Nested oscillatory dynamics in cortical organoids model early human brain network development

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SUMMARY

Structural and transcriptional changes during early brain maturation follow fixed developmental programs defined by genetics. However, whether this is true for functional network activity remains unknown, primarily due to experimental inaccessibility of the initial stages of the living human brain. Here, we analyzed cortical organoids that spontaneously developed periodic and regular oscillatory network events that are dependent on glutamatergic and GABAergic signaling. These nested oscillations exhibit cross-frequency coupling, proposed to coordinate neuronal computation and communication. As evidence of potential network maturation, oscillatory activity subsequently transitioned to more spatiotemporally irregular patterns, capturing features observed in preterm human electroencephalography (EEG). These results show that the development of structured network activity in the human neocortex may follow stable genetic programming, even in the absence of external or subcortical inputs. Our model provides novel opportunities for investigating and manipulating the role of network activity in the developing human cortex.

KEYWORDS: brain organoids, network oscillations, stem cells, phase-amplitude coupling, preterm electroencephalography, Methyl-CpG-binding protein 2 (MECP2).

HIGHLIGHTS

- Early development of human functional neural networks and oscillatory activity can be modeled *in vitro*.

- Cortical organoids exhibit phase-amplitude coupling between delta oscillation (2 Hz) and high-frequency activity (100-400 Hz) during network-synchronous events.

- Differential role of glutamate and GABA in initiating and maintaining oscillatory network activity.

- Developmental impairment of MECP2-KO cortical organoids impacts the emergence of oscillatory activity.

- Cortical organoid network electrophysiological signatures are similar to human preterm neonatal EEG features.

IN BRIEF

Brain oscillations are a candidate mechanism for how neural populations are temporally organized to instantiate cognition and behavior. Cortical organoids initially exhibit periodic and highly regular nested oscillatory network events that eventually transition to more spatiotemporally complex activity, mimicking features of late-stage preterm infant electroencephalography. Functional neural circuitry in cortical organoids exhibits emergence and development of oscillatory network dynamics similar to features found in the developing human brain.

INTRODUCTION

Diverse and hierarchical cellular networks develop into circuits with patterns of functional

spatiotemporal activity to form the human brain. Neural oscillations, a prominent, rhythmic brain

signal found across species, robustly track cognitive, behavioral, and disease states (Buzsáki and

Draguhn, 2004; Fries, 2005; de Hemptinne et al., 2015; Henriques and Davidson, 1991; Khan et

al., 2013; Uhlhaas and Singer, 2010) and have long been leveraged in cognitive and systems

neuroscience due to their ubiquity and accessibility. These complex network dynamics emerge

early in development, and is unclear if shaped exclusively by biological programming prenatally

(Blankenship and Feller, 2010; Johnson, 2001; Power et al., 2010). *In vitro* and *in vivo* rodent

studies have shown that a conserved repertoire of organized network activity, such as traveling

waves, giant depolarizing potentials, and early network oscillations, develop according to a

consistent timeline prior to and immediately after birth (Allene et al., 2008; Khazipov and

Luhmann, 2006; Uhlhaas et al., 2010). However, due to an inability to interrogate the

electrophysiology of intact embryonic brains, it remains unknown whether the same happens in

humans. As a result, our knowledge about human brain functional development rests upon

extrapolations from nonhuman model systems (Power et al., 2010).

Organoids generated from induced pluripotent stem cells (iPSC) have emerged as a

scaled-down and three-dimensional model of the human brain, mimicking various developmental

features at the cellular and molecular levels (Camp et al., 2015; Lancaster and Knoblich, 2014;

Lancaster et al., 2013; van de Leemput et al., 2014; Luo et al., 2016; Mariani et al., 2012; Paşca

et al., 2015; Qian et al., 2016; Renner et al., 2017). Despite recent advances in the understanding

of their vast cellular diversity, there is no evidence that these organoids show complex and

functional neural network activity that resembles early human brain formation (Birey et al., 2017;

Quadrato et al., 2017). Therefore, researchers have not yet clearly determined whether organoids

are a suitable model for neural network dynamics (Kelava and Lancaster, 2016; Paşca, 2018).

Here, we use human iPSCs to generate cortical organoids that exhibit evolving and nested

oscillatory network dynamics over the span of several months. We subsequently investigated the

molecular basis of human brain oscillatory activity formation, maintenance, and temporal control

by gene targeting. Finally, we applied unsupervised machine learning to evaluate the similarity

between electrophysiological activity patterns of the *in vitro* model and human preterm neonatal

electroencephalogram (EEG). Our findings suggest that organoid models are suitable for the

investigation of the physiological basis of network formation at early and late stages of the human

brain development. This prolonged evaluation of cortical organoid activity expands our

understanding of the emergence of network-level neurodynamics in humans.

RESULTS

Development of functional cortical organoids

Despite the structural and transcriptional similarities between brain organoids and the

developing nervous system, the emergence of higher-level complex network activity comparable

to the living human brain remains largely untested (Figure 1A). To investigate the formation of a

functional network, we promoted cortical specification by modifying previously described

protocols (Paşca et al., 2015; Thomas et al., 2016) (Figure 1B, see Methods for details). At the

beginning of differentiation, an abundance of proliferative neural progenitor cells (NPCs) (Ki67+,

SOX2+ and Nestin+) that self-organized into a polarized neuroepithelium-like structure was

observed. Similar to human cortical development *in vivo*, the proliferative zone around a lumen

delimited by β-catenin+ cells was surrounded by progenitor cells. Progressively, the organoids

increased in size and in the proportion of mature neurons (NeuN+ and MAP2+) to ultimately

develop into concentric multi-layer structures composed of NPCs, intermediate progenitors

(TBR2+, also known as EOMES), and lower (CTIP2+, also known as BCL11B) and upper

(SATB2+) cortical layer neurons (Figure 1B-E and S1A-C). Although the initial fraction of glial

cells was less than 5%, this population increased to about 30-40% after 6 months of differentiation

(Figure 1D, 1E and S1D-H). The maturation level of the cells is reflected by the presence of

pyramidally-shaped neurons and formation of dendritic spine-like protrusions and synaptic

structures (Figure 1F and 1G).

To further characterize the cellular diversity of a cortical organoid, we performed single-

cell gene expression profiling in 6-month-old organoids and used unbiased clustering to classify

the main existing cell types. From two independent differentiation replicates (Figure S2), seven

distinct clusters were characterized based on their differential gene expression patterns (Figure

S3, S4 and Table S1) including: progenitors, glia, and cortical neurons, which could be further

subdivided into lower and upper layer based on the expression of the layer-specific markers

CTIP2 and SATB2, respectively (Figure 1H-K and Figure S1).

Figure 1. Cellular and molecular development of human cortical organoids. (A) Overview of human neural network formation and dynamics evaluation using organoids. (B) Schematic of the protocol used to generate cortical organoids. Scale bar, 200 μm. (C) Organoid growth during different developmental stages. (D) Representative immunostainings showing proliferating NPCs (Ki67+ and Nestin+), lower (TBR1+ and CTIP2+) and upper (SATB2+) cortical layer neurons and

glial cells (GFAP+) overtime. Scale bar, 50 μm. (E) Population analysis of specific markers

indicating stages of maturation and multiple neuronal subtypes. The data are shown as mean ±

s.e.m. (*n = 8*). (F) Representative image of a pyramidal neuron (left panel); dendritic spine-like

structures (arrow) are observed in cells transduced with the SYN:EGFP reporter (middle panel;

scale bar, 5 μm). Immunohistochemical detection of the synaptic protein Syn1 (right panel; scale

bar, 50 μm). (G) Electron microscopy of synaptic structures in 4-month-old cortical organoids

(blue). (H) *t*-distributed stochastic neighbor embedding (*t*SNE) plot of 3,491 cells from 6-month-

old organoids. Colors denote seven main cell clusters. (I) *t*SNE plots depicting cell-type specific

marker expression levels (red denotes higher expression). (J) Heatmap of average expression

for representative gene markers by cluster and cell-type (see also Figure S4). (K) Violin plots

showing transcript levels for representative markers of each cluster (see Figure S3 for additional

markers).

Emergence of nested oscillatory network activity

Considering the observed cellular diversity and expression of synaptic markers, we further

interrogated the presence of functional network activity. We performed weekly extracellular

recordings of spontaneous electrical activity using multi-electrode arrays (MEA). We separately

analyzed single-channel and population firing characteristics derived from channel-wise spike

times, and the local field potential (LFP); a measure of aggregate synaptic currents and other

slow ionic exchanges (Buzsáki et al., 2012) (Figure 2A). The spikes from each channel do not

represent putative single-unit action potentials. Since the spatial resolution of MEA electrodes

was sparse, the total population spiking of a well was submitted for further analysis, rather than

individual spike trains. Over the course of 10 months, organoids exhibited consistent increases in

electrical activity, as parametrized by channel-wise firing rate, burst frequency, and spike

synchrony (Chen et al., 2009; Lisman, 1997), which indicates a continually-maturing neural

network (Figure 2B-D and S5). Organoid firing rates were far higher than previously observed in

studies using iPSC-derived neurons or cerebral organoids (Figure S6). Additionally, the variability

between replicates over 40 weeks of differentiation was significantly lower compared to iPSC-

derived neurons in monolayer cultures (Figure 2C inset and S5E).

Population-level signals typically observed in *in vivo* electrophysiology were analyzed to

further probe the network properties of cortical organoids. During individual recordings, cultures

displayed a robust pattern of activity, switching between long periods of quiescence and short

bursts of spontaneous network-synchronized spiking (hereafter referred to as "network events").

These network events are periodic but infrequent early in development (~2 months), occurring

roughly every 20 seconds and decayed monotonically after the initial onset, similar to previously

reported network "oscillations" in primary cultures and organoids (Figure 2E). From 4-months

onwards, a secondary peak emerged 300-500 ms after the initial network activation, leading to

the presence of a nested fast oscillatory (2-3 Hz) pattern up to 6-months in culture (Figure 2F and

Figure S7). Notably, this robust fast timescale oscillation was not observed in 3D neurospheres,

suggesting that the spherical arrangement of neurons is insufficient for the emergence of nested

oscillations (Figure S8). The regular oscillatory activity during network events transitioned to

stronger, yet more variable, oscillations over time. To quantify this network complexity, we tracked

the regularity (coefficient of variation of inter-event intervals, CV) and the spatial and temporal

correlation between spontaneous network events. The inter-event interval CV consistently

increased over 10 months of differentiation (Figure 2G), from extremely regular latencies (CV $\cong$

0) at 2 months to irregular, Poisson-like (CV $\cong$ 1) at 10 months. This indicates increased variability

between consecutive network events initiation. Additionally, spatial and temporal irregularity on a

shorter time-scale (within-event) also increased with development, suggesting a breakdown of

deterministic population dynamics from the onset of network events (Figure S7G).

Periodic oscillatory activity is often defined as a "bump" over the characteristic *1/f*

background noise in the power spectral density (PSD) of extracellular signals above-and-beyond

the aperiodic *1/f* signal (Buzsáki et al., 2013; Gao et al., 2017). In organoid LFPs, we observed

both prominent oscillatory peaks in the low-frequency range (1-4 Hz) and in the aperiodic signal

characteristic of neural recordings (Ben-Ari, 2001; Voytek et al., 2015). The development of

oscillatory activity in cortical organoids over time was quantified by computing the PSD for each

LFP recording (Figure 2H, inset). Oscillatory power in the delta range (1-4 Hz) increased for up

to 24 weeks in culture, tapering off slightly in subsequent recordings and plateauing during the

last 10 weeks. This inverted-U trajectory reflects the network's initial acquisition of oscillatory

modes at steady frequencies and the dispersion of this regularity at later time points. The LFP

results reveal the development of the cortical organoid cultures across different network states:

from sparse activity with extreme rigidity and regularity, to one that acquires repetitive, perhaps

overly-regular oscillatory patterns (Voytek and Knight, 2015), until it finally reaches a stage of

higher spatiotemporal complexity and variability that is reminiscent of self-organized critical

networks (Tetzlaff et al., 2010) (Figure S7C-G).

Figure 2. Oscillatory network dynamics in long-term cortical organoids. (A) Schematic of the organoid signal processing pipeline. Raw MEA data is analyzed as population spiking and LFP separately. Synchronous network events are highlighted in yellow. (B) Raster plot of network spiking activity after 1.5 and 6 months of maturation. A 3-s interval of activity over 5 channels is shown in the upper right corners. (C) Cortical organoids show elevated and continuously increasing mean firing rate compared to 2D monolayer neurons (*n = 8* organoid cultures, and *n = 12* for 2D neurons). Inset, correlation of the firing rate vector over 12 weeks of differentiation (from 8 to 20) between pairs of cultures showing reduced variability among organoid replicates. (D)

Temporal evolution of cortical organoid network activity. Detailed definitions and further

parameters are presented in Figure 5B and 5C. (E) Time series of population spiking and LFP

during network events in cortical organoid development. Each trace represents a single event

during the same recording session. (F) Oscillatory dynamics within network events develop

nonlinearly, following an inverted-U trajectory. (G) Increase of network variability dynamics

throughout development. (H) Oscillatory power increases up to the 25th week in culture and

plateaus at 30 weeks. Inset, Oscillatory power is calculated by fitting a straight line (dashed) over

the aperiodic portion of the PSD and taken as the height of narrow peaks rising above the linear

fit. The data shown in C, D, F, G and H are presented as mean ± s.e.m. *P < 0.05, **P < 0.01,

***P < 0.001, unpaired Student's *t*-test (C), quadratic (F) and linear (G) regression.

Oscillatory coordination of neural ensembles and its synaptic mechanisms

Oscillatory dynamics in the functioning brain have been postulated to coordinate spiking

across neural ensembles[1]. In the LFP and other mesoscopic brain signals, this manifests as a

phenomenon known as cross-frequency phase-amplitude coupling (PAC) (Voytek and Knight,

2015), wherein the high-frequency content of the LFP is entrained to the phase of slow oscillations

(Manning et al., 2009; Miller et al., 2007; Mukamel et al., 2005). PAC in the neocortex and

hippocampus has been shown to be functionally relevant in a range of behaviors and neurological

disorders (de Hemptinne et al., 2015; Voytek and Knight, 2015; Voytek et al., 2015). In the

organoids, we observed greater PAC between oscillatory delta (1-4 Hz) and broadband gamma

activity (100-400 Hz, see Methods) during network events compared to quiescent periods (Figure

3A-C). This result suggests that oscillations in the organoid may reproduce dynamics relevant for

the intact brain and could serve as a model to understand the fundamental mechanisms behind

the emergence of oscillatory networks in the developing human brain.

We further evaluated the role of glutamatergic and GABAergic synaptic transmission in

forming oscillations by pharmacological intervention. Organoid neural networks were susceptible

to both glutamate receptor antagonists (AP5 and CNQX; NMDA and AMPA/kainate, respectively)

and GABA receptor agonists (muscimol, $GABA_A$; baclofen, $GABA_B$) by significantly reducing the

number of spikes and bursts, with a subsequent extinction of synchronous activity. The electrical

activity was abolished in the presence of tetrodotoxin (TTX) (Figure 3D and 3E). Notably,

blockade of GABAergic transmission by bicuculline increased the number of network-

synchronized events and did not affect peak population firing rates, but abolished nested 2 Hz

oscillatory activity by erasing subsequent reverberant peaks (Figure 3F). The findings suggest

that GABA transmission is crucial for the maintenance, but not the initiation of faster oscillatory

activity. This is consistent with accounts of inhibition rhythmically coordinating pyramidal

populations activity during early development (Opitz et al., 2002).

Figure 3. Cortical organoid serves as a model of functional oscillations and their synaptic

mechanisms. (A-C) Phase-amplitude coupling is observed in organoid LFP during network

events, a phenomenon proposed to mediate neural communication *in vivo*. (A) Example of raw

LFP during a network event decomposed into its low-frequency component (1-4 Hz delta) and the

amplitude envelope of the high-frequency, broadband gamma component (200-400 Hz). Analysis

was repeated for 100-200 Hz with near identical effect size and significance. (B) Normalized

gamma amplitude binned by delta phase during network events (black) shows greater modulation

depth by low frequency delta than during non-event periods (red). (C) Phase-amplitude coupling

during network events is significantly greater than non-event periods in all batches. (D) Effect of

selective drug treatments on neuronal electrical activity in 6-month-old organoids. Representative

raster plots and burst measurements of untreated and treated organoids. Scale bar, 20 s.

Exposure to AP5 + CNQX, baclofen and muscimol reversibly extinguish the network bursts

(synchrony), while no changes were promoted by bicuculline. (E-F) Pharmacological perturbation

of oscillatory activity during network events in 6-month-old organoids. Application of bicuculline

increases the number of network events, while CNQX + AP5 and baclofen completely abolish

synchronized network events. Bicuculline blocks oscillatory network activity but not the network

event itself. Data are shown as mean ± s.e.m.; unpaired Student's *t*-test.

MECP2 is essential for the timely emergence of network oscillations

In addition to modeling the typically-developing brain, cortical organoids can also shed

light on the mechanism behind functional deficits in neurodevelopmental disorders (Birey et al.,

2017; Lancaster et al., 2013; Thomas et al., 2016). Normal oscillatory network dynamics in the

brain are often shown to break down in psychiatric and neurological conditions (Uhlhaas and

Singer, 2010). However, the mechanisms by which that happens and its impact on the circuit are

difficult to elucidate. Thus, we next investigated whether cortical organoids could be used to model

oscillatory network defects. Previous work evidenced that patients with autism spectrum disorder

exhibit reduced alpha oscillation power (8-12 Hz) and evoked gamma (40-60 Hz) response, as

well as reduced PAC (Khan et al., 2013; Mohammad-Rezazadeh et al., 2016). Mutations in the

Methyl-CpG-binding protein 2 (*MECP2*) gene lead to a severe disruption in cortical development

that account for many symptoms of Rett syndrome, autism, schizophrenia and other neurological

disorders (Amir et al., 1999; Cohen et al., 2002; Du et al., 2016; Liu et al., 2016; Wen et al., 2017).

MECP2 is involved in the epigenetic regulation of target genes by binding to methylated CpG

dinucleotides promoter regions, acting as a transcriptional modulator (Figure 4A).

To model MECP2 deficiency during neurodevelopment, we a generated pluripotent stem

cell model with two different cell lines, each carrying a distinct *MECP2* mutation that lead to a

nonfunctional protein (Figure S9). Human *MECP2*-mutant neurons *in vitro* exhibit fewer synapses,

smaller soma size, altered calcium signaling and electrophysiological defects compared to

controls (Marchetto et al., 2010). Based on the observed reduction in the number of layer V

neurons in *Mecp2*-mutant mice (Stuss et al., 2012) and documented clinical data of microcephaly

in Rett syndrome patients (Amir et al., 1999), we sought to examine transcriptomics, cellular and

structural differences using MECP2-KO cortical organoids. The delay in the maturation process

was accompanied by a significant decrease in the diameter of MECP2-KO organoids, spine-like

density and synaptic puncta at later stages of differentiation (Figure 4B-D). Additionally, a

significant reduction in the proportion of CTIP2+ and SATB2+ neurons was observed by targeted

single-cell analysis (Figure 4E-G) and corroborated by immunostaining (Figure 4h). MECP2-KO

cortical organoids also showed reduced neural activity leading to an absence of network

oscillations, which supports a delay in the maturation process (Figure 4I and 4J). The inability to

entrain into a functionally connected network at early stages of development might underlie the

core deficits found in MECP2-deficient related disorders. More importantly, these results highlight

the contribution of specific genes in the formation of a network circuitry and the emergence of

oscillatory activity.

Figure 4. MECP2 contribution to the emergence of network oscillations. (A) MECP2-knockout neurons (MECP2-KO) show reduced spine-like density and soma size compared to controls. (B) Organoid diameter quantification (CTR, *n = 210* organoids; KO, *n = 333* organoids). (C) Spine-like density and (D) synaptic puncta are reduced in MECP2-KO neurons. Scale bar, 50 μm. (E-H) Targeted single-cell analysis of neural markers and cortical layer-related genes over defined control *Ct* value. In 3-month-old cortical organoids, a significant decrease in the number of CTIP2+ and SATB2+ neurons was observed. (I) MECP2-KO cortical organoids show decreased mean firing rate after 5 months of maturation (*n = 6* organoid cultures). (J) Lack of oscillatory network events in 5-month-old MECP2-KO organoids. Each trace represents a single event during the same recording session. For B, C, D, G, H, I and J, data are shown as mean ± s.e.m.; *P < 0.05, **P < 0.01, ***P < 0.001, unpaired Student's *t*-test.

Organoid network development recapitulates preterm EEG

Despite similarities between the complex oscillatory network activity in organoids and the

in vivo brain, it is unclear whether the spontaneous developmental trajectory observed is

representative of programmed early neurodevelopment. While network activity from organoids

does not exhibit the full temporal complexity seen in adults, the pattern of alternating periods of

quiescence and network-synchronized events is similar to electrophysiological signatures present

in preterm human infant EEG. During *trace discontinu* (Tolonen et al., 2007), quiescent periods

are punctuated by high-amplitude oscillations (spontaneous activity transients, SATs) lasting a

few seconds. Intervals of complete quiescence disappear as infants become of term, and the

EEG is dominated by continuous and low-amplitude desynchronized activity in adult brains

(Figure 5A). The time-frequency representation of network events in organoids also resembled

the oscillatory bursts in preterm EEG, with power localized in the low frequencies and often

accentuated within a narrow oscillatory band (Figure S10).

To quantitatively compare network activity in cortical organoids to preterm human EEG,

we trained (with cross-validation) a regularized regression model (L1 & L2 regularized, ElasticNet)

on a subset of features relating to SATs from a dataset of 567 preterm neonatal EEGs (Stevenson

et al., 2017) (24-38 post-conception weeks, PCW). We emphasize that the regression model was

thus only optimized to predict preterm infant age based on their own brain features, and has not

seen any organoid data whatsoever up to this point. After training, we submitted analogous

features computed from organoid LFPs to the model and asked it to predict organoid "brain age"

over time (Figure 5B). Notably, the mean model-generated organoid "brain age" was

indistinguishable from its "true age" (*in vitro*) after 28 weeks (Figure 5C). In other words, organoids

past 28 weeks in culture exhibit similar developmental trajectories of electrophysiological features

as preterm neonates. Next, we examined the similarities between brain organoids and preterm

humans by looking at each specific feature (Figure 5C and 5D). Of all features, "SATs per hour"

("events per hour" in organoids) showed strikingly similar values and growth, while "root-mean-

square SAT duration" showed a similar decline (but not in absolute value) over 25 to 38 weeks in

both datasets (Figure 5E, S10B and 10C). Therefore, while the developmental trajectory of

cortical organoids is not identical to that of the fetal brain, a machine learning model trained only

on preterm neonatal EEG features was able to predict organoid culture age, demonstrating that

the observed network electrophysiological features may share similarities representative of

genetically programmed developmental timelines.

Figure 5. Organoid network dynamics mimic premature neonates after 28 weeks of maturation. (A) Representative LFP trace from cortical organoid, highlighting instances of network events (yellow). Comparable events between periods of quiescence (discontinuous network dynamics) are shown in human preterm neonate EEG at 35 weeks gestational age, while a different pattern of continuous activity is observed in adult EEG. SAT: spontaneous activity transient. (B) Schematic of machine learning pipeline for organoid "brain-age" prediction: 9 EEG features from 39 premature babies (*n* = 567 recordings) between 25 and 38 PCW were used to train and cross-validate a regularized regression model (ElasticNet) to optimally predict neonate brain age, which was then applied directly to organoid LFP features to predict organoid "brain-age". (C) Predicted organoid "brain age" plotted against actual organoid age. Black stars denote time points where mean predicted age is not significantly different from actual age under 1-sample *t*-test (P < 0.05, *n* = 8). (D) Resampled Pearson's correlation coefficient between age and electrophysiological features for both organoid and premature neonates show different degrees of developmental similarity for individual features. (E) EEG/LFP features over time for organoids and premature neonates show various levels of similarity.

DISCUSSION

Development of functional human brain networks is an activity-dependent process guided by genetic and molecular programs, shaped by emerging cellular diversity. Neonatal neural networks share many features with adult brains, despite the fundamental structural differences (Power et al., 2010). Even though the chronological stages of the human cortical network formation are not well understood, it is suggested that emerging cognitive functions during infancy are a result of different brain regions and environmental cues (Johnson, 2001). However, *in utero* development is vital for the establishment of neuronal circuitry and healthy functioning of the brain. The second and third trimester of gestation are when the corticothalamic network is formed *via* transient connections of the subplate GABAergic neurons and the emergence of synchronized

301 network activity (Kostović and Judaš, 2010). Thus, early cortical functional maturation follows an

302 independent sensory-input pathway, guided by spontaneous activity and associated with synaptic

303 regulating mechanisms (Uhlhaas et al., 2010).

304   Here we report the formation of small-scale functional electrophysiological networks in

305 cortical organoids, similar to those observed in the developing brain. While we do not claim

306 functional equivalence between the organoids and a full neonatal cortex, the current results

307 represent the first step towards an *in vitro* model that captures the complex spatiotemporal

308 oscillatory dynamics of the human brain. Robust extracellular electrical activity was established

309 at earlier stages and progressively developed into an organized oscillatory network similar to that

310 observed in human EEG. As such, we show that features of early functional network dynamics

311 (e.g., spontaneous activity transients) can be recapitulated by an *in vitro* model of the developing

312 cortex, with no additional constraints other than structural and genetic similarities. This offers

313 strong evidence for a convergent experience-independent neurodevelopmental program of the

314 neocortex prior to birth. Given the potential roles of synchronized and oscillatory network

315 dynamics in coordinating information flow between developed cortical brain regions during human

316 cognition (Uhlhaas et al., 2010), these results highlight the potential for cortical organoids to

317 advance our understanding of functional electrophysiology, brain development, and neuro-

318 genetic disorders. Finally, our findings may ultimately reframe the ethical discussions on human

319 brain organoid research and offer an innovative link between microscale organoid physiology and

320 cognitive neuroscience.

REFERENCES

Allene, C., Cattani, A., Ackman, J.B., Bonifazi, P., Aniksztejn, L., Ben-Ari, Y., and Cossart, R. (2008). Sequential Generation of Two Distinct Synapse-Driven Network Patterns in Developing Neocortex. J. Neurosci. *28*, 12851–12863.

Amin, H., Maccione, A., Marinaro, F., Zordan, S., Nieus, T., and Berdondini, L. (2016). Electrical Responses and Spontaneous Activity of Human iPS-Derived Neuronal Networks Characterized for 3-month Culture with 4096-Electrode Arrays. Front. Neurosci. *10*, 121.

Amir, R.E., Van den Veyver, I.B., Wan, M., Tran, C.Q., Francke, U., and Zoghbi, H.Y. (1999). Rett syndrome is caused by mutations in X-linked MECP2, encoding methyl-CpG-binding protein 2. Nat. Genet. *23*, 185–188.

Bardy, C., van den Hurk, M., Eames, T., Marchand, C., Hernandez, R. V., Kellogg, M., Gorris, M., Galet, B., Palomares, V., Brown, J., et al. (2015). Neuronal medium that supports basic synaptic functions and activity of human neurons in vitro. Proc. Natl. Acad. Sci. *112*, E2725–E2734.

Barz, F., Livi, A., Lanzilotto, M., Maranesi, M., Bonini, L., Paul, O., and Ruther, P. (2017). Versatile, modular 3D microelectrode arrays for neuronal ensemble recordings: from design to fabrication, assembly, and functional validation in non-human primates. J. Neural Eng. *14*, 036010.

Ben-Ari, Y. (2001). Developing networks play a similar melody. Trends Neurosci. *24*, 353–360.

Birey, F., Andersen, J., Makinson, C.D., Islam, S., Wei, W., Huber, N., Fan, H.C., Metzler, K.R.C., Panagiotakos, G., Thom, N., et al. (2017). Assembly of functionally integrated human forebrain spheroids. Nature *545*, 54–59.

Blankenship, A.G., and Feller, M.B. (2010). Mechanisms underlying spontaneous patterned activity in developing neural circuits. Nat. Rev. Neurosci. *11*, 18–29.

Brown, J.P., Hall, D., Frank, C.L., Wallace, K., Mundy, W.R., and Shafer, T.J. (2016). Editor's Highlight: Evaluation of a Microelectrode Array-Based Assay for Neural Network Ontogeny Using Training Set Chemicals. Toxicol. Sci. *154*, 126–139.

Buzsáki, G., and Draguhn, A. (2004). Neuronal oscillations in cortical networks. Science *304*, 1926–1929.

Buzsáki, G., Anastassiou, C.A., and Koch, C. (2012). The origin of extracellular fields and currents — EEG, ECoG, LFP and spikes. Nat. Rev. Neurosci. *13*, 407–420.

Buzsáki, G., Logothetis, N., and Singer, W. (2013). Scaling Brain Size, Keeping Timing: Evolutionary Preservation of Brain Rhythms. Neuron *80*, 751–764.

Camp, J.G., Badsha, F., Florio, M., Kanton, S., Gerber, T., Wilsch-Bräuninger, M., Lewitus, E., Sykes, A., Hevers, W., Lancaster, M., et al. (2015). Human cerebral organoids recapitulate gene expression programs of fetal neocortex development. Proc. Natl. Acad. Sci. *112*, 201520760.

Cesca, F., Satapathy, A., Ferrea, E., Nieus, T., Benfenati, F., and Scholz-Starke, J. (2015). Functional Interaction between the Scaffold Protein Kidins220/ARMS and Neuronal Voltage-Gated Na $^+$ Channels. J. Biol. Chem. *290*, 18045–18055.

Chen, L., Deng, Y., Luo, W., Wang, Z., and Zeng, S. (2009). Detection of bursts in neuronal spike trains by the mean inter-spike interval method. Prog. Nat. Sci. *19*, 229–235.

Clements, I.P., Millard, D.C., Nicolini, A.M., Preyer, A.J., Grier, R., Heckerling, A., Blum, R.A., Tyler, P., McSweeney, K.M., Lu, Y.-F., et al. (2016). Optogenetic stimulation of multiwell MEA plates for neural and cardiac applications. In Proceedings of the SPIE, Volume 9690, Id. 96902C 10 Pp. (2016)., S.J. Madsen, V.X.D. Yang, E.D. Jansen, Q. Luo, S.K. Mohanty, and N. V. Thakor, eds. p. 96902C.

Cohen, D., Lazar, G., Couvert, P., Desportes, V., Lippe, D., Mazet, P., and Héron, D. (2002). MECP2 mutation in a boy with language disorder and schizophrenia. Am. J. Psychiatry *159*, 148–149.

Cotterill, E., Hall, D., Wallace, K., Mundy, W.R., Eglen, S.J., and Shafer, T.J. (2016).
Characterization of Early Cortical Neural Network Development in Multiwell Microelectrode
Array Plates. J. Biomol. Screen. *21*, 510–519.
Du, F., Nguyen, M.V.C., Karten, A., Felice, C.A., Mandel, G., and Ballas, N. (2016). Acute and
crucial requirement for MeCP2 function upon transition from early to late adult stages of
brain maturation. Hum. Mol. Genet. *25*, 1690–1702.
Fries, P. (2005). A mechanism for cognitive dynamics: neuronal communication through
neuronal coherence. Trends Cogn. Sci. *9*, 474–480.
Gao, R., Peterson, E.J., and Voytek, B. (2017). Inferring synaptic excitation/inhibition balance
from field potentials. Neuroimage *158*, 70–78.
Gore, A., Li, Z., Fung, H.-L., Young, J.E., Agarwal, S., Antosiewicz-Bourget, J., Canto, I.,
Giorgetti, A., Israel, M.A., Kiskinis, E., et al. (2011). Somatic coding mutations in human
induced pluripotent stem cells. Nature *471*, 63–67.
Harrill, J.A., Chen, H., Streifel, K.M., Yang, D., Mundy, W.R., and Lein, P.J. (2015). Ontogeny of
biochemical, morphological and functional parameters of synaptogenesis in primary
cultures of rat hippocampal and cortical neurons. Mol. Brain *8*, 10.
de Hemptinne, C., Swann, N.C., Ostrem, J.L., Ryapolova-Webb, E.S., San Luciano, M.,
Galifianakis, N.B., and Starr, P.A. (2015). Therapeutic deep brain stimulation reduces
cortical phase-amplitude coupling in Parkinson's disease. Nat. Neurosci. *18*, 779–786.
Henriques, J.B., and Davidson, R.J. (1991). Left frontal hypoactivation in depression. J.
Abnorm. Psychol. *100*, 535–545.
Johnson, M.H. (2001). Functional brain development in humans. Nat. Rev. Neurosci. *2*, 475–
483.
Kelava, I., and Lancaster, M.A.A. (2016). Stem Cell Models of Human Brain Development. Cell
Stem Cell *18*, 736–748.
Khan, S., Gramfort, A., Shetty, N.R., Kitzbichler, M.G., Ganesan, S., Moran, J.M., Lee, S.M.,
Gabrieli, J.D.E., Tager-Flusberg, H.B., Joseph, R.M., et al. (2013). Local and long-range
functional connectivity is reduced in concert in autism spectrum disorders. Proc. Natl.
Acad. Sci. U. S. A. *110*, 3107–3112.
Khazipov, R., and Luhmann, H.J. (2006). Early patterns of electrical activity in the developing
cerebral cortex of humans and rodents. Trends Neurosci. *29*, 414–418.
Kostović, I., and Judaš, M. (2010). The development of the subplate and thalamocortical
connections in the human foetal brain. Acta Paediatr. *99*, 1119–1127.
Lancaster, M.A., and Knoblich, J.A. (2014). Generation of cerebral organoids from human
pluripotent stem cells. Nat. Protoc. *9*, 2329–2340.
Lancaster, M. a, Renner, M., Martin, C.-A., Wenzel, D., Bicknell, L.S., Hurles, M.E., Homfray, T.,
Penninger, J.M., Jackson, A.P., and Knoblich, J. a (2013). Cerebral organoids model
human brain development and microcephaly. Nature *501*, 373–379.
van de Leemput, J., Boles, N.C., Kiehl, T.R., Corneo, B., Lederman, P., Menon, V., Lee, C.,
Martinez, R.A., Levi, B.P., Thompson, C.L., et al. (2014). CORTECON: a temporal
transcriptome analysis of in vitro human cerebral cortex development from human
embryonic stem cells. Neuron *83*, 51–68.
Lisman, J. (1997). Bursts as a unit of neural information: making unreliable synapses reliable.
Trends Neurosci. *20*, 38–43.
Liu, Z., Li, X., Zhang, J.-T., Cai, Y.-J., Cheng, T.-L., Cheng, C., Wang, Y., Zhang, C.-C., Nie, Y.-
H., Chen, Z.-F., et al. (2016). Autism-like behaviours and germline transmission in
transgenic monkeys overexpressing MeCP2. Nature *530*, 98–102.
Luo, C., Lancaster, M.A., Castanon, R., Nery, J.R., Knoblich, J.A., and Ecker, J.R. (2016).
Cerebral Organoids Recapitulate Epigenomic Signatures of the Human Fetal Brain. Cell
Rep. *17*, 3369–3384.
Manning, J.R., Jacobs, J., Fried, I., and Kahana, M.J. (2009). Broadband Shifts in Local Field

Potential Power Spectra Are Correlated with Single-Neuron Spiking in Humans. J. Neurosci. *29*, 13613–13620.

Marchetto, M.C., Belinson, H., Tian, Y., Freitas, B.C., Fu, C., Vadodaria, K.C., Beltrao-Braga, P.C., Trujillo, C.A., Mendes, A.P.D., Padmanabhan, K., et al. (2017). Altered proliferation and networks in neural cells derived from idiopathic autistic individuals. Mol. Psychiatry *22*, 820–835.

Marchetto, M.C.N.N., Carromeu, C., Acab, A., Yu, D., Yeo, G.W., Mu, Y., Chen, G., Gage, F.H., and Muotri, A.R. (2010). A model for neural development and treatment of Rett syndrome using human induced pluripotent stem cells. Cell *143*, 527–539.

Mariani, J., Simonini, M. V., Palejev, D., Tomasini, L., Coppola, G., Szekely, A.M., Horvath, T.L., and Vaccarino, F.M. (2012). Modeling human cortical development in vitro using induced pluripotent stem cells. Proc. Natl. Acad. Sci. *109*, 12770–12775.

McSweeney, K.M., Gussow, A.B., Bradrick, S.S., Dugger, S.A., Gelfman, S., Wang, Q., Petrovski, S., Frankel, W.N., Boland, M.J., and Goldstein, D.B. (2016). Inhibition of microRNA 128 promotes excitability of cultured cortical neuronal networks. Genome Res. *26*, 1411–1416.

Miller, K.J., Leuthardt, E.C., Schalk, G., Rao, R.P.N., Anderson, N.R., Moran, D.W., Miller, J.W., and Ojemann, J.G. (2007). Spectral Changes in Cortical Surface Potentials during Motor Movement. J. Neurosci. *27*, 2424–2432.

Mohammad-Rezazadeh, I., Frohlich, J., Loo, S.K., and Jeste, S.S. (2016). Brain connectivity in autism spectrum disorder. Curr. Opin. Neurol. *29*, 137–147.

Mukamel, R., Gelbard, H., Arieli, A., Hasson, U., Fried, I., and Malach, R. (2005). Coupling Between Neuronal Firing, Field Potentials, and fMRI in Human Auditory Cortex. Science *309*, 951–954.

Nageshappa, S., Carromeu, C., Trujillo, C.A., Mesci, P., Espuny-Camacho, I., Pasciuto, E., Vanderhaeghen, P., Verfaillie, C.M., Raitano, S., Kumar, A., et al. (2016). Altered neuronal network and rescue in a human MECP2 duplication model. Mol. Psychiatry *21*, 178–188.

Odawara, A., Saitoh, Y., Alhebshi, A.H., Gotoh, M., and Suzuki, I. (2014). Long-term electrophysiological activity and pharmacological response of a human induced pluripotent stem cell-derived neuron and astrocyte co-culture. Biochem. Biophys. Res. Commun. *443*, 1176–1181.

Odawara, A., Katoh, H., Matsuda, N., and Suzuki, I. (2016). Physiological maturation and drug responses of human induced pluripotent stem cell-derived cortical neuronal networks in long-term culture. Sci. Rep. *6*, 26181.

Opitz, T., De Lima, A.D., and Voigt, T. (2002). Spontaneous Development of Synchronous Oscillatory Activity During Maturation of Cortical Networks In Vitro. J. Neurophysiol. *88*, 2196–2206.

Pașca, A.M., Sloan, S.A., Clarke, L.E., Tian, Y., Makinson, C.D., Huber, N., Kim, C.H., Park, J.-Y., O'Rourke, N.A., Nguyen, K.D., et al. (2015). Functional cortical neurons and astrocytes from human pluripotent stem cells in 3D culture. Nat. Methods *12*, 671–678.

Pașca, S.P. (2018). The rise of three-dimensional human brain cultures. Nature *553*, 437–445.

Pedregosa, F., Varoquaux, G., Gramfort, A., Michel, V., Thirion, B., Grisel, O., Blondel, M., Prettenhofer, P., Weiss, R., Dubourg, V., et al. (2011). Scikit-learn: Machine Learning in Python. J. Mach. Learn. Res. *12*, 2825–2830.

Power, J.D., Fair, D.A., Schlaggar, B.L., and Petersen, S.E. (2010). The Development of Human Functional Brain Networks. Neuron *67*, 735–748.

Qian, X., Nguyen, H.N., Song, M.M., Hadiono, C., Ogden, S.C., Hammack, C., Yao, B., Hamersky, G.R., Jacob, F., Zhong, C., et al. (2016). Brain-Region-Specific Organoids Using Mini-bioreactors for Modeling ZIKV Exposure. Cell *165*, 1238–1254.

Quadrato, G., Nguyen, T., Macosko, E.Z., Sherwood, J.L., Min Yang, S., Berger, D.R., Maria, N., Scholvin, J., Goldman, M., Kinney, J.P., et al. (2017). Cell diversity and network

dynamics in photosensitive human brain organoids. Nature *545*, 48–53.
Quiroga, R.Q., Nadasdy, Z., and Ben-Shaul, Y. (2004). Unsupervised spike detection and
sorting with wavelets and superparamagnetic clustering. Neural Comput. *16*, 1661–1687.
Renner, M., Lancaster, M.A., Bian, S., Choi, H., Ku, T., Peer, A., Chung, K., and Knoblich, J.A.
(2017). Self- organized developmental patterning and differentiation in cerebral organoids.
EMBO J. *36*, 1316–1329.
Roy, S., Zhao, L., and Wang, X. (2016). Distinct Neural Activities in Premotor Cortex during
Natural Vocal Behaviors in a New World Primate, the Common Marmoset (Callithrix
jacchus). J. Neurosci. *36*, 12168–12179.
Stevenson, N.J., Oberdorfer, L., Koolen, N., O'Toole, J.M., Werther, T., Klebermass-Schrehof,
K., and Vanhatalo, S. (2017). Functional maturation in preterm infants measured by serial
recording of cortical activity. Sci. Rep. *7*, 12969.
Strickland, J.D., LeFew, W.R., Crooks, J., Hall, D., Ortenzio, J.N.R., Dreher, K., and Shafer, T.J.
(2016). In vitro screening of silver nanoparticles and ionic silver using neural networks
yields differential effects on spontaneous activity and pharmacological responses.
Toxicology *355–356*, 1–8.
Stuss, D.P., Boyd, J.D., Levin, D.B., and Delaney, K.R. (2012). MeCP2 Mutation Results in
Compartment-Specific Reductions in Dendritic Branching and Spine Density in Layer 5
Motor Cortical Neurons of YFP-H Mice. PLoS One *7*, e31896.
Tetzlaff, C., Okujeni, S., Egert, U., Wörgötter, F., and Butz, M. (2010). Self-organized criticality
in developing neuronal networks. PLoS Comput. Biol. *6*, e1001013.
Chailangkarn, T., Trujillo, C.A., Freitas, B.C., Hrvoj-Mihic, B., Herai, R.H., Yu, D.X., Brown, T.T.,
Marchetto, M.C., Bardy, C., McHenry, L., et al. (2016). A human neurodevelopmental
model for Williams syndrome. Nature *536*, 338–343.
Thomas, C.A., Tejwani, L., Trujillo, C.A., Negraes, P.D., Herai, R.H., Mesci, P., Macia, A., Crow,
Y.J., and Muotri, A.R. (2017). Modeling of TREX1-Dependent Autoimmune Disease using
Human Stem Cells Highlights L1 Accumulation as a Source of Neuroinflammation. Cell
Stem Cell *21*, 319–331.e8.
Tolonen, M., Palva, J.M., Andersson, S., and Vanhatalo, S. (2007). Development of the
spontaneous activity transients and ongoing cortical activity in human preterm babies.
Neuroscience *145*, 997–1006.
Tort, A.B.L., Komorowski, R., Eichenbaum, H., and Kopell, N. (2010). Measuring Phase-
Amplitude Coupling Between Neuronal Oscillations of Different Frequencies. J.
Neurophysiol. *104*, 1195–1210.
Tukker, A.M., de Groot, M.W.G.D.M., Wijnolts, F.M.J., Kasteel, E.E.J., Hondebrink, L., and
Westerink, R.H.S. (2016). Is the time right for in vitro neurotoxicity testing using human
iPSC-derived neurons? ALTEX *33*, 261–271.
Uesaka, N., Hayano, Y., Yamada, A., and Yamamoto, N. (2007). Interplay between laminar
specificity and activity-dependent mechanisms of thalamocortical axon branching. J.
Neurosci. *27*, 5215–5223.
Uhlhaas, P.J., and Singer, W. (2010). Abnormal neural oscillations and synchrony in
schizophrenia. Nat. Rev. Neurosci. *11*, 100–113.
Uhlhaas, P.J., Roux, F., Rodriguez, E., Rotarska-Jagiela, A., and Singer, W. (2010). Neural
synchrony and the development of cortical networks. Trends Cogn. Sci. *14*, 72–80.
Vessoni, A.T., Herai, R.H., Karpiak, J. V., Leal, A.M.S., Trujillo, C.A., Quinet, A., Agnez Lima,
L.F., Menck, C.F.M., and Muotri, A.R. (2016). Cockayne syndrome-derived neurons
display reduced synapse density and altered neural network synchrony. Hum. Mol. Genet.
25, 1271–1280.
Voytek, B., and Knight, R.T. (2015). Dynamic network communication as a unifying neural basis
for cognition, development, aging, and disease. Biol. Psychiatry *77*, 1089–1097.
Voytek, B., Kayser, A.S., Badre, D., Fegen, D., Chang, E.F., Crone, N.E., Parvizi, J., Knight,

R.T., and D'Esposito, M. (2015). Oscillatory dynamics coordinating human frontal
networks in support of goal maintenance. Nat. Neurosci. *18*, 1318–1324.
Wallace, K., Strickland, J.D., Valdivia, P., Mundy, W.R., and Shafer, T.J. (2015). A multiplexed
assay for determination of neurotoxicant effects on spontaneous network activity and
viability from microelectrode arrays. Neurotoxicology *49*, 79–85.
Wen, Z., Cheng, T.-L., Li, G.-Z., Sun, S.-B., Yu, S.-Y., Zhang, Y., Du, Y.-S., and Qiu, Z. (2017).
Identification of autism-relatedMECP2mutations by whole-exome sequencing and
functional validation. Mol. Autism *8*, 43.
Xu, X., Tay, Y., Sim, B., Yoon, S.-I., Huang, Y., Ooi, J., Utami, K.H., Ziaei, A., Ng, B.,
Radulescu, C., et al. (2017). Reversal of Phenotypic Abnormalities by CRISPR/Cas9-
Mediated Gene Correction in Huntington Disease Patient-Derived Induced Pluripotent
Stem Cells. Stem Cell Reports *8*, 619–633.
Yang, Y., Huang, J., Mis, M.A., Estacion, M., Macala, L., Shah, P., Schulman, B.R., Horton,
D.B., Dib-Hajj, S.D., and Waxman, S.G. (2016). Nav1.7-A1632G Mutation from a Family
with Inherited Erythromelalgia: Enhanced Firing of Dorsal Root Ganglia Neurons Evoked
by Thermal Stimuli. J. Neurosci. *36*, 7511–7522.
Zhang, Z.-N.Z.-N., Freitas, B.C.B.C., Qian, H., Lux, J., Acab, A., Trujillo, C.A.C.A., Herai,
R.H.R.H., Huu, V.A.N., Wen, J.H.J.H., Joshi-Barr, S., et al. (2016). Layered hydrogels
accelerate iPSC-derived neuronal maturation and reveal migration defects caused by
MeCP2 dysfunction. *113*, 3185–3190.
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SUPPLEMENTARY INFORMATION

Supplemental information includes Supplemental Experimental Procedures, 10 Figures, 2 tables

can be found with this article online.

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AUTHOR CONTRIBUTIONS

C.A.T., R.G. and P.D.N. should be considered co-first authors as they each designed the

experiments and conducted the analyses with input from A.R.M., B.V.; P.D.N. and C.A.T.

generated and characterized the cortical organoids and performed the MEA recordings. C.A.T.

performed C1 single-cell analyses and synaptic quantification. I.A.C. performed and analyzed

10X Genomics single-cell experiments. A.Do. processed 10X Genomics single-cell data. G.W.Y.

led and funded the single-cell RNA-seq analyses. M.V. and A.De. performed the functional

experiment. P.D.N. analyzed the MEA data using the Axion Biosystems Neural Metrics Tool. R.G.

performed the custom MEA and EEG analyses. A.R.M. and B.V. should be considered co-senior

authors as they contributed equally to directing the overall study design, with A.R.M. leading the

cortical organoid development and analyses, and B.V. leading the electrophysiological design

and analyses. C.A.T., R.G., P.D.N., B.V. and A.R.M wrote the manuscript. All authors reviewed

the manuscript for publication.

CONFLICT OF INTERESTS

Dr. Muotri is a co-founder and has equity interest in TISMOO, a company dedicated to genetic

analysis focusing on therapeutic applications customized for autism spectrum disorder and other

neurological disorders with genetic origins. The terms of this arrangement have been reviewed

and approved by the University of California San Diego in accordance with its conflict of interest

policies.

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FIGURE LEGENDS

Figure 1. Cellular and molecular development of human cortical organoids. (A) Overview of

human neural network formation and dynamics evaluation using organoids. (B) Schematic of the

protocol used to generate cortical organoids. Scale bar, 200 μm. (C) Organoid growth during

different developmental stages. (D) Representative immunostainings showing proliferating NPCs

(Ki67+ and Nestin+), lower (TBR1+ and CTIP2+) and upper (SATB2+) cortical layer neurons and

glial cells (GFAP+) overtime. Scale bar, 50 μm. (E) Population analysis of specific markers

indicating stages of maturation and multiple neuronal subtypes. The data are shown as mean ±

s.e.m. (*n* = 8). (F) Representative image of a pyramidal neuron (left panel); dendritic spine-like

structures (arrow) are observed in cells transduced with the SYN:EGFP reporter (middle panel;

scale bar, 5 μm). Immunohistochemical detection of the synaptic protein Syn1 (right panel; scale

bar, 50 μm). (G) Electron microscopy of synaptic structures in 4-month-old cortical organoids

(blue). (H) *t*-distributed stochastic neighbor embedding (*t*SNE) plot of 3,491 cells from 6-month-

old organoids. Colors denote seven main cell clusters. (I) *t*SNE plots depicting cell-type specific

marker expression levels (red denotes higher expression). (J) Heatmap of average expression

for representative gene markers by cluster and cell-type (see also Figure S4). (K) Violin plots

showing transcript levels for representative markers of each cluster (see Figure S3 for additional

markers).

Figure 2. Oscillatory network dynamics in long-term cortical organoids. (A) Schematic of

the organoid signal processing pipeline. Raw MEA data is analyzed as population spiking and

LFP separately. Synchronous network events are highlighted in yellow. (B) Raster plot of network

spiking activity after 1.5 and 6 months of maturation. A 3-s interval of activity over 5 channels is

shown in the upper right corners. (C) Cortical organoids show elevated and continuously

increasing mean firing rate compared to 2D monolayer neurons (*n* = 8 organoid cultures, and *n* =

12 for 2D neurons). Inset, correlation of the firing rate vector over 12 weeks of differentiation (from

8 to 20) between pairs of cultures showing reduced variability among organoid replicates. (D)

Temporal evolution of cortical organoid network activity. Detailed definitions and further

parameters are presented in Figure 5B and 5C. (E) Time series of population spiking and LFP

during network events in cortical organoid development. Each trace represents a single event

during the same recording session. (F) Oscillatory dynamics within network events develop

nonlinearly, following an inverted-U trajectory. (G) Increase of network variability dynamics

throughout development. (H) Oscillatory power increases up to the 25th week in culture and

plateaus at 30 weeks. Inset, Oscillatory power is calculated by fitting a straight line (dashed) over

the aperiodic portion of the PSD and taken as the height of narrow peaks rising above the linear

fit. The data shown in C, D, F, G and H are presented as mean ± s.e.m. *$P < 0.05$, **$P < 0.01$,

***$P < 0.001$, unpaired Student's *t*-test (C), quadratic (F) and linear (G) regression.

Figure 3. Cortical organoid serves as a model of functional oscillations and their synaptic

mechanisms. (A-C) Phase-amplitude coupling is observed in organoid LFP during network

events, a phenomenon proposed to mediate neural communication *in vivo*. (A) Example of raw

LFP during a network event decomposed into its low-frequency component (1-4 Hz delta) and the

amplitude envelope of the high-frequency, broadband gamma component (200-400 Hz). Analysis

was repeated for 100-200 Hz with near identical effect size and significance. (B) Normalized

gamma amplitude binned by delta phase during network events (black) shows greater modulation

depth by low frequency delta than during non-event periods (red). (C) Phase-amplitude coupling

during network events is significantly greater than non-event periods in all batches. (D) Effect of

selective drug treatments on neuronal electrical activity in 6-month-old organoids. Representative

raster plots and burst measurements of untreated and treated organoids. Scale bar, 20 s.

Exposure to AP5 + CNQX, baclofen and muscimol reversibly extinguish the network bursts

(synchrony), while no changes were promoted by bicuculline. (E-F) Pharmacological perturbation

of oscillatory activity during network events in 6-month-old organoids. Application of bicuculline

increases the number of network events, while CNQX + AP5 and baclofen completely abolish

synchronized network events. Bicuculline blocks oscillatory network activity but not the network

event itself. Data are shown as mean ± s.e.m.; unpaired Student's *t*-test.

Figure 4. MECP2 contribution to the emergence of network oscillations. (A) MECP2-

knockout neurons (MECP2-KO) show reduced spine-like density and soma size compared to

controls. (B) Organoid diameter quantification (CTR, *n = 210* organoids; KO, *n = 333* organoids).

(C) Spine-like density and (D) synaptic puncta are reduced in MECP2-KO neurons. Scale bar, 50

µm. (E-H) Targeted single-cell analysis of neural markers and cortical layer-related genes over

defined control *Ct* value. In 3-month-old cortical organoids, a significant decrease in the number

of CTIP2+ and SATB2+ neurons was observed. (I) MECP2-KO cortical organoids show

decreased mean firing rate after 5 months of maturation (*n = 6* organoid cultures). (J) Lack of

oscillatory network events in 5-month-old MECP2-KO organoids. Each trace represents a single

event during the same recording session. For B, C, D, G, H, I and J, data are shown as mean ±

s.e.m.; *P < 0.05, **P < 0.01, ***P < 0.001, unpaired Student's *t*-test.

Figure 5. Organoid network dynamics mimic premature neonates after 28 weeks of

maturation. (A) Representative LFP trace from cortical organoid, highlighting instances of

network events (yellow). Comparable events between periods of quiescence (discontinuous

network dynamics) are shown in human preterm neonate EEG at 35 weeks gestational age, while

a different pattern of continuous activity is observed in adult EEG. SAT: spontaneous activity

transient. (B) Schematic of machine learning pipeline for organoid "brain-age" prediction: 9 EEG

features from 39 premature babies (*n = 567* recordings) between 25 and 38 PCW were used to

train and cross-validate a regularized regression model (ElasticNet) to optimally predict neonate

brain age, which was then applied directly to organoid LFP features to predict organoid "brain-

age". (C) Predicted organoid "brain age" plotted against actual organoid age. Black stars denote

time points where mean predicted age is not significantly different from actual age under 1-sample

t-test (P < 0.05, *n = 8*). (D) Resampled Pearson's correlation coefficient between age and

electrophysiological features for both organoid and premature neonates show different degrees

of developmental similarity for individual features. (E) EEG/LFP features over time for organoids

and premature neonates show various levels of similarity.

EXPERIMENTAL PROCEDURES

Cell source. iPSC lines derived from control individuals have been previously characterized elsewhere (Gore et al., 2011; Nageshappa et al., 2016). Human embryonic stem cell (ESC) and iPSC colonies were expanded on Matrigel-coated dishes (BD Biosciences, San Jose, CA, USA) with mTeSR1 medium (StemCell Technologies, Vancouver, Canada). The cells were routinely checked by karyotype and CNV arrays to avoid genomic alterations in the culture. The study was approved by the University of California San Diego IRB/ESCRO committee (protocol 141223ZF).

Teratoma formation. iPSC colonies were dissociated, re-suspended in PBS-Matrigel, and injected subcutaneously in NOD SCID mice. The tumor was dissected, fixed in and paraffin embedded after 8 weeks. Sections of 10 µm thickness were stained with hematoxylin and eosin, and analyzed for the presence of the three germ layer tissues. Protocols were approved by the UCSD Institutional Animal Care and Use Committee.

MECP2-KO cell line generation. MECP2-deficient cell lines were generated by inducing pluripotency in fibroblasts derived from a male patient. Additionally, we used H9 human ESC with the CRISPR/Cas9 genome-editing system to induce frameshift mutations in the *MECP2* locus. This incorporation resulted in the creation of early stop codons rendering a non-functional MECP2 protein. Mutagenesis and off-targets were confirmed by exome sequencing techniques. The CRISPR-Cas protocol can be found elsewhere (Thomas et al., 2017). Once we confirmed the pluripotency state of the cellular models, we differentiated them into 2D neuronal monolayer cultures (Thanathom et al., 2016) and cortical organoids.

Generation of cortical organoids. Feeder-free iPSCs were fed daily with mTeSR1 for 7 days. Colonies were dissociated using Accutase (Life Technologies, Carlsbad, CA, USA) in PBS (1:1) for 10 minutes at 37 °C and centrifuged for 3 minutes at 150 x *g*. The cell pellet was resuspended

in mTeSR1 supplemented with 10 µM SB431542 (SB; Stemgent, Cambridge, MA, USA) and 1 µM

Dorsomorphin (Dorso; R&D Systems, Minneapolis, MN, USA). Approximately 4×10^6 cells were

transferred to one well of a 6-well plate and kept in suspension under rotation (95 rpm) in the

presence of 5 µM ROCK inhibitor (Y-27632; Calbiochem, Sigma-Aldrich, St. Louis, MO, USA) for

24 hours to form free-floating spheres. After 3 days, mTeSR1 was substituted by Media1

[Neurobasal (Life Technologies) supplemented with Glutamax, 2% Gem21 NeuroPlex (Gemini

Bio-Products, West Sacramento, CA, USA), 1% N2 NeuroPlex (Gemini Bio-Products), 1% MEM

nonessential amino acids (NEAA; Life Technologies), 1% penicillin/streptomycin (PS; Life

Technologies), 10 µM SB and 1 µM Dorso] for 7 days. Then, the cells were maintained in Media2

[Neurobasal with Glutamax, 2% Gem21 NeuroPlex, 1% NEAA and 1% PS] supplemented with

20 ng/mL FGF2 (Life Technologies) for 7 days, followed by 7 additional days in Media2

supplemented with 20 ng/mL of FGF2 and 20 ng/mL EGF (PeproTech, Rocky Hill, NJ, USA).

Next, cells were transferred to Media3 [Media2 supplemented with 10 µg/mL of BDNF, 10 µg/mL

of GDNF, 10 µg/mL of NT-3 (all from PeproTech), 200 µM L-ascorbic acid and 1 mM dibutyryl-

cAMP (Sigma-Aldrich)]. After 7 days, cortical organoids were maintained in Media2 for as long as

needed, with media changes every 3-4 days.

Mycoplasma testing. All cellular cultures were routinely tested for mycoplasma by PCR. Media

supernatants (with no antibiotics) were collected, centrifuged, and resuspended in saline buffer.

Ten microliters of each sample were used for a PCR with the following primers: Forward:

GGCGAATGGGTGAGTAAC; Reverse: CGGATAACGCTTGCGACCT. Only negative samples

were used in the study.

Immunofluorescence staining. Cortical organoids were fixed with 4% paraformaldehyde

overnight at 4°C and then transferred to 30% sucrose. After the 3D structures sink, they were

embedded in O.C.T. (Sakura, Tokyo, Japan) and sliced in a cryostat (20 µm slices). Following air

dry, the slides containing the sliced samples were permeabilized/blocked with 0.1% triton X-100

and 3% FBS in PBS for 2 hours at room temperature, and incubated with primary antibodies

overnight at 4°C. Primary antibodies used in this study were: mouse anti-Nestin, Abcam

(Cambridge, UK) ab22035, 1:250; rat anti-CTIP2, Abcam ab18465, 1:500; rabbit anti-SATB2,

Abcam ab34735, 1:200; chicken anti-MAP2, Abcam ab5392, 1:2000; rabbit anti-Synapsin1, EMD-

Millipore AB1543P, 1:500; mouse anti-NeuN, EMD-Millipore MAB377, 1:500; rabbit anti-Ki67,

Abcam ab15580, 1:1000; rabbit anti-SOX2, Cell Signaling Technology 2748, 1:500; rabbit anti-

GFAP, DAKO Z033429, 1:1000; rabbit anti-TBR1, Abcam ab31940, 1:500; rabbit anti-TBR2,

Abcam ab23345, 1:500; rabbit anti-beta-catenin, Abcam E247, 1:200; mouse anti-GABA, Abcam

ab86186, 1:200; rabbit anti-PROX1, Abcam ab101651, 1:250. Next, the slices were washed with

PBS and incubated with secondary antibodies (Alexa Fluor 488-, 555- and 647-conjugated

antibodies, Life Technologies, 1:1000) for 2 hours at room temperature. The nuclei were stained

using DAPI solution (1 µg/mL). The slides were mounted using ProLong Gold antifade reagent

and analyzed under a fluorescence microscope (Axio Observer Apotome, Zeiss).

Synaptic puncta quantification. Pre-synaptic Syn1+ puncta were quantified after 3D

reconstruction of z-stacks of random images from randomly selected regions of all lines and from

two independent experiments. Only puncta overlapping MAP2-positive processes were scored.

Immuno-gold electron microscopy (EM). Immuno-gold EM was performed at the CMM Electron

Microscopy Facility at University of California San Diego. Four-month-old organoids were fixed

using 4% paraformaldehyde in 0.1M phosphate buffer (pH 7.4). Fixed cells were pelleted and

washed with 0.15 M glycine/phosphate buffer, embedded in 10% gelatin/phosphate buffer and

infused with 2.3 M sucrose/phosphate buffer. Blocks of cells with 1 mm^3 were mounted onto

specimen holders and snap frozen in liquid nitrogen. Ultracryomicrotomy was carried out at –

100°C on a Leica Ultracut UCT with EM FCS cryoattachment (Leica, Bannockburn, IL) using a

Diatome diamond knife (Diatome US, Hatfield, PA). 80 to 90 nm frozen sections were picked up

with a 1:1 mixture of 2.3 M sucrose and 2% methyl cellulose (15cp) and transferred onto Formvar

and carbon-coated copper grids. Briefly, grids were placed on 2% gelatin at 37 °C for 20 min,

rinsed with 0.15 M glycine/PBS and the sections were blocked using 1% cold water fish-skin

gelatin. Grids were analyzed using a Tecnai G2 Spirit BioTWIN transmission electron microscope

equipped with an Eagle 4k HS digital camera (FEI, Hilsboro, OR).

Targeted single-cell qRT-PCR and analysis. Specific target amplification was performed in

individual dissociated cortical organoids using C1 Single-Cell and BioMark HD Systems (Fluidigm,

San Francisco, CA, USA), according to the manufacturer's protocol and as previously described

(Thanathom et al., 2016). Briefly, cortical organoids were mechanically dissociated after 30

minutes of incubation in Accumax (Innovative Cell Technologies, San Diego, CA, USA) at 37 °C

under rotation. After passing through 100-µm and 40-µm strainers, cells were centrifuged and

resuspended in Media2 (see *Generation of cortical organoids*). Single cortical cells were captured

on a C1 medium chip and cell viability was assessed using a LIVE/DEAD Cell Viability/Cytotoxicity

kit (Life Technologies). The targeted single-cell qPCR was performed using DELTAgene primer

pairs in the 96.96 Dynamic Array IFC chip. The results were analyzed using Fluidigm Real-time

PCR Analysis Software and Singular Analysis Toolset 3.0 (Fluidigm).

10X genomics single-cell and analysis. After organoid dissociation, single cells were processed

through the Chromium Single Cell Gene Expression Solution using the Chromium Single Cell 3'

Gel Bead, Chip and Library Kits v2 (10X Genomics, Pleasanton) as per the manufacturer's

protocol. In brief, single cells were resuspended in 0.1% BSA in PBS. Five thousand cells were

added to each channel with an average recovery rate of 1,746 cells. The cells were then

partitioned into Gel Beads in Emulsion in the Chromium instrument, where cell lysis and barcoded

reverse transcription of RNA occurred, followed by amplification, shearing and 5′ adaptor and

sample index attachment. Libraries were sequenced on an Illumina HiSeq 2500. De-multiplexing,

alignment to the hg19 transcriptome and unique molecular identifier (UMI)-collapsing were

performed using the Cellranger toolkit (version 2.0.1) provided by 10X Genomics. A total of 3,491

cells with approximately 53,000 reads per cell were processed. Analysis of output digital gene

expression matrices was performed using the Seurat R package. Matrices for replicates were

merged with the MergeSeurat function and all genes that were not detected in at least 5% of all

single cells were discarded, leaving 10,594 genes for further analyses. Cells with fewer than 600

or more than 8,000 expressed genes as well as cells with more than 50,000 UMIs or 0.1%

mitochondrial expressed genes were removed from the analysis. Data were log normalized and

scaled to 10,000 transcripts per cell. Variable genes were identified with the FindVariableGenes

function. Principal components were evaluated for statistically significant gene expression signals

using the JackStraw function. PCA was carried out, and the top 36 principal components were

retained. With these principal components, t-SNE was applied with the RunTSNE function to

visualize the cells in two dimensions and identified distinct cell clusters with the FindClusters

function with resolution = 0.30. Differential expression to identify cluster markers was performed

using the FindAllMarkers function.

Data availability. All data and/or analyses generated during the current study are available from

the corresponding author upon reasonable request. Single-cell RNA sequencing data that support

the findings of this study have been deposited at NCBI GEO: GSE113089.

Multi-electrode array (MEA) recording. Six-week-old cortical organoids were plated per well in

12-well MEA plates (Axion Biosystems, Atlanta, GA, USA). Each well contains 64 platinum

microelectrodes with 30 µm of diameter spaced by 200 µm, yielding a total of 512 channels. The

plate was previously coated with 100 µg/mL poly-L-ornithine and 10 µg/ml laminin, and we

performed four independent experiments in duplicates. Cells were fed twice a week and

measurements were collected 24 hours after the medium was changed, once a week, starting at

two weeks after plating (8 weeks of organoid differentiation). Recordings were performed using a

Maestro MEA system and AxIS Software Spontaneous Neural Configuration (Axion Biosystems)

with a customized script for band-pass filter (0.1-Hz and 5-kHz cutoff frequencies). Spikes were

detected with AxIS software using an adaptive threshold crossing set to 5.5 times the standard

deviation of the estimated noise for each electrode (channel). The plate was first allowed to rest

for three minutes in the Maestro device, and then four minutes of data were recorded. For the

MEA analysis, the electrodes that detected at least 5 spikes/min were classified as active

electrodes using Axion Biosystems' Neural Metrics Tool. Bursts were identified in the data

recorded from each individual electrode using an inter-spike interval (ISI) threshold requiring a

minimum number of 5 spikes with a maximum ISI of 100 ms. A minimum of 10 spikes under the

same ISI with a minimum of 25% active electrodes were required for network bursts in the well.

The synchrony index was calculated using a cross-correlogram synchrony window of 20 ms.

Bright-field images were captured from each well to assess for neural density and electrode

coverage over time.

Custom MEA analysis. Custom MEA analysis and neonatal EEG/organoid LFP regression

model can be found in: https://github.com/voytekresearch/OscillatoryOrganoids. Raw MEA

recordings were converted to *.mat* files using Axion-provided functions and analyzed offline using

custom MATLAB functions and scripts. Local field potential signals (LFP) from each of the 64

electrodes were generated by low-pass filtering (FIR filter) and downsampling raw signals from

12,500 Hz to 1,000 Hz (*resample.m*). Multi-unit spikes were detected as follows: each channel

was first referenced to the well median (64 channels). The median was used instead of the mean

to avoid biasing the reference during high firing rate periods. Next, the re-referenced signal was

bandpass filtered for 300-3,000 Hz with a 3rd-order Butterworth filter (*butter.m*). The spike

threshold was set to be 5.5 standard deviations, where the standard deviation was estimated as

previously described (Quiroga et al., 2004) to avoid biasing the threshold for channels with high

firing rates (thus an artificially high threshold). Spike timestamps were taken as the peak time

after the absolute value of the signal crossed the threshold, but at least 1 ms from another spike

(*findpeaks.m*). Spike timestamps were then converted into binary vectors (1 ms bin size), summed

across 64 channels, and smoothed (*conv.m*) with a normalized 100-point Gaussian window

(*gausswin.m*) to create a population spiking vector for each MEA well. Note that spikes from each

channel do not represent putative single-unit action potentials, as the spatial resolution of MEA

electrodes were too sparse. Multi-unit spiking were not sorted since total population spiking (of

well) was submitted for further analysis, rather than individual spike trains.

Network event analysis. A network event was detected when population spiking was i) greater

than 80% of the maximum spiking value over the length of the recording; ii) at least 1 spike/s; and

iii) 1 second away from any other network events. The first peak after all 3 criteria was satisfied

was marked as t = 0, and the window of data from 0.5 s before to 2.5 s after the peak was collected

as the network event. Nearly all spiking channels experienced a significant firing rate increase

during network events. LFP data from all 64 channels from the same timeframe were also

collected for analysis. All events from different MEA wells obtained on the same recording day

were aggregated for statistical analysis and plotting. Subpeaks within an event were identified

using *findpeaks.m*, where a subpeak must satisfy the following: i) peak height of at least 25% of

the first peak; ii) peak width of at least 50 ms; iii) at least 200 ms away from the previous peak;

and iv) peak prominence of 1 over Peak 1 height. Subpeak time and the height relative to the

initial peak were recorded. The inter-event interval coefficient of variation (IEI CV) was calculated

as the standard deviation of the inter-event interval divided by its mean, where IEI is the time

between consecutive network events within the same MEA well. Event temporal correlation was

calculated as the mean Pearson correlation coefficient of population spiking vector during each

network event with every other network event in the same MEA well across a single recording

session. Event spatial correlation was calculated as the mean Pearson correlation coefficient

between all pairs of 64 LFP channels during each 3-s network event.

Oscillatory spectral power analysis. Power spectral density (PSD) estimates were computed

using Welch's method (*pwelch.m*), with a window length of 2 s and overlap of 1 s. Oscillatory

power was defined as peaks in the PSD above the aperiodic *1/f* power law decay. Thus, for each

channel, a straight line was fit over the PSD in double-log space between 0.5-20 Hz using robust

fit (*robustfit.m*), and oscillatory power was computed as the difference between the mean log PSD

power and the mean log fitted power (baseline), over 2.5-4.5 Hz.

Regression models. For analysis in Figure 2F, G and S7C, F, G, we fit regression models

(*LinearModel.fit*,*MATLAB*) using organoid age (in days) as input and electrophysiological features

as output. Order-1 (linear) models were fit for Figure 2G and and S7C, G, and order-2 (quadratic)

models were fit for Figure 2F, 3C and Figure S7F. Reported R^2 and p values are model statistics

over the entire dataset. All events from different MEA wells on the same recording day were

aggregated as samples drawn from the same distribution. To predict culture age, we used 3

electrophysiological features as input: event latency, event peak spiking, and oscillatory power;

and their square roots to account for the nonlinear inverted-U features. These were used to build

a regression model. Within-well models were fit over all data points of the same well, and

goodness-of-fit was reported as the model R^2 and the RMSE. Across-well models were trained

and evaluated using leave-1-out cross-validation, and goodness-of-fit is reported as the R^2 and

the RMSE computed over the validation set, not the training set.

Phase Amplitude Coupling (PAC). LFP data from all 64 channels of each well was first

lowpass/bandpass filtered (*eegfilt.m*, EEGLAB) for delta (0-4 Hz) and high-frequency, broadband

gamma (100-400 Hz) activity. Delta phase was extracted by taking the phase angle of the

bandpassed delta signal Hilbert transform (*hilbert.m, angle.m*), while gamma power was extracted

by taking the squared magnitude of the filtered gamma. Gamma power was smoothed with the

same delta-band filter for display purposes, but not for subsequent analysis. Note that analysis

was done for 100-200 Hz and 200-400 Hz separately, as LFP spectrum follows an inverse power

law (1/f), and grouping a wide frequency band (100-400 Hz) together will bias power estimates

towards lower frequency limits (~100 Hz). To compute PAC, instantaneous delta phase was

binned into 20 equidistant bins between $-\pi$ and π, and gamma power was sorted based on the

corresponding delta phase at the same sample time and averaged across the same phase bin.

This procedure was performed separately for event and non-event indices, where event indices

are the same 3-s windows as described above in *Network Event Analysis*. Modulation Index was

computed as the Kullback-Leibler divergence between the sum-normalized distribution of gamma

power across phase bins and a uniform distribution (Tort et al., 2010). Figure 3C presents well-

averaged MI across all 64 channels. For visualization in Figure 3b, the binned gamma vector for

each channel was circularly shifted such that the phase of maximum gamma power was $-\pi$.

Pharmacology. The pharmacological manipulation was performed using the following drugs: 10

µM bicuculline, 50 µM muscimol, 20 µM CNQX, 20 µM AP5, 25 µM baclofen and 1 µM TTX. In

this assessment, baseline recordings were obtained immediately before and 15 min after the

addition of the compound. Three washes with PBS for total removal of the drug were performed

in washout experiments; fresh media was added and another recording was conducted after 2

hours.

Preterm neonatal EEG. A preterm neonatal EEG dataset was obtained elsewhere (Stevenson

et al., 2017). Raw recordings were not available due to patient confidentiality concerns. The

dataset includes 567 recordings from 39 preterm neonates (24-38 weeks old conception age),

consisting of 23 EEG features computed from the entirety of each recording, as well as during

"low-activity periods" (46 features in total), and the post-conception age in weeks.

Neonate-organoid age prediction model. To compare the developmental trajectory of cortical

organoids and the preterm human brain, we trained an Elastic Net (L1- and L2- regularized)

regression model on only the preterm neonatal EEG features and used that model (with all

parameters held the same) to generate an equivalent organoid "brain-age" for each recording

time point over 40 weeks in culture. Specifically, the training dataset consists of a subset of the

preterm EEG data; of the 46 included features, we discarded all "low-activity-period" features

(Lisman, 1997) since there was no equivalent period for organoid recordings, as well as features

for which we could not sensibly compute from organoid LFPs, such as interhemispheric

synchrony. This selection was done *a priori*, and 13 features remained, including 4 features for

relative spectral power in distinct frequency bands, which were further discarded due to

frequency-dependent filtering properties of the skull and difference in spatial integration of

currents in macroscopic EEG electrodes compared to microscopic planar MEA electrodes. The

remaining 9 features correspond to aspects of spontaneous activity transient (SAT) timing, such

as SATs per hour and SAT duration, which were similarly computed on organoid LFPs after

network event detection described earlier (see Supplementary Table 2 for a full list of included

and rejected features). This latter organoid LFP test dataset was never seen by the regression

model until prediction time. Training was performed using scikit-learn linear model module

[(ElasticNetCV (Pedregosa et al., 2011)], with K-Group shuffle split cross-validation on

regularization hyperparameters, where K = 25% of groups, N = 200 shuffles. In other words, we

found the best regularized linear model possible for predicting the conception age of preterm

neonates using those 9 precomputed EEG features. This model was directly applied on organoid

LFP features to determine the corresponding "brain age" of the organoids during 40 weeks in

culture. 1-sample *t*-tests were performed from every time point to test whether the mean predicted

"brain age" was significantly different from the organoid culture age.

Resampled feature correlation. We computed Pearson's correlation coefficient between

neonate age and each of the 9 EEG features, after a leave-K-groups-out resampling procedure

N times, where K is the number of neonates from whom all recordings were left out in computing

the correlation (50% of all neonates, resampling N = 100). An identical procedure was performed

to compute the correlation between organoid culture age and LFP features (K = 4 out of 8, 50%,

N = 100). Mean and standard deviation were then computed over all resampled draws in order to

compare between organoid LFP and neonatal EEG.

Statistical analysis. Data are presented as mean ± s.e.m., unless otherwise indicated, and it was

obtained from different samples. No statistical method was used to predetermine the sample size,

and no adjustments were made for multiple comparisons. The statistical analyses were performed

using Prism software (GraphPad, San Diego, CA, USA). Student's *t*-test, Mann–Whitney-test, or

ANOVA with post hoc tests were used as indicated. Significance was defined as P < 0.05(*), P <

0.01(**), or P < 0.001(***). Blinding was used for comparing affected and control samples.

SUPPLEMENTARY FIGURE LEGENDS

Supplementary Figure 1. Cellular and molecular characterization of human cortical

organoids. (A) Schematic of the protocol used to generate cortical organoids. Scale bar, 200 μm.

(B) Reproducibility of organoid size at 2 months of maturation (*n = 20* independent experiment, 7

different cell lines). (C) Organoids are composed of a proliferative region surrounded by

intermediate progenitor cells, cortical and GABA+ neurons. Scale bar, 50 μm. (D) Principal

component analysis (PCA) of cells projected onto the first two components. Overlaid populations

of 2- and 10-month-old cortical organoids are compared to 2-month-old 2D monolayer neurons.

All timelines for this and the subsequent experiments consider the iPSC stage as day 0 (*n = 2*

independent cell lines for each cortical culture; *n = 3* for 2D monolayer neurons). (E-F) Violin plots

illustrate the differences in single-cell expression of target genes in cortical organoids and 2D

neurons. (G-H) Unsupervised hierarchical clustering single-cell analysis. Genes were clustered

using the Pearson correlation method and cells were clustered using the Euclidean method.

Supplementary Figure 2. Reproducibility and single-cell characterization. (A) Schematic

showing the single-cell approach performed to access reproducibility of organoid generation using

two control iPSC lines. (B) *t*SNE plot of single-cell mRNA sequencing data from 6-month-old

organoids color-coded by replicate. (C) Split Dot Plot depicting the correlation between expression

patterns of representative markers and cell populations identified within the dataset. The size of

the dots represents the percentage of cells expressing a given gene, while the intensity of the

color denotes the average expression level (grey, low expression; red/blue, high expression). (D)

Population ratio of each cluster by replicate.

Supplementary Figure 3. Cell diversity in cortical organoids. Violin and *t*SNE plots of selected

genes depicting the proportion of cells contributing to each cluster. For the violin pots, the dot

denotes a cell while colors correspond to their cluster identity. The *t*SNE plots show the

contribution of an individual cell-type marker within each cluster (red denotes higher expression).

Supplementary Figure 4. Cell type identity of 6-month-old cortical organoids. Heat map

reports scaled expression of discriminative gene sets for clusters defined in Figure 1h with AUC

cutoff ≥ 0.80. Color scheme is based on z-score distribution from –2.5 (blue) to 2.5 (red). For gene

lists and AUC values see Supplementary Table 1.

Supplementary Figure 5. Long-term MEA network activity. (A) Representative bright-field

images of cortical organoids over time on the MEA plate. (B) Schematic representation of the

electrical activity features analyzed from the MEA recordings. Each bar represents a spike; and

a spike cluster (in blue) represents a burst. Bursts occurring at the same time in different channels

characterize a network burst. The synchrony index is based on the cross-correlogram and

represents a measure of similarity between two spike trains. (C) Temporal evolution of network

activity characterized by different parameters. (D) Raster plots illustrating the development of

network activity. (E) Consistent and reproducible development of electrical activity in cortical

organoids over time. The data are shown as mean ± s.e.m ($n = 8$, independent experiments

performed in duplicates using two clones of a control iPSC line).

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Supplementary Figure 6. MEA electrical activity comparison of cortical organoids with

available published data from iPSC-derived neurons, organoids, rodent primary cultures

and primate models. (A) Long-term network activity of our cortical organoids is shown for

individual wells. Comparison of network activity between cortical organoids and iPSC-derived

cortical neurons (B), rodent primary neuronal cultures and primate models (C). The data shown

in B and C for cortical organoids are presented as mean ± s.e.m. ($n = 8$, independent experiments

performed in duplicates) (Amin et al., 2016; Bardy et al., 2015; Barz et al., 2017; Brown et al.,

2016; Cesca et al., 2015; Clements et al., 2016; Cotterill et al., 2016; Harrill et al., 2015; Marchetto

et al., 2016; McSweeney et al., 2016; Odawara et al., 2014, 2016; Roy et al., 2016; Strickland et

al., 2016; Tukker et al., 2016; Uesaka et al., 2007; Vessoni et al., 2016; Wallace et al., 2015; Xu

et al., 2017; Yang et al., 2016).

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Supplementary Figure 7. Extended characterization of network electrophysiology. (A)

Spikes detected on 9 channels. Black traces represent single spikes, blue and red traces

represent the average of positive and negative spikes, respectively. Spike trains are not sorted

for their polarity in the subsequent analyses, as total population spiking is the main feature of

interest. (B) Representative oscillatory network events. Each overlapping trace represents a

single occurrence of an event recorded on the same channel. LFP polarity of events differs

between channels due to the spatial configuration of cells around the electrode. (C) Event onset

peak (Peak 1) increases in amplitude until 30 weeks, while (D) subpeak amplitude continues to

increase (for the 2nd-4th peak) throughout development. (E) Subsequent peaks occur with a

consistent latency of ~400 ms after the previous peak, particularly for Peak 3 and 4. (F) Temporal

similarity of network events during the 3-s window is high at early time points, but decreases with

development, acquiring more variable dynamics within an event. (G) Temporal similarity of

network events during the 3-s window is high at early time points, but decreases with

development, acquiring more variable dynamics within an event. The data showed in C, F and G

are presented as mean ± s.e.m., linear (C, G) or quadratic (F) model regression.

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Supplementary Figure 8. MEA recording from 3-month-old neurospheres. (A) Comparison

of the protocol for neurosphere and cortical organoid generation. (B) Network-wide giant

depolarizing potentials occur at a similar rate to those found in organoids recordings, and visible

perturbations are observed in the LFP trace. However, the network recruitment in neurospheres

is lower than in organoids (less than 8 spikes/s), and events have significantly shorter duration.

No coherent low-frequency depolarizations are observed in filtered LFP events (C).

Supplementary Figure 9. MECP2-KO cell line characterization. (A) Schematic overview of the

MECP2 locus in iPSCs derived from fibroblasts of a male patient (Q83X), and CRISPR/Cas9

induced *MECP2* mutation in an embryonic stem cell line (K82fs, H9 ESC). Q83X cell line

characterization is shown elsewhere (Zhang et al., 2016). DNA sequence chromatogram shows

the nucleotide deletion in the *MECP2* gene leading to a frameshift mutation (K82fs) and a

predicted premature stop-codon at the end of exon 3 (asterisk). The WT82 and WT83 were used

as controls. The Q83X and K82fs do not express MECP2 protein. Blue line represents the guide

RNA target locus. (B) Gel images showing Surveyor nuclease assay of genomic DNA extracted

from FACs sorted H9 ESC. Expected PCR products were 278 bp and 220 bp. (C) Exome

sequencing analysis to evaluate CRISPR off-target mutations. Numbers indicate the amount of

reads across the lines. Off-target gene mutations induced by *MECP2* CRISPR/Cas9 are shown

in the lower table. (D) Isogenic pairs of *MECP2*-mutant and control cell line colonies showing the

expression of the pluripotency marker Nanog. Scale bar, 100 µm. (E) Eosin and Hematoxylin

stains of teratomas showing the presence of all three germ layers. Scale bar, 200 µm. (F) Western

blot of the isogenic pluripotent stem cells showing the absence of MECP2 in the mutant line. (G)

Karyotypes of cell lines displaying no chromosomal abnormality. (H and I) Expression of

pluripotency markers and *MECP2* by qPCR. GAPDH was used as housekeeping gene.

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Supplementary Figure 10. Network activity in cortical organoids mimics oscillatory

features in the developing human brain. (A) Spectral representation of time series data from a

6-month-old cortical organoid, demonstrating oscillatory phenomenon. Spectrogram (left) of

organoid LFP shows bursts of activity localized at low frequencies, while power spectral density

(PSD, right) displays canonical *1/f* power law decay and a narrow oscillatory peak at 3 Hz. (B)

Comparison of 9 preterm neonate EEG and cortical organoid features over time. For included

EEG features, see Table S2. (C) Distributions of resampled Pearson correlation coefficients

between feature and age for preterm neonate and organoid.

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1064 **SUPPLEMENTARY TABLES**
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1066 **Supplementary Table 1. Top expressed genes of each cell cluster.**

Cluster	Gene	myAUC	avg_diff	power	avg_logFC	pct.1	pct.2	p_val_adj
Cortical neurons	SOX11	0.889	1.29996	0.778	1.29996	0.996	0.864	NA
Cortical neurons	NEUROD2	0.886	1.366603	0.772	1.366603	0.944	0.382	NA
Cortical neurons	GPM6A	0.885	1.12235	0.77	1.12235	0.992	0.679	NA
Cortical neurons	SOX4	0.879	0.985057	0.758	0.985057	1	0.965	NA
Cortical neurons	MLLT11	0.856	0.916514	0.712	0.916514	0.998	0.869	NA
Cortical neurons	CCNI	0.843	0.707003	0.686	0.707003	1	0.994	NA
Cortical neurons	SLA	0.833	1.424488	0.666	1.424488	0.821	0.303	NA
Cortical neurons	MARCKSL1	0.832	0.578678	0.664	0.578678	0.999	0.981	NA
Cortical neurons	DCX	0.806	0.81224	0.612	0.81224	0.969	0.576	NA
Progenitors	NES	0.976	1.785855	0.952	1.785855	0.997	0.303	NA
Progenitors	ANXA2	0.972	2.407607	0.944	2.407607	0.976	0.149	NA
Progenitors	GYPC	0.963	1.587675	0.926	1.587675	0.954	0.065	NA
Progenitors	SPARC	0.958	1.745727	0.916	1.745727	0.978	0.24	NA
Progenitors	SDC2	0.944	1.388854	0.888	1.388854	0.924	0.08	NA
Progenitors	CRABP2	0.942	1.564316	0.884	1.564316	0.939	0.11	NA
Progenitors	NTRK2	0.941	1.61904	0.882	1.61904	0.912	0.057	NA
Progenitors	CCND1	0.941	1.505771	0.882	1.505771	0.909	0.046	NA
Progenitors	LGALS1	0.938	2.0633	0.876	2.0633	0.94	0.17	NA
Progenitors	SERF2	0.934	0.95158	0.868	0.95158	1	0.903	NA
Progenitors	MDK	0.933	1.279235	0.866	1.279235	0.996	0.832	NA
Progenitors	VGLL3	0.931	1.237999	0.862	1.237999	0.887	0.032	NA
Progenitors	S100A13	0.917	1.839522	0.834	1.839522	0.893	0.12	NA
Progenitors	PDLIM7	0.916	1.185298	0.832	1.185298	0.94	0.25	NA

Progenitors	ANXA5	0.902	1.221643	0.804	1.221643	0.926	0.184	NA
Progenitors	PRSS23	0.901	1.501512	0.802	1.501512	0.836	0.06	NA
Progenitors	RPL41	0.897	0.625131	0.794	0.625131	1	0.999	NA
Progenitors	NPC2	0.895	1.182853	0.79	1.182853	0.951	0.407	NA
Progenitors	SEC11A	0.894	0.828695	0.788	0.828695	0.98	0.64	NA
Progenitors	PRDX6	0.892	0.981071	0.784	0.981071	0.98	0.555	NA
Progenitors	TPM1	0.887	1.731952	0.774	1.731952	0.938	0.518	NA
Progenitors	RHOC	0.887	0.962424	0.774	0.962424	0.907	0.206	NA
Progenitors	NEAT1	0.883	1.352256	0.766	1.352256	0.948	0.285	NA
Progenitors	RPL12	0.882	0.706881	0.764	0.706881	0.999	0.992	NA
Progenitors	RPL7A	0.881	0.613375	0.762	0.613375	1	0.997	NA
Progenitors	EEF1A1	0.879	0.651914	0.758	0.651914	1	1	NA
Progenitors	RPL28	0.876	0.592999	0.752	0.592999	1	0.995	NA
Progenitors	RPS6	0.871	0.711767	0.742	0.711767	0.997	0.994	NA
Progenitors	RPL23A	0.867	0.568383	0.734	0.568383	0.999	0.994	NA
Progenitors	TIMP1	0.865	0.772749	0.73	0.772749	0.895	0.173	NA
Progenitors	RPL8	0.864	0.572428	0.728	0.572428	0.999	0.997	NA
Progenitors	METRN	0.863	0.835332	0.726	0.835332	0.907	0.229	NA
Progenitors	WLS	0.859	0.916782	0.718	0.916782	0.736	0.023	NA
Progenitors	RPL27A	0.858	0.534803	0.716	0.534803	1	0.998	NA
Progenitors	CTGF	0.857	1.335629	0.714	1.335629	0.727	0.017	NA
Progenitors	RCN1	0.857	0.806462	0.714	0.806462	0.967	0.377	NA
Progenitors	PFN1	0.857	0.738107	0.714	0.738107	0.99	0.844	NA
Progenitors	PMP22	0.855	1.601169	0.71	1.601169	0.778	0.101	NA
Progenitors	ITGB8	0.855	1.138802	0.71	1.138802	0.868	0.201	NA
Progenitors	SERPINH1	0.854	0.713982	0.708	0.713982	0.846	0.143	NA
Progenitors	VIM	0.853	1.146246	0.706	1.146246	1	0.77	NA
Progenitors	NME4	0.852	0.813408	0.704	0.813408	0.945	0.457	NA
Progenitors	RPS7	0.852	0.558045	0.704	0.558045	0.999	0.997	NA
Progenitors	MYL12A	0.85	0.739735	0.7	0.739735	0.84	0.157	NA
Progenitors	RPS20	0.849	0.558658	0.698	0.558658	1	0.991	NA

Progenitors	RPS2	0.848	0.524557	0.696	0.524557	0.999	1	NA
Progenitors	RPLP1	0.848	0.514123	0.696	0.514123	1	0.998	NA
Progenitors	RAB13	0.846	0.808108	0.692	0.808108	0.86	0.204	NA
Progenitors	TUBB6	0.845	0.757197	0.69	0.757197	0.806	0.121	NA
Progenitors	CRNDE	0.843	0.802352	0.686	0.802352	0.954	0.472	NA
Progenitors	TTYH1	0.84	0.971997	0.68	0.971997	0.963	0.416	NA
Progenitors	RPL23	0.84	0.546833	0.68	0.546833	1	0.997	NA
Progenitors	RPS19	0.84	0.516859	0.68	0.516859	1	1	NA
Progenitors	RPL29	0.84	0.464037	0.68	0.464037	1	0.997	NA
Progenitors	RPS14	0.839	0.462974	0.678	0.462974	1	0.999	NA
Progenitors	RPL3	0.838	0.497988	0.676	0.497988	1	0.998	NA
Progenitors	SLC25A6	0.835	0.71474	0.67	0.71474	0.995	0.891	NA
Progenitors	SPATS2L	0.831	0.9606	0.662	0.9606	0.811	0.193	NA
Progenitors	QPRT	0.83	0.651751	0.66	0.651751	0.855	0.198	NA
Progenitors	RPL35	0.83	0.470972	0.66	0.470972	0.999	0.993	NA
Progenitors	RPS18	0.828	0.49256	0.656	0.49256	1	1	NA
Progenitors	CLIC1	0.827	0.723496	0.654	0.723496	0.937	0.427	NA
Progenitors	RPS3	0.827	0.526597	0.654	0.526597	1	0.997	NA
Progenitors	RPL10A	0.827	0.523565	0.654	0.523565	1	0.994	NA
Progenitors	RPS28	0.825	0.506021	0.65	0.506021	1	0.993	NA
Progenitors	CD63	0.824	0.710828	0.648	0.710828	0.991	0.76	NA
Progenitors	PDPN	0.824	0.65191	0.648	0.65191	0.699	0.046	NA
Progenitors	ACTG1	0.824	0.488252	0.648	0.488252	1	1	NA
Progenitors	CCNG1	0.823	0.727443	0.646	0.727443	0.924	0.38	NA
Progenitors	CD99	0.82	0.68859	0.64	0.68859	0.953	0.405	NA
Progenitors	B2M	0.817	0.787786	0.634	0.787786	0.947	0.392	NA
Progenitors	CHCHD10	0.817	0.645222	0.634	0.645222	0.84	0.211	NA
Progenitors	RPLP0	0.817	0.469741	0.634	0.469741	1	0.997	NA
Progenitors	RPS27L	0.816	0.744701	0.632	0.744701	0.995	0.664	NA
Progenitors	COL1A2	0.815	0.896012	0.63	0.896012	0.647	0.019	NA
Progenitors	PFN2	0.815	0.622861	0.63	0.622861	0.991	0.763	NA

Progenitors	UBB	0.813	0.783749	0.626	0.783749	0.978	0.588	NA
Progenitors	RPL37	0.813	0.465752	0.626	0.465752	1	0.995	NA
Progenitors	CRABP1	0.811	1.087669	0.622	1.087669	0.737	0.133	NA
Progenitors	RPL7	0.811	0.467728	0.622	0.467728	1	0.998	NA
Progenitors	FSTL1	0.81	0.761788	0.62	0.761788	0.737	0.123	NA
Progenitors	RPL36	0.81	0.434708	0.62	0.434708	1	0.992	NA
Progenitors	RPL19	0.81	0.401045	0.62	0.401045	1	1	NA
Progenitors	FGFR1	0.809	0.608769	0.618	0.608769	0.839	0.204	NA
Progenitors	ENO1	0.808	0.582772	0.616	0.582772	0.996	0.869	NA
Progenitors	RPS15	0.806	0.381154	0.612	0.381154	1	0.999	NA
Progenitors	MYL6	0.805	0.530039	0.61	0.530039	1	0.986	NA
Progenitors	GSTP1	0.804	0.634369	0.608	0.634369	0.996	0.92	NA
Progenitors	PODXL	0.804	0.622402	0.608	0.622402	0.67	0.06	NA
Progenitors	CNN3	0.804	0.616921	0.608	0.616921	0.992	0.669	NA
Progenitors	GNG11	0.803	0.751478	0.606	0.751478	0.668	0.064	NA
Progenitors	RPS4Y1	0.803	0.680093	0.606	0.680093	0.963	0.62	NA
Progenitors	AHNAK	0.803	0.651782	0.606	0.651782	0.64	0.036	NA
Progenitors	CST3	0.802	0.645478	0.604	0.645478	0.963	0.567	NA
Progenitors	RPS23	0.801	0.419435	0.602	0.419435	1	0.998	NA
Progenitors	RPL13A	0.801	0.409875	0.602	0.409875	1	1	NA
Glia	SFRP1	0.94	2.001041	0.88	2.001041	0.952	0.385	NA
Glia	SOX2	0.909	1.356804	0.818	1.356804	0.946	0.321	NA
Glia	C1orf61	0.893	1.500525	0.786	1.500525	0.984	0.749	NA
Glia	FABP7	0.887	1.707591	0.774	1.707591	0.985	0.736	NA
Glia	SLC1A3	0.88	1.56662	0.76	1.56662	0.807	0.119	NA
Glia	SYNE2	0.876	1.218806	0.752	1.218806	0.919	0.445	NA
Glia	PAX6	0.871	1.251984	0.742	1.251984	0.83	0.186	NA
Glia	HMGN3	0.866	0.91378	0.732	0.91378	0.978	0.849	NA
Glia	ID4	0.851	1.407158	0.702	1.407158	0.875	0.381	NA
Glia	MYO10	0.85	1.025069	0.7	1.025069	0.857	0.338	NA
Glia	DBI	0.842	1.242287	0.684	1.242287	0.958	0.709	NA

Glia	PTN	0.836	1.579917	0.672	1.579917	0.948	0.752	NA
Glia	QKI	0.83	0.909655	0.66	0.909655	0.891	0.502	NA
Glia	LINC01158	0.818	0.903364	0.636	0.903364	0.901	0.546	NA
Glia	ZFHX4	0.817	1.004117	0.634	1.004117	0.707	0.132	NA
Glia	HES1	0.812	1.171994	0.624	1.171994	0.718	0.17	NA
Glia	HMGB2	0.809	1.270445	0.618	1.270445	0.921	0.594	NA
Glia	LHX2	0.806	0.931067	0.612	0.931067	0.846	0.398	NA
Lower cortex	SNAP25	0.942	1.540645	0.884	1.540645	0.987	0.415	NA
Lower cortex	GRIA2	0.892	1.185847	0.784	1.185847	0.96	0.352	NA
Lower cortex	CNTNAP2	0.88	1.447084	0.76	1.447084	0.876	0.272	NA
Lower cortex	CELF4	0.863	1.071334	0.726	1.071334	0.886	0.265	NA
Lower cortex	NSG2	0.851	1.031537	0.702	1.031537	0.96	0.403	NA
Lower cortex	SYT1	0.85	0.985569	0.7	0.985569	0.983	0.61	NA
Lower cortex	YWHAH	0.841	0.785308	0.682	0.785308	0.973	0.805	NA
Lower cortex	SNCA	0.839	0.953942	0.678	0.953942	0.914	0.451	NA
Lower cortex	BASP1	0.838	0.734567	0.676	0.734567	1	0.943	NA
Lower cortex	DOK6	0.831	1.000188	0.662	1.000188	0.814	0.264	NA
Lower cortex	RTN1	0.823	0.898627	0.646	0.898627	0.985	0.519	NA
Lower cortex	RUNX1T1	0.82	0.94366	0.64	0.94366	0.852	0.281	NA
Lower cortex	FAM49A	0.817	0.920672	0.634	0.920672	0.821	0.28	NA
Lower cortex	MAP1B	0.817	0.603691	0.634	0.603691	1	0.995	NA
Lower cortex	SYT4	0.816	0.939245	0.632	0.939245	0.821	0.262	NA
Lower cortex	B3GALT2	0.815	1.017411	0.63	1.017411	0.757	0.2	NA
Lower cortex	GABRB2	0.815	0.991632	0.63	0.991632	0.675	0.062	NA
Lower cortex	LMO3	0.814	1.36195	0.628	1.36195	0.688	0.101	NA
Lower cortex	SCG3	0.811	0.757346	0.622	0.757346	0.939	0.415	NA
Lower cortex	UCHL1	0.809	0.66339	0.618	0.66339	0.99	0.906	NA
Lower cortex	VAMP2	0.809	0.606955	0.618	0.606955	0.994	0.939	NA
Lower cortex	TMEM161B -AS1	0.808	0.816917	0.616	0.816917	0.941	0.63	NA
Lower cortex	LY6H	0.806	0.807691	0.612	0.807691	0.88	0.34	NA
Lower cortex	MAPT	0.805	0.73704	0.61	0.73704	0.962	0.486	NA

Lower cortex	CDKN2D	0.802	0.762383	0.604	0.762383	0.878	0.4	NA
Lower cortex	RAB3A	0.801	0.697869	0.602	0.697869	0.924	0.413	NA
Upper cortex	MEF2C	0.954	2.051853	0.908	2.051853	0.986	0.369	NA
Upper cortex	STMN2	0.885	1.043931	0.77	1.043931	1	0.644	NA
Upper cortex	NSG2	0.883	1.126043	0.766	1.126043	1	0.441	NA
Upper cortex	ARPP21	0.88	1.115469	0.76	1.115469	0.883	0.189	NA
Upper cortex	STMN4	0.874	0.982886	0.748	0.982886	1	0.696	NA
Upper cortex	MAPT	0.87	0.908315	0.74	0.908315	1	0.518	NA
Upper cortex	GRIN2B	0.869	1.002716	0.738	1.002716	0.9	0.246	NA
Upper cortex	CALM1	0.868	0.733117	0.736	0.733117	1	0.988	NA
Upper cortex	NELL2	0.861	0.95751	0.722	0.95751	0.973	0.409	NA
Upper cortex	SCD5	0.855	0.913699	0.71	0.913699	0.931	0.478	NA
Upper cortex	SATB2	0.853	0.902036	0.706	0.902036	0.811	0.125	NA
Upper cortex	PKIA	0.849	0.808509	0.698	0.808509	0.952	0.445	NA
Upper cortex	MAP1B	0.849	0.669352	0.698	0.669352	1	0.995	NA
Upper cortex	INA	0.847	0.831367	0.694	0.831367	0.966	0.437	NA
Upper cortex	STMN1	0.845	0.783568	0.69	0.783568	1	0.979	NA
Upper cortex	NEUROD6	0.843	1.007963	0.686	1.007963	0.986	0.502	NA
Upper cortex	VAMP2	0.843	0.689091	0.686	0.689091	0.993	0.943	NA
Upper cortex	DOK5	0.841	0.93379	0.682	0.93379	0.935	0.559	NA
Upper cortex	RASL11B	0.841	0.930199	0.682	0.930199	0.821	0.209	NA
Upper cortex	SNCA	0.841	0.896556	0.682	0.896556	0.952	0.482	NA
Upper cortex	R3HDM1	0.84	0.924861	0.68	0.924861	0.89	0.386	NA
Upper cortex	TTC9B	0.84	0.868857	0.68	0.868857	0.959	0.435	NA
Upper cortex	RAC3	0.83	0.70783	0.66	0.70783	0.945	0.624	NA
Upper cortex	CXADR	0.827	0.785512	0.654	0.785512	0.993	0.719	NA
Upper cortex	HN1	0.827	0.602815	0.654	0.602815	1	0.961	NA
Upper cortex	CAMK2B	0.822	0.749623	0.644	0.749623	0.897	0.279	NA
Upper cortex	RTN1	0.819	0.807888	0.638	0.807888	1	0.553	NA
Upper cortex	CHL1	0.819	0.775621	0.638	0.775621	0.918	0.374	NA
Upper cortex	NSG1	0.818	0.708593	0.636	0.708593	0.997	0.528	NA

Upper cortex	TUBB2A	0.817	0.659235	0.634	0.659235	1	0.946	NA
Upper cortex	GABBR2	0.815	0.777596	0.63	0.777596	0.79	0.182	NA
Upper cortex	RBFOX2	0.814	0.677032	0.628	0.677032	0.99	0.662	NA
Upper cortex	CRMP1	0.813	0.666121	0.626	0.666121	0.979	0.79	NA
Upper cortex	GAP43	0.811	0.737576	0.622	0.737576	0.997	0.816	NA
Upper cortex	UCHL1	0.809	0.645161	0.618	0.645161	1	0.911	NA
Upper cortex	CDKN2D	0.808	0.694482	0.616	0.694482	0.935	0.43	NA
Upper cortex	NCAM1	0.805	0.694452	0.61	0.694452	0.955	0.551	NA
Upper cortex	MSRA	0.804	0.734229	0.608	0.734229	0.814	0.288	NA
Upper cortex	GPR85	0.801	0.76111	0.602	0.76111	0.766	0.189	NA
Upper cortex	DAAM1	0.801	0.628961	0.602	0.628961	0.993	0.776	NA
Other	ALDOA	0.917	1.757415	0.834	1.757415	0.963	0.838	NA
Other	EIF1	0.888	0.999198	0.776	0.999198	1	0.999	NA
Other	FTL	0.883	1.541462	0.766	1.541462	1	0.997	NA
Other	BNIP3	0.87	1.504624	0.74	1.504624	0.844	0.345	NA
Other	FAM162A	0.857	1.366057	0.714	1.366057	0.881	0.459	NA
Other	ARF4	0.848	1.242187	0.696	1.242187	0.889	0.715	NA
Other	ENO1	0.845	1.199331	0.69	1.199331	0.978	0.894	NA
Other	P4HA1	0.832	1.239505	0.664	1.239505	0.741	0.175	NA
Other	TRMT112	0.825	0.918451	0.65	0.918451	0.926	0.735	NA
Other	RPS13	0.822	0.756328	0.644	0.756328	0.993	0.998	NA
Other	TPT1	0.817	0.840456	0.634	0.840456	0.993	0.998	NA
Other	SEC61G	0.812	0.841716	0.624	0.841716	0.963	0.881	NA
Other	PGK1	0.809	1.333477	0.618	1.333477	0.881	0.803	NA
Other	GADD45A	0.802	1.332596	0.604	1.332596	0.741	0.3	NA
Other	ST13	0.801	0.866714	0.602	0.866714	0.963	0.878	NA
Neural crest	TAGLN3	0.922	1.681741	0.844	1.681741	1	0.686	NA
Neural crest	PBX3	0.917	1.457984	0.834	1.457984	0.878	0.154	NA
Neural crest	CRABP1	0.886	2.63702	0.772	2.63702	0.892	0.257	NA
Neural crest	MEG3	0.872	2.436136	0.744	2.436136	0.824	0.289	NA
Neural crest	ACTG1	0.851	0.573491	0.702	0.573491	1	1	NA

Neural crest	MIAT	0.82	1.008958	0.64	1.008958	0.932	0.671	NA
Neural crest	KCNQ1OT1	0.818	1.242528	0.636	1.242528	0.905	0.547	NA
Neural crest	NEAT1	0.806	0.991861	0.612	0.991861	0.865	0.427	NA
Neural crest	ELAVL2	0.806	0.728978	0.612	0.728978	0.932	0.464	NA
Neural crest	RGMB	0.804	1.190676	0.608	1.190676	0.703	0.168	NA

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1074   **Supplementary Table 2. Electrophysiological features in preterm neonatal EEG dataset and**

1075   **analogous features computed in organoid LFP.**

Neonatal EEG features	Computed organoid LFP features
Envelope (50%)	None
Envelope (5%)	None
Envelope (95%)	None
rEEG (50%)	None
rEEG (5%)	None
rEEG (95%)	None
SATs per hour	Network Events per hour
RMS SAT duration	RMS network event duration
SAT duration (50%)	Network event duration (50%)
SAT duration (5%)	Network event duration (5%)
SAT duration (95%)	Network event duration (95%)
RMS Inter-SAT Duration	RMS Inter-event Duration
Inter-SAT duration (50%)	Inter-event duration (50%)
Inter-SAT duration (5%)	Inter-event duration (5%)
Inter-SAT duration (95%)	Inter-event duration (95%)
Temporal Theta Power	None
Activation Synchrony Index	None
Interhemispheric Correlation	None
Total Spectral Power	None
Relative Delta Power	Relative Delta Power
Relative Theta Power	Relative Theta Power
Relative Alpha Power	Relative Alpha Power
Relative Beta Power	Relative Beta Power

1076   Shaded cells indicate features used in the age-prediction model.

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