Supplementary**

Table 2). Among the up-regulated genes, we observed induced expression of *NPAS4*,

FOS, and *NR4A1*, as well as cytokine-related genes *CCL3, CCL4, OSM,* and *RGS1.*

Notably, these genes were not significantly enriched for previously identified genes

induced in regions showing seizure activity in the human brain **(Extended Data Fig. 2)**

[14]. Enrichment network analysis was used to identify the pathways most represented

among the 124 differentially expressed genes in the stimulation paradigm. The

pathways include transcription at RNA polymerase II promoter, positive regulation of

DNA-dependent transcription, cytokine activity, chemokine activity, and cytokine

receptor binding **(Extended Data Fig. 3)**. Additional protein-protein interaction (PPI)

analysis of the stimulated samples revealed two significant clusters enriched with genes

involved in DNA-binding transcription activator activity (RNA Pol II) and cytokine activity

(Fig. 1d). RNA-seq analysis comparing unstimulated samples with baseline identified

differential expression of only 16 genes, with 9 up-regulated and 7 down-regulated

genes; only NR4A3 overlapped between stimulated and unstimulated groups **(Fig. 1e,**

Supplementary Table 3). The lack of extensive overlap between the differentially

expressed genes observed in our unstimulated and stimulated groups suggests that the

selective changes in gene expression that we see following electrical stimulation do not

reflect disease state or surgical conditions such as craniotomy, brain temperature, and

anesthesia, but reflect stimulation-induced changes. To investigate if these gene

expression changes are unique to human samples and to further determine if they are

related to disease state[14,15], we used a similar electrical stimulation paradigm in mouse

non-primary auditory cortex and observed the upregulation of genes associated with

DNA-binding transcription factor activity (*Fos*, *Fosb*, and *Egr2*) and cytokine activity

(*Ccl3* and *Ccl4*) (**Extended Data Fig. 4**). Thus, our findings of activity-dependent genes

in response to electrical stimulation in the human brain reveal a molecular signature that

is conserved across species.

Next, we investigated the cell types exhibiting differential gene expression following

electrical stimulation in the human brain by single nuclei multiomics (RNA and ATAC) on

samples from the stimulated paradigm (**Fig 2a**). We sequenced 18,342 nuclei and

detected 46,849 unique molecular identifiers and 2,133 median genes per nucleus

(**Extended Data Fig. 5a**). Cell clustering analysis identified 7 major cell types in our

samples (**Fig. 2b, c**). Importantly, the distribution and proportion of cell types was

consistent across baseline and stimulated conditions (**Extended Data Fig. 5b**). We

identified differentially expressed genes following electrical stimulation for the following

cell types—excitatory neurons, microglia, vip-Sncg-Lamp5 inhibitory neurons, pvalb-Sst

inhibitory neurons, oligodendrocytes, oligodendrocytes precursor cells (OPC), and

astrocytes (**Fig. 2d-f, Supplementary Table 4**). Microglia displayed the highest

differential gene expression of all cell types with 306 up- and 296 down-regulated genes

(**Fig. 2d**). Genes related to cytokine activity (*CCL3*, *CCL4*, *IL1B*, *CCL2*, *IL1A*, *OSM* and

RGS1) were upregulated exclusively within microglia (**Fig. 2e; Extended Data Fig. 6a**).

In contrast, genes related to DNA-binding transcription activity (*FOS*, *EGR1*, *JUNB,* and

EGR3) were upregulated in neurons and microglia, whereas *NPAS4* and *EGR4* were

exclusively upregulated within excitatory and inhibitory neurons (**Fig. 2f, Extended Data**

Fig. 6b). Gene expression changes from microglia in the single nuclei multiomic

experiment significantly correlated with the bulk RNA-seq (**Fig. 2g, Extended Data Fig.**

7-9). Interestingly, among the upregulated genes identified in bulk RNA-seq, we

discovered that 37 were upregulated in microglia. These results reveal that electrical

stimulation activates gene expression involved in transcriptional regulation in multiple

cell types and selectively activates genes involved in cytokine activity in microglia.

To investigate this cell-type-specific molecular signature further, we assessed chromatin

accessibility for activity-induced genes using single nuclear assay for transposase-

accessible chromatin with sequencing (snATAC-seq)[16] on human samples from the

stimulated paradigm. We found enriched promoter accessibility for 21 genes in

microglia that exhibited upregulated gene expression in the bulk RNA seq and

snRNAseq data (**Fig. 3a-b, Supplementary Table 5**), showing upregulation of

transcription factors *FOS*, *NR4A1*, *NR4A2*, and *NR4A3* and cytokine-related genes

CCL4, CCL4L2 and *OSM.* Next, we performed transcription factor motif analysis using

the sn-ATAC seq data from microglia and found an enrichment of binding motifs for

SPIC, KLF6, SPI1, HOXB13, REL, and CREB1 (**Fig. 3c**). Notably, CREB, a master

regulator of activity-induced genes has been previously shown to be activated in

microglia[17]. pREL/NF-kB is a critical regulator of proinflammatory gene expression[18],

including genes encoding cytokines *IL1A* and *IL1B*, which were upregulated in our

snRNA-seq data (**Fig. 2d**). SPI1 is a central transcription factor essential for microglia

development and activation[19], and we found specific enrichment of SPI1 on the

promotor region for *CCL4* only in microglia, consistent with our snRNA-seq data (**Fig.**

3d). Within neuronal populations, the promoter region for *NPAS4* exhibited increased

accessibility in excitatory and inhibitory neurons in a region bound by CBP (**Fig. 3e**), a

transcriptional coactivator and lysine acetyltransferase that promotes the expression of

activity-induced genes[20]. Thus, our sn-ATAC-seq reveals a signature of transcription

factor motifs and chromatin accessibility to regulate activity-dependent gene expression

in specific cell types in response to electrical stimulation.

This work is the first to define activity-induced gene expression in the human brain,

revealing that electrical stimulation induces a distinct transcriptomic and epigenomic

signature in specific cell types in the human brain. Genes related to DNA-binding

transcription factor activity and cytokine signaling within microglia showed the greatest

induction pattern, and this was conserved across species. We observed the

hypothesized induction of the "classic" activity-dependent genes in neurons, but to our

surprise, our single nuclei multiomics experiments revealed pronounced microglia-

specific transcriptomic activation following electrical stimulation. The key observation of

an upregulation of the microglial response to electrical activation supports a paradigm

shift in interpreting the transcriptomic activation pattern following neural stimulation.

Microglia are critical modulators of neuronal activity, acting to suppress excessive

activity by inhibiting surrounding neurons, including excitatory neurons[21]. Researchers

have correlated human brain transcriptomics with prior recorded oscillatory signatures

of memory consolidation in human subjects [22,23], but this prior work did not identify

changes in gene expression driven by activity and they did not observe microglial-

specific changes. This identification of a microglial transcriptomic response following

electrical stimulation presents an important conceptual advance in our understanding of

activity-dependent gene expression in the human brain.

Our analyses identified critical molecular components that drive activity-dependent

changes in the function of brain circuits. Within neuronal cell types, the highest fold

change was observed for the *NPAS4*, which encodes a master transcriptional regulator

of learning-induced genes and is critical for memory consolidation[24]. Within microglia,

we identified the induction of cytokine-related genes including *CCL4*, which mediates

intracellular chemokine signaling, altering microglial process extension and motility,

influencing neuronal-microglial interactions, and shaping neuronal connectivity [21,25-27].

These mechanisms enable microglia to respond to neuronal activation and sculpt circuit

function. Our study of chromatin accessibility defines a cell-type-specific signature of

transcription factors driving these processes. Thus, our findings reveal distinct cell-type

specific mechanisms of activity-dependent changes in brain function, laying the

groundwork for future studies to link human brain transcription to closed-loop stimulation

and natural experience.

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Author contributions:

S.C., M.A.H. and T.A. conceived the project, designed the experiments, and interpreted

the data and wrote the manuscript with inputs from all the authors. H.K. performed human

surgery, electrical stimulation, and resected the tissue. A.E.R .and C.K.K. processed with

IRB and MRI imaging registration. H.O, M.A.H, T.N-J, K.V.L provided advise on surgical

procedure and electrical stimulation. M.M.H provided pathological assessment. L.C.L.,

K.V.N., and B.J.P. collected the tissue and images during resection. B.J.P., S.C. and

L.C.L. generated the bulk RNA, single nuclei multiomics (RNA+ATAC) data. Y.V.

performed the bioinformatics analysis with inputs from E.B. and J.J.M. S.A.H. performed

the mouse surgery and electrical stimulation experiments. K.V.N, C.K.K, Z.K. Y.K, C.I.P,

M.H, J.J.M, E.B, U.M, and T.N.J. provided input on data analysis and interpretation. C.I.P.

and L.L. helped with manuscript writing. All authors discussed the results and commented

on the manuscript.

Competing interests

T.A. is a scientific advisor to Aditum Bio and Radius Health and he serves on the

scientific advisory board of Embark Neuro. T.A serves on the Scientific Advisory Board

of EmbarkNeuro and is a scientific advisor to Aditum Bio and Radius Health. The other

authors declare no conflicting interests.

Figure legends

Figure 1. **Stimulation alone induces gene expression changes in cytokine activity**

and DNA-binding transcription factor activity. **a,b**. Schematics of stimulated (**a**) and

unstimulated (**b**) paradigms in the human anterior temporal lobe. For both paradigms

sample A was taken at T = 0 minutes then an adjacent sample B was taken at either T =

30 minutes after stimulation (**a**, stimulated paradigm, n=4 subjects) or T = 30 minutes

after sample A was taken (**b**, unstimulated paradigm, n=4 subjects). **c.** Volcano plots

showing gene expression changes in the stimulated paradigm. The most significant

genes (FDR < 0.05) are labeled in red (upregulated) or in blue (downregulated). **d.**

STRING network of significantly affected genes from the stimulated paradigm showing a

cytokine activity network in teal and a DNA-binding transcription factor activity network

in green. The gene labels are colored based on the directionality of gene expression

changes (blue = downregulated, red = upregulated). **e**. Volcano plots showing gene

expression changes in the unstimulated paradigm. The most significant genes (FDR <

0.05) are labeled in red (upregulated) or in blue (downregulated).

Figure 2. Cell-type specific gene expression changes following electrical

stimulation in human brain. a-c. Our multiomic approach (**a**) leads to the identification

of specific cell-types (**b**) validated by the expression of specific biomarkers (**c**) using the

RNA part of the assay. **d**. Heat map showing cell type specific expression of genes that

were found to be differentially expressed in the bulk RNA seq. The fold-change of each

gene is represented from blue (down-regulated) to red (up-regulated). **e,f.** Violin plots

showing gene expression changes of CCL3, CCL4, NPAS4 and EGR4 in each cell-type

for baseline (blue) and stimulated (red) conditions. A gene is either significantly

upregulated (FDR number in red above the plot) or not significant (N.S. above the plot).

g. Quadrant plot comparing gene expression changes (log10(FDR)*log2fold-change)

between our bulk RNA-seq experiment (x-axis) and our multiomic snRNA-seq (y-axis)

after stimulation. Genes in red in the top-right corner of the plot are significantly

upregulated in both experiments. FDR thresholds of 0.05 are represented by dotted

lines. The dashed line represents the linear regression applied to this quadrant plot. The

R-squared value and its Pearson score statistic of the linear regression is displayed in

the top right corner of the plot. The doted lines represent the FDR < 0.05 threshold.

Most significant genes affected are labeled.

Figure 3. **Differential transcription start site accessibility correlates with gene**

expression changes after simulation. **a**. Volcano plot showing differential transcription

start site accessibility in microglia after stimulation. A gene is labeled if its gene

expression and transcription start site accessibility are significantly increased after

stimulation in both bulk RNA-seq and snATAC-seq respectively. **b**. Quadrant plot

comparing changes (log10(FDR)*log2fold-change) between gene expression of the

RNA assay (x-axis) and transcription start site accessibility (y-axis) in the microglia

cluster after stimulation. Genes in red in the top-right corner of the plot are significantly

upregulated in both experiments. FDR thresholds of 0.05 are represented by dotted

lines. The dashed line represents the linear regression applied to this quadrant plot. The

R-squared value and its Pearson score statistic of the linear regression is displayed in

the top right corner of the plot. The doted lines represent the FDR < 0.05 threshold.

Most significant genes affected are labeled. **c**. DNA motifs that are overrepresented in a

set of peaks that are differentially accessible in microglia after stimulation. Motifs are

ranked based on significance from the most significant left to right. **d-e**. Coverage plot

for CCL4 **(d)** and NPAS4 **(e)** from our multiomic experiment. Each track represents

normalized chromatin accessibility signal from the ATAC assay for each cell-type and

each condition (baseline or stimulated). At the end of each track there is a violin plot

showing gene expression changes of the gene from the RNA assay (**** = FDR <

0.0001). Chip-seq datasets of SPI1 from Human Fujioka acute myeloid leukaemia cells

[28] and CBP from human macrophages [29] are represented in the bigwig track. Genome

annotation is represented under the "Genes" track with blue rectangles representing

exons and an arrow showing the direction of transcription. Individual peak computed

from the peak calling is represented under the "Peak" by a grey rectangle. Each peak

that may regulate the gene is linked to its transcription start site by blue arcs under the

"Links" track. Genomic location and scale are located at the bottom of the plot.

Materials and Methods:

Subjects: The study subjects were 8 adult neurosurgical patients (6 female, 2 male, age

19-63 years old, median age 41 years old) with medically refractory epilepsy. The patients

were undergoing surgical resection of seizure foci following non-invasive video

electroencephalography (EEG) or invasive iEEG monitoring. All subjects were diagnosed

with intractable epilepsy. Additionally, Subject L472 had a cavernoma and Subject L475

had a dysembryoplastic neuroepithelial tumor. All subjects except #6 were non-smokers.

Subjects' age, sex, surgery, and awake or sedative information were recorded (**Extended**

Data Table 1). All subjects were native English speakers, 7 were right-handed, 1 was left-

handed, and all had left language dominance as determined by Wada tests. All subjects

underwent audiometric evaluation before the study, and none were found to have hearing

deficits or word recognition scores deemed sufficient to affect the findings presented in

this study. The vision was self-reported as normal or corrected to normal with glasses or

contact lenses. As determined by standard neuropsychological assessments, cognitive

function was in the average range in all subjects. Research protocols were approved by

the University of Iowa Institutional Review Board (IRB 201910791, 201911084) and the

National Institutes of Health, and written informed consent was obtained from all subjects.

Procedure: Surgery was performed under general anesthesia or monitored anesthetic

care. Standard craniotomy was performed by the same senior epilepsy surgeon in all

patients to reach the epilepsy focus, which involved the anterior and medial temporal lobe

in all patients except one who had a temporal encephalocele and surrounding

anterolateral temporal cortical focus. Cortical tissue from the anterior temporal lobe was

sampled for analysis. The experimental condition was defined by an electrical "stimulation

paradigm" and a control "no-stimulation paradigm". The location of the sampled tissue is

plotted on anatomic brain reconstructions **(Extended data fig 1).** All subjects underwent

resection surgery for epilepsy of various etiologies **(Extended data fig 1).** There were 4

subjects (1 iEEG and 3 EEG patients) who underwent the "stimulation paradigm" and 4

subjects (2 iEEG and 2 EEG patients) who underwent the "no-stimulation paradigm"

(Extended Data Table 5).

In the "stimulation paradigm", a baseline sample was obtained from the anterior temporal

cortex that would be included in the planned surgical resection. The area directly adjacent

to where the baseline sample was collected was stimulated with direct bipolar electric

stimulation (frequency 50 Hz, pulse duration of 0.2 ms, stimulation duration 2 min, voltage

10 V, a commonly used stimulation parameters for deep brain stimulation for example).

The stimulated area was then sampled after a period of 30 minutes to allow for gene

expression[30,31]. In the "no stimulation paradigm", no direct electric stimulation was

performed and the area directly adjacent to the baseline sample was collected 30 minutes

after initial baseline sampling.

After sampling they were immediately placed in a sterile container on dry ice. The average

weight of the baseline sample was 88.0 ± 33.2 mg (mean, standard deviation) and the

adjacent sample was 113.4 ± 62.7 mg. After the collection of all samples in this fashion,

they were weighed and transferred to a freezer at -80° C for storage until further testing.

Sample Localization to MNI space: All samples were from the same cortical region.

Intraoperative photos of the sample sites were obtained during the time of surgery. Using

subject matched preoperative T1 sequence MRI, the sample sites were mapped onto

their anatomic brain reconstructions **(Extended data fig. 1)**. They were also mapped onto

MNI space coordinates.

RNA extraction, library preparation, and sequencing: Total RNA was extracted from

sampled human brains using miRNeasy Mini Kit (Qiagen, CA, USA). The tissue

samples were homogenized in QIAzol (Qiagen, CA. USA) stainless steel beads

(Qiagen, CA, USA). Chloroform was then used for phase separation. RNA containing

an aqueous layer was further purified using the RNeasy MinElute spin column. RNA

was finally eluted in RNase-free water. RNA concentrations were estimated using a

Nanodrop (Thermo Fisher Scientific, MA, USA) and Qubit (Thermo Fisher Scientific,

MA, USA). RNA libraries were prepared at the Iowa Institute of Human Genetics (IIHG),

Genomics Division, using the Illumina Stranded Total RNA Prep, Ligation with Ribo-Zero

Plus (Illumina Inc., San Diego, CA). The KAPA Illumina Library Quantification Kit (KAPA

Biosystems, Wilmington, MA) was used to measure library concentrations. Pooled

libraries were sequenced on Illumina NovaSeq6000 sequencers with 150-bp paired-end

chemistry (Illumina) at the Iowa Institute of Human Genetics (IIHG) core.

Bulk RNA sequencing analysis: RNA-seq data were processed with the bcbio-nextgen

pipeline (https://github.com/bcbio/bcbio-nextgen, version 1.2.9). The pipeline uses

STAR[32] to align reads to the hg38 genome build (GENCODE release M10, Ensembl 89

annotation) and quantifies expression at the gene level with featureCounts [33]. All further

analyses were performed using R. For gene-level count data, the R package EDASeq

was used to account for sequencing depth (upper quartile normalization)[34]. Latent

sources of variation in expression levels were assessed and accounted for using RUVSeq

(RUVs mode using all features)[35]. Appropriate choice of the RUVSeq parameter k was

guided through inspection of principal components analysis (PCA) plots. Specifically, the

smallest value k was chosen where PCA plots demonstrated replicate sample clustering

in the first three principal components[36]. Differential expression analysis was conducted

using the edgeR package[37]. Codes to reproduce the RNA-seq differential gene

expression analysis are available at https://github.com/YannVRB/Human-brain-

stimulation.git.

All the transcriptomics data have been deposited in NCBI's Gene Expression Omnibus

and are accessible through GEO Series accession number GSE224952.

Downstream pathway analysis: Enrichment analysis of differentially expressed genes-

associated pathways and molecular functions from the stimulated and unstimulated RNA-

seq was performed with the Gene Ontology (GO–molecular function) databases. Only the

pathways with an adjusted p-value < 0.05 were considered as significant and displayed.

Data were visualized using NetworkAnalyst (www.networkanalyst.ca). The protein-protein

interactive network was constructed using STRING (version 11.5), which uses the

STRING database (http://string-db.org/). The PPI network was constructed to identify the

interactions between proteins encoded by differentially expressed genes (FDR<0.05)

based on experimental data. The differentially expressed genes names were pasted into

the "STRING protein query." Active interaction sources, including text mining,

experiments, databases, coexpression, neighborhood, gene fusion, and co-occurrence,

were applied, and high interaction score confidence (0.700) was selected to construct the

PPI network. Full network was constructed, where the edges indicate both functional and

physical protein associations. The network edges were constructed based on evidence,

where line color indicates the type of interaction evidence.

Single-nuclei multiomics (nuclei isolation, library preparation, sequencing): Nuclei

were isolated from brain tissue using the Chromium Nuclei Isolation Kit (10X Genomics).

Briefly, frozen tissue was dissociated with pestle in lysis buffer, passed through nuclei

isolation column and spun at 16,000 rcf for 20 sec at 4^0C. Flowthrough was vortexed and

spun at 500 rcf for 3 mins at 4^0C. Pellet was resuspended with debris removal buffer and

centrifuged at 700 rcf for 10 mins at 4^0C, nuclei resuspended in wash buffer and

centrifuged again at 500 rcf for 5 mins at 4^0C. Pellet was resuspended in resuspension

buffer and nuclei were counted using a hemocytometer. Nuclei were directly processed

for droplet capture for single cell multiome ATAC + gene expression using a chromium

controller (10X Genomics). Chromium Next GEM Single Cell Multiome ATAC + Gene v1

chemistry was used to create single nuclei ATAC and RNA libraries from the same cell.

Two baseline and two stimulated samples were used for independent replicates. Libraries

were sequenced on an Illumina Novaseq 6000 with a 150 bp paired end read setup.

Single-nuclei multiomic data processing and analysis:

Raw sequencing data were processed using the Cell Ranger ARC pipeline (v2.0.2) with

the cellranger-arc mm10 reference. Default parameters were used to align reads, count

unique fragments or transcripts, and filter high-quality nuclei. Individual HDF5 files for

each sample containing RNA counts and ATAC fragments per cell barcode were loaded

into Seurat (Read10X_h5) resulting in four Seurat objects, each containing both RNA and

ATAC assays. Nuclei with outliers ATAC and RNA QC metrics (<1,000 and >100,000

ATAC read counts, <1,000 and >25,000 RNA read counts, nucleosomal signal > 2, TSS

enrichment < 1, and percentage of mitochondrial reads > 20) were removed. To correctly

identify cell type-specific signature, the RNA assay was chosen because it leads to less

background noise for the expression of biomarkers.

To analyze the RNA part of the human brain stimulation multiomic data, gene counts were

normalized and log transformed (LogNormalize), and the top 2,000 most variable features

between   each   nuclei   were   identified   using   FindVariableFeatures

(selection.method = 'vst'). Features that are repeatedly variable across nuclei and

datasets were selected for integration (SelectIntegrationFeatures). We then identified

anchors (FindIntegrationAnchors), which took the list of 4 individual Seurat objects for

each sample as input and used these anchors to integrate the four datasets together

(IntegrateData). The following analyses were performed on the integrated Seurat object.

Linear dimensionality reduction was performed by principal component analysis (runPCA,

npcs = 25). A k-nearest-neighbors graph was constructed based on Euclidean distance in

PCA space and refined (FindNeighbors, npcs = 30), then nuclei were clustered using the

Louvain algorithm (FindClusters, resolution = 0.5). Clusters were visualized with UMAP

(runUMAP, dims = 30). Cell types were annotated by label transfer cell labels from an

existing human primary motor cortex reference dataset from the Allen Institute (doi:

10.1038/s41586-021-03465-8) (FindTransferAnchors and TransferData). Cell types

identification was validated by expression of specific biomarkers (Fig. 2c). Differentially

expressed genes (DEGs) in individual clusters between baseline and stimulated samples

were calculated (FindMarkers, test.use = 'wilcox', Padj < 0.05, logfc.threshold > |0.2|).

To analyze ATAC part of the human brain stimulation multiomic data, prior to integrating

the four Seurat object, the default assay was switched to ATAC, and peak calling was

performed. Since the set of peaks identified by Cellranger often merges distinct peaks

that are close together, creating a problem for motif enrichment analysis and peak-to-

gene linkage, we identified a more accurate set of peaks by calling peaks using MACS2

(CallPeaks) on all cells together. Peaks on nonstandard chromosomes and in genomic

blacklist regions were removed (keepStandardChromosomes and subsetByOverlaps).

Normalization was performed with a frequency-inverse document frequency

normalization which normalizes across cells and peaks (RunTFIDF). Then, a feature

selection was performed using all the peaks as input (FindTopFeatures). The dimensional

reduction was performed on the TF-IDF normalized matrix with the selected peaks using

a singular value decomposition (RunSVD). To mimic the open chromatin conformation of

a gene, a gene activity matrix was calculated using a window of 1000bp before and after

the transcription start site of each protein coding gene (GeneActivity). Differentially

accessible transcription start sites in individual clusters between baseline and stimulated

samples were calculated using a logistic regression framework (FindMarkers, test.use =

'LR', latent.vars = 'nCount_peaks', Padj < 0.05). Motif and transcription factor enrichment

analysis of transcription start sites gene activity for each cluster was performed using

FindMotifs. The top six enriched motifs in microglia cluster are shown in **Figure. 3c**.

Genomic locations of typical genes like CCL4 and NPAS4 were presented (CoveragePlot)

and includes chip-seq datasets (bigwig) of SPI1 from Human Fujioka acute myeloid

leukaemia cells [28] and CBP from human macrophages [29]. It also includes co-accessibility

between peaks and transcription start site of genes. Codes to reproduce the multiomic

data analysis are available at https://github.com/YannVRB/Human-brain-stimulation.git.

Animals: Adult male C57BL/6J mice were purchased from The Jackson Laboratory were

3 to 4 months of age during experiments. All mice had free access to food and water;

lights were maintained on a 12-hour light/12-hour dark cycle.

Mouse electrical stimulation: Stimulation experiments were performed in anesthetized

adult male C57BL6/J mice. Anesthesia was induced with 5% isoflurane by inhalation

and maintained at 1.8-2% for the duration of the experiment. The mouse was placed in

a stereotax (Kopf) and a midline incision was made and the skin retracted to expose the

temporal muscle bilaterally. The dorsal insertion of both temporal muscles was

removed, and the muscles retracted. A 2-3 mm craniotomy was made over area AuV

(centered at 2.9 mm posterior, 4.2 mm lateral, 2.8 mm ventral from Bregma based on

Paxinos atlas) bilaterally to expose the cortical surface and a small square of gel foam

soaked in ACSF was applied on top of the dura to prevent it from dehydrating. For each

mouse the side of electrical stimulation and sham stimulation were alternated, with the

sham side serving as the baseline control for gene expression profiling. Electrical

stimulation was delivered through a bipolar ball electrode constructed from two silver

wires in which the uninsulated tips were melted under a butane flame (1 mm tip size, 2

mm tip spacing). For both electrical and sham stimulations, the gel foam was removed

and the electrode was gently lowered to make contact with the cortical surface. For

electrical stimulation, a biphasic pulse train was then delivered for two minutes (8 mA,

50 Hz, 200 µs pulse width). For the sham stimulation no current was delivered but the

electrode was left in place for 2 minutes. Following electrical or sham stimulation the

electrode was slowly retracted, and the exposed dura was covered with gel foam.

Selection for hemisphere was performed randomly, which resulted in the order of

electrical and sham stimulation alternating from mouse to mouse. No more than 5

minutes elapsed between electrical or sham stimulation of both sides. After both sides

were stimulated (electrical or sham) the mouse was left in the stereotax under

anesthesia for 30 minutes before euthanasia and tissue collection. Tissue samples were

immediately stored at -80^0C in RNA later solution (Ambion).

RNA extraction, cDNA preparation and qPCRs from mouse auditory cortex: Tissue

samples were homogenized in Qiazol (Qiagen) using stainless steel beads (Qiagen).

Chloroform was added and centrifuged at 12,000g at room temperature for 15 min to

separate RNA in the aqueous phase. RNA was precipitated in ethanol and cleared using

RNeasy kit (Qiagen). RNA eluted in nuclease-free water was then treated with DNase

(Qiagen) at room temperature for 25 min to remove genomic DNA. RNA was further

precipitated in ethanol, sodium acetate (pH 5.2) and glycogen overnight at $-20°$C. RNA

was precipitated by centrifugation at 30,000g for 20 min, precipitate washed with 70%

ethanol and the dried RNA pellet was resuspended in nuclease-free water. RNA

concentration was measured using NanoDrop (Thermo Fisher Scientific). 1 µg of RNA

was used for complementary DNA (cDNA) preparation using the SuperScript IV First-

Strand Synthesis System (Ambion). Real-time reverse transcription polymerase chain

reactions (RT-PCRs) were performed on the QuantStudio 7 Flex Real-Time PCR System

(Applied Biosystems, Life Technologies). Data were normalized to housekeeping genes

(*Tubulin*, *Pgk1*, and *Actin*), and $2^{(-\Delta\Delta Ct)}$ method was used for gene expression analysis.

Statistics: For the qPCR analysis, the Wilcoxon matched pairs signed rank test and one

sample Wilcoxon test was performed.

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Figure 1

Figure 2

Figure 3