Host and rabies virus gene expression is shaped by human brain cell type and reveals a preexisting pro-viral transcriptional state in astrocytes

Authors

Lena Feige[1,2#,] Karl Young[3], Juan Pablo Cerapio[4-8], Tatsuya Kozaki[9], Lauriane Kergoat[1], Valentina Libri[10], Florent Ginhoux[9,11-12], Milena Hasan[10], Lamya Ben Ameur[3], Gregory Chin[3], Zach Goode[3], Hervé Bourhy[1*] and Arpiar Saunders[3#$*]

[1] Institut Pasteur, Université Paris Cité, Lyssavirus Epidemiology and Neuropathology, F-75015, Paris, France

[2] Université de Paris Cité, F-75015, Paris, France

[3] Vollum Institute, Oregon Health & Science University, Portland, OR, 97239, USA

[4] Centre de Recherches en Cancérologie de Toulouse, INSERM UMR1037, Toulouse, France

[5] Toulouse University, Toulouse, France

[6] CNRS UMR 5071, Toulouse, France

[7] Institut Universitaire du Cancer-Oncopole de Toulouse, Toulouse, France

[8] Laboratoire d'Excellence 'TOUCAN-2', Toulouse, France

[9] Singapore Immunology Network, Agency for Science, Technology and Research, Singapore 138648, Singapore

[10] Single Cell Biomarkers UTechS, Institute Pasteur, 28 rue du docteur Roux, 75015 Paris, France, Université Paris Cité, Paris, France

[11] Shanghai Institute of Immunology, Shanghai JiaoTong University School of Medicine, 280 South Chongqing Road, Shanghai 200025, China

[12] Translational Immunology Institute, SingHealth Duke-NUS Academic Medical Center, 20 College Road, Discovery Tower Level 8, Singapore 169856, Singapore

# equal contribution
$ lead contact
*Correspondence: saundear@ohsu.edu (A.S.), herve.bourhy@pasteur.fr (H.B.)

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Summary

Rabies virus (RABV) proteins play dual roles during the infection of complex neural tissue, the generation and spread of new virions and the active inhibition of cellular innate immune pathways, both contributing to rabies' lethality. While spatially-distinct RABV protein residues specializing in virus-centric and immune-inhibitory functions have been identified, how these dual functions interact to shape infection outcomes across diverse types of host brain cells is unknown. To "unmask" and study how innate immune inhibition affects the transcriptional regulation of the human and viral genome with cellular resolution, we performed single-cell RNA sequencing of co-cultured human brain cell types, comparing infection dynamics of a wild-type RABV isolate virus to a mutant virus in which six critical point mutations in the phosphoprotein (P) and matrix (M) RABV proteins selectively neuter antagonism of interferon- and NF-κB- dependent cellular responses. Our analysis reveals that RABV gene expression is shaped by host cell type and that wild-type RABV infection induces small-scale, cell-type conserved transcriptional programs that may support infection by hijacking transcriptional feedback systems that control pro-viral host cell factors while minimizing anti-viral responses. In contrast to accepted models, disinhibited innate immune signaling increases RABV transcriptional output across infected cell types. Most strikingly, we discovered a subpopulation of astrocytes that supports an average of 6-fold higher viral mRNA expression through a massive host cell transcriptional change involving ~38% of astrocyte expressed genes. Our analysis suggests that these astrocytes we term "pro-viral" are a rare subtype present in the human brain and are primed to play a protective role during viral infection in concert with interferon-sensitive microglia recalcitrant to infection.

Introduction

Viruses possess diverse mechanisms that shape the cellular and molecular properties of host cells through direct viral-host protein interactions. Due to historic technical limitations, the molecular consequences of these interactions have been difficult to characterize, especially across diverse primary cell types that constitute complex tissue such as the human central nervous system (CNS). The neurotropic Rabies virus (RABV) – a prototypic member of the negative-stranded RNA *Lyssavirus* genus – has evolved specialized mechanisms of immune evasion in the CNS, contributing to fatal encephalomyelitis and approximately 60,000 deaths annually[1]. Immune evasion is a critical feature of RABV pathogenesis, as the virus must travel undetected for long distances from peripheral muscle into the CNS, leveraging neurons and neuronal synapses for retrograde (dendrite-to-axon) transport[2]. Remarkably, neuronal viability and function are preserved during infection of isolate, non-cell culture adapted RABV strains as brains often show minimal macroscopic and histopathological alterations[3,4]. While neurons possess mechanisms to detect and respond to infection, neuronal immune responses are comparatively restricted to those of neighboring glia[5,6], functionally-distinct brain cell types that form intimate physical interactions with neuronal processes and perform myriad functions. Recent *in vivo* evidence suggests RABV can infect astrocytes and Schwann cells, challenging the notion of exclusive neuron-specific tropism[7–9]. Astrocytes in particular are crucial for IFN-β signaling during RABV infection[10] and can enter "reactive" molecular states in response to diverse insults, including viral infection[11]. Microglia too are involved in RABV pathogenesis[12], but it remains unclear whether viral antigens observed within microglia are due to active infection or because of phagocytosis of infected neuronal material. Despite this unresolved debate, numerous reports indicate microglia transcribe pro-inflammatory genes (such as *ISG15*, *OASL1*, *IFIT2*, *CCL5*, *CXCL10* and *IL-6*) in response to RABV infection[9,13–15]. To counteract cellular innate immune pathways, RABV proteins evolved mechanisms to sabotage the *nuclear factor 'kappa-light-chain-enhancer' of activated B-cells* (NF-κB)[16,17] and the Janus kinases (JAK) - Signal Transducers and Activators of Transcription (STAT) pathways[18–20], and thus potently inhibit host cell transcriptional responses downstream of interferon (IFN) type I signaling[21]. Although significant mechanistic insights have been made into immune inhibitory function of RABV proteins using cell lines, the consequences of these physical interactions on properties of infection in neurons and glia are largely unknown. Importantly, many viruses, including RABV, appear to have co-opted host cell proteins (including innate immune detectors[22]) for their life cycle[23], suggesting that infection outcomes may depend on a complex "arms race" between anti- and pro-viral factors[24], the nature of which remains to be fully elucidated.

In this study, we developed an experimental system using Tha isolate RABV, co-cultured stem cell-derived human brain cell types and single-cell RNA-sequencing (scRNA-seq) to discover how active inhibition of IFN and NF-κB signaling shapes transcriptional responses across the viral and human genomes at single-cell resolution. Of the five RABV proteins encoded by five genes in the negative-stranded RNA genome (**Figure 1A,B**), the phosphoprotein (P) and matrix protein (M) potently inhibit key pinch-points in cellular innate immune signaling. Specifically, P protein selectively binds and inhibits phosphorylated targets downstream of IFN signaling, including STAT1/2/3[18–20,25–27] transcription factors in the cytoplasm or nucleus, as well as TBK kinase[28]. M binds and inhibits RelAp43[16], disturbing NF-κB transcriptional complexes (**Figure 1C**). Foundational work has 1) shown that rabies adaptation to cell culture genetically erodes the potency of innate immune inhibition[21] and alters viral tropism *in vivo*[7] and 2) has identified mutations in outward facing residues in P (W265G, M287V; "2P")[29] and

M (R77K, D100A, A104S, M110L; "4M")[16] that prevent pSTAT1/2 and RelAp43 binding,
respectively, yet leave canonical viral functions intact[14] (**Figure 1D,E**). Thus, we sought to
"unmask" the otherwise potent innate immune inhibition of Tha virus using the 2P4M knock-in
mutations and study the consequences of intact and unmasked innate immunity on viral and
host transcriptional signatures across brain cell types.

Our analysis reveals several important discoveries. First, we show that Tha RABV gene
transcription is coupled to transcription of the host cell genome and shaped by the host cell
type. Second, we demonstrate that Tha virus induces a conserved transcriptional response in
both neurons and astrocytes, increasing RNAs encoding proteins that are likely "pro-viral" and
thus promoting infection, while decreasing RNAs encoding interferon-related transcription
factors that control anti-viral responses. Third, we show, counterintuitively, that 2P4M-based
disinhibition of innate immune signaling *increases* viral transcription across cell types.
Increased viral transcription is most strikingly observed in a subpopulation of "pro-viral"
astrocytes, likely enabled by large-scale changes in the astrocytic molecular milieu including
increased expression of NF-κB effectors and reduced expression of genes supporting protein
translation and mitochondrial function. Additional analysis suggests that "pro-viral" astrocytes
are likely a rare subpopulation present in nominally uninfected human brain. Finally, we
demonstrate that microglia are almost completely recalcitrant to infection but nonetheless
respond to infection of other cell types through an interferon-stimulated gene (ISG) expression
response that is potentiated by both higher viral titer and 2P4M mutations. Through the lens of
gene expression, our data collectively suggest that innate immune inhibition by isolate RABV
maintains infection stealth by restricting viral gene expression, avoiding "pro-viral" astrocytes
and limiting ISGs in microglia.

Results

Discerning infection states and host cell types from single-cell RNA sequencing data
To study how isolate Tha RABV alters the molecular properties of human brain cell types at
single-cell resolution - and to "unmask" and then characterize how antagonism of IFN and NF-
κB by Tha RABV P- and M-proteins sculpt these changes through regulation of both the human
and Tha RABV genome - we performed scRNA-seq analysis (10x Genomics Chromium 3'
v3.1) of co-cultured human neurons, astrocytes and microglia 48 hours after bath application
of Tha (multiplicity of infection (MOI) 0.5 or MOI 5) or Tha2P4M (MOI 0.5) or from uninfected
control wells ("No Infection")(**Figure 1F**). Brain cell co-cultures were seeded with
approximately equal proportions of hNSC-derived neurons and astrocytes (~47% each) as well
as a small population of human-induced microglia (~6%)(**Methods**). The presence of these
differentiated cell classes and Tha RABV infection was confirmed using a Tha virus expressing
eGFP followed by immunolabeling of cell-type-specific marker proteins (**Figure 1G**). After
quality control, our analysis focused on n=23, 457 single-cell RNA profiles derived from acutely
dissociated cells with >2,000 RNA transcripts (as defined by unique molecular identifiers;
UMIs) collected across multiple biological replicates (No Infection control, n=3; Tha(0.5), n=3;
Tha(5), n=2; and Tha2P4M (0.5), n=2)(**Methods**; **Figure S2A,B**).

We next sought to accurately distinguish infected cells and uninfected "bystander" cells and
assign host cell type identities to each RNA profile. Because infected cells may contain variable
levels of viral mRNA, and bystander cells may accrue viral transcripts by chance during cell
dissociation and scRNA-seq library preparation, we developed a data-driven computational
approach using expectation-maximization to iteratively refine viral RNA distributions for

infected and bystander populations, accounting for variability in viral RNAs driven by biological
and technical factors (**Figure 2A,B**; **Methods**). The resulting "viral load" distributions – defined
as the percentage of total cellular mRNA derived from the Tha genome – clearly delineated
populations of infected and bystander cells (Infected, mean = 3.9 ± 0.03 sem; range: 0.38 –
64.8; Bystander, mean = 0.17 ± 0.002 sem; range: 0-0.64)(**Figure 2C**). Simulated viral
expression data based on these inferred distributions closely matched that of real data,
confirming the accuracy of our approach (**Figure S2C**). Throughout this study, we use both
qualitative infection categories as well as a quantitative metric of infection progression ("viral
load") to guide our analysis of host and virus gene expression relationships at single-cell
resolution.

To assign single-cell RNA profiles to transcriptionally-defined brain cell types, we clustered cell
profiles using only genes from the human genome (**Methods**). The resulting clusters
corresponded to 5 major brain cell populations: neural stem cells (10.7%; n=2,526), mitotic
cells 3.3%; n=781), astrocytes (16.9%; n=3,975), microglia (5.2%; n=1,218) and two groups of
neurons (*OTP+* and *SHOX*2+, (31.2%; n=7,312 and 32.6%; n=7,645, respectively) (**Figure
1D**). Each clustered cell population was robustly delineated by hundreds of differentially
expressed genes, including well-established "markers" that confirmed cell type identities
(**Figure S2D**). Throughout our analysis, we used both OTP+ and SHOX2+ populations when
analyzing neurons. RNA expression relationships were consistent with a dynamic
developmental continuum visible in the two-dimensional UMAP embedding, with a population
of hNSCs differentiating into both neurons and astrocytes, as well as a population of markedly
distinct microglia, consistent with unique developmental and experimental origin.

We next evaluated the type and proportion of infected cells across cell types and Tha RABV
infection conditions (**Figure 2E**). While microglia exhibited strikingly low infection percentages
across all conditions (~1%), all other cell types exhibited infection percentages between 79.7-
91.1% at MOI 0.5 and 96.8-98.4% at MOI 5. We observed no differences in cell-type rate of
infection between Tha(0.5) and Tha2P4M(0.5), suggesting that mutations in the RABV P- and
M-proteins had little effect on infection probability. Collectively, our scRNA-seq data and
analysis framework confirm the tenets of our human cell type co-culture system experimental
system and enable properties of Tha infection and the consequences of innate immune
inhibition to be analyzed at single-cell resolution in the context of host cell type.

Tha2P4M mutations increase viral transcription
We next sought to understand how RABV transcription is shaped by human host cell type and
the 2P4M mutations. Because *lyssavirus* infection involves both negative-stranded RNA
genomes and positive-stranded anti-genomes and transcripts, we first evaluated the genomic
locations of our Tha RABV scRNA-seq reads to determine which RNA species were counted
in our dataset. Consistent with exclusive mRNA capture and 3' RNA sequencing, we observed
sense-read pileups immediately adjacent to viral polyadenylation signals, with negligible sense
or anti-sense reads mapped to other genomic locations. As expected, reads from bulk
sequencing of whole Tha mRNAs[30] fully covered the five RABV gene bodies (**Figure S3A,B**).
Next, we evaluated mRNA-based viral load distributions across cell types and experimental
conditions. We observed that mRNA viral load scores did vary by both cell type (p < 4.8E-11)
and experimental condition (p < 2E-16; ANOVA test). Strikingly, Tha2P4M(0.5) infections
exhibited a robust, consistent doubling of viral load across cell types (range of means = 4.8 –
7.7%) as compared to Tha(0.5) and Tha(5) infections consistently (range of means: Tha(0.5),

3.3 – 3.8%; Tha(5), 3.2 – 3.8%. These results indicate that disinhibited IFN and NF-κB
signaling is unexpectedly associated with an increase rather than a restriction of viral
transcription across cell types. Moreover, a subset of Tha2P4M infected astrocytes exhibited
strikingly high viral load scores (>10%) not observed in other Tha2P4M infected cell types
(**Figure 3A,B** and **Figure S3C**). Since the 2P4M mutations do not directly alter the function of
RABV transcription or replication[14], these data suggest that activation of innate immune
signaling by 2P4M mutations may alter the molecular milieu of Tha RABV-infected cells in
ways that contribute to higher levels of viral transcription, an effect that is especially
pronounced in a subpopulation of human astrocytes. Therefore, these results confirm that one
key function of wild-type Tha P and M proteins is to indirectly restrict viral RNA expression by
modulating molecular responses downstream of IFN and NF-κB transcriptional regulators in
infected cells.

Tha RABV gene expression is shaped by host cell type and viral mutations that restore
host innate immune responses
We next asked whether the transcription of *individual* Tha RABV genes is shaped by host cell
type and 2P4M mutations, as we observed for aggregate viral mRNA expression. Foundational
work of *rhabdovirus* transcription in cell lines has established the accepted "start-stop"
transcriptional model, in which the output of the RABV transcriptional complex (composed of
RNA-dependent RNA polymerase L and the phosphoprotein P) tracks the viral genome order
(3′ *N-P-M-G-L* 5'), with *N* RNAs expressed at the highest levels and *L* RNAs expressed at the
lowest levels[31–33]. After the RABV transcription complex binds to the nucleoprotein wrapped 3'
end of the negative-stranded RNA genome and transcribes the non-polyadenylated leader
RNA, each intergenic region probabilistically causes the transcriptional complex to dissociate,
leading to reduced gene-specific occupancy and a decline in expressed RNA (**Figure 3C**).
Interestingly, both bulk and scRNA-seq measurements of Tha mRNAs levels were not strictly
explained by genome order, with N, P, and M expressed at high levels and *G* and *L* at much
lower levels (range mean % viral mRNA, bulk: *N* = 24.3-24.6, *P* = 32-33, *M* = 38-38.2, *G* = 3.3-
3.7, *L* = 0.8-1.0, scRNA: *N* = 29-31, *P* = 44-46, *M* = 21-22, *G* = 0.9-1.2, *L* = 1.1-1.2)(**Figure
S3B**). While cross-gene expression comparisons are potentially influenced by the
methodologies used to prepare sequencing libraries, intra-gene expression comparison across
scRNA profiles are unaffected by these potential technical artifacts. Therefore, we compared
the relative expression of each Tha RABV gene to total viral RNAs across scRNA profiles
stratified by cell type and infection condition. Because the accepted "start-stop" transcriptional
model includes no role for feedback from host cell type or molecular state, we hypothesized
that 2P4M mutations and host cell type should not influence the expression of each Tha gene.
In contrast to our hypothesis, we observed influences of the both cell type and the Tha infection
condition on relative expression of Tha RABV genes (**Figure 3D** and **Figure S3C,D**). Most
strikingly, across all Tha RABV infection conditions, relative *L* RNA levels were doubled in
neurons compared to astrocytes (mean % *L* of viral RNA, Neurons: 1.9±0.01 sem; Astrocytes:
0.99±0.02; p < 2E-16; Mann-Whitney test). While MOI had only a marginal effect on Tha gene
expression by host cell type (**Figure S3D**), *N* and *P* levels differed across Tha2P4M infected
neurons and astrocytes (p < 2E-16; Mann-Whitney test), with neurons having slightly lower
levels of *N* (mean %, Neurons: 26.8±0.11 sem; Astrocytes: 28.6±0.24) and slightly higher
levels of *P* (mean %, Neurons: 47.3±0.08 sem; Astrocytes: 43.9±0.19) RNAs (**Figure 3D**).
These results suggest that the amount of different Tha RABV mRNAs is sculpted by host cell

type and that disinhibited innate immune signaling subtly alters viral gene transcription and/or
the stability of the corresponding viral mRNAs in a cell-type-specific manner.
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Tha RABV infection induces a cell-type-conserved pro- and anti-viral transcriptional
response involving a small number of genes
Viral infections - including by various strains of RABV – can alter transcriptional regulation of
the host cell genome in ways that have complex effects on host cell and tissue function[30,34,35].
However, systematic molecular descriptions of how isolate RABV infection might alter the
transcriptome of distinct human brain cell types – including the consequences of innate
immune antagonism induced by wild-type P and M proteins – have yet to be described at
single-cell resolution. Therefore, we compared genome-wide expression data across cells
stratified by cell type and experimental condition to evaluate how Tha RABV infection and
2P4M-sensitive innate immune disinhibition shapes neuron and astrocyte specific
transcriptional responses.

To characterize transcriptional changes driven by Tha RABV infection and compare these
changes across distinct host brain cell types, we performed genome-wide differential
expression testing across cell-type-identified scRNA profiles from Tha RABV-infected (Tha0.5)
versus "No Infection" cells, with a primary focus on neurons and astrocytes (**Figure 4** and
Figure S4A; **Table S1; Methods**). Using false-discovery rate corrected p-values (FDR < 0.05)
as a threshold, we identified 13 and 60 differentially expressed genes (DEGs) in neurons and
astrocytes, respectively (**Figure 3A**). To determine the degree to which transcriptional
responses to Tha RABV infection were shared or unique across neurons and astrocytes, we
compared gene-specific fold-change for all differentially expressed genes in astrocytes or
neurons while also tracking gene expression level in uninfected neurons (**Figure 3B**). Neuron
and astrocyte specific responses to Tha-infection were well-correlated (r = 0.64), with a small
set of human genes robustly induced in each cell type; genes with significant reductions in
astrocytes also tended to be reduced in neurons, but low baseline neuronal expression likely
limited further reductions and the sensitivity of our testing. Shared, strongly induced RNAs
include those from *DYNLL1*, *DYNLL2* and *HSPA8* genes and the long non-coding RNA *NRAV*
(located in anti-sense orientation int the *DYNLL1* gene locus). The striking induction of *DYNLL1*
and *DYNLL2* was also observed after infection of another negative-stranded RNA virus,
Ebola[36], and could be driven by a positive transcriptional feedback pathway through which
lower cellular availability of DYNLL1/2 (perhaps by viral sequestration of dynein-light chain
proteins[37], including RABV P[38–40] and L[41]) disinhibits transcription of the *DYNLL1* gene locus
through the ASCIZ transcription factor[42]. In turn, higher levels of DYNLL1/2 promote RABV
transcription and replication, a pro-viral effect that depends on P and L binding[39,43]. *HSPA8*
encodes a member of the HSP70 family that is induced upon infection of RABV and other
viruses and promotes viral replication and transcription, likely due in part to interactions in
RABV Negri Bodies[44]. *NRAV* too has described pro-viral functions[45]. RNAs depleted from Tha
RABV infected cells were largely restricted to genes encoding components of the IFN
signaling, including *STAT1*, *IRF9*, *IFIT1* and *ISG15*, supporting previous observations that
wild-type Tha RABV infection is sufficient to suppresses IFN-induced expression of innate
immune genes encoding detectors and early-stage infection effectors[14] (even to levels lower
than those observed in uninfected cells)(**Figure S4B**). Gene expression comparisons based
on ten-fold higher MOI (Tha5) resulted in highly similar transcriptional changes (**Figure S4A**).
These results demonstrate that during Tha RABV infection - in which an average of ~3% of all
mRNAs are viral (**Figure 3B**) - neurons and astrocytes tended to share changes in RNA levels

from just a handful of genes: increases in RNAs encoding host cell factors with described or
likely pro-viral functions, and reductions in RNAs associated with genes encoding IFN-
activated anti-viral transducer or effector proteins. In aggregate, these results suggest two
functionally distinct transcriptional signatures that likely promote RABV replication while
minimizing innate immune detection and response that are conserved across brain cell types.

Tha2P4M mutations unmask an astrocyte-specific transcriptional response to infection
involving hundreds of genes
To unmask and compare the transcriptional responses inhibited by wild-type Tha P and M
proteins across brain cell types, we performed differential expression testing of infected, cell-
type-identified scRNA profiles across Tha(0.5) and Tha2P4M(0.5) conditions (**Figure S4A**).
We observed 15 DEGs in neurons, 14 of which were upregulated (**Figure 4C**). This
upregulated gene set included a subset of those same IFN-related genes that were
downregulated in Tha RABV-infected astrocytes (*IRF9, ISG15, SAMD9, STAT1, PLSCR*),
demonstrating this downregulation by Tha RABV infection was driven by effects downstream
of wild-type P and M proteins. Astrocytes, however, exhibited significant expression changes
in 445 up or down-regulated genes (**Figure 4C**). Gene-specific fold change comparisons to
neurons confirmed that a small subset of the upregulated genes in Tha2P4M-infected
astrocytes were cell-type conserved (n=6 of 204), while the vast majority of upregulated genes
(n=198 of 204) and nearly all down-regulated genes (n=241) were unique and selective to
astrocytes (**Figure 4D**). These results demonstrate that host brain cell type plays a profound
role in the breadth and capacity for transcriptional responses triggered by innate immune
signaling pathways typically inhibited by wild-type Tha P and M proteins. Analysis of enriched
Biological Pathway gene sets in these 445 genes underscored that genes selectively induced
in Tha2P4M-infected astrocytes were associated with innate immune responses and viral
infection (**Figure 4E; Methods**).

A subpopulation of astrocytes endows a pro-viral RNA cellular environment through a
massive transcriptional change
We next determined whether the large-scale transcriptional response observed in the grouped
comparison of Tha2P4M infected astrocytes was driven by a specific subpopulation of
astrocytes. To do this, we clustered astrocyte scRNA profiles from all experimental conditions
using exclusively human genes. Our analysis identified a major (Cluster 1: n=3,759 cells;
94.6%) and a minor (Cluster 2: n=216 cells; 5.4%) astrocyte population (**Figure 5A**). The
experimental composition of Cluster 2 cells strongly deviated from the full dataset (p<2.2E-16;
Chi-square test), with a 3.5-fold enrichment of Tha2P4M infected astrocytes, yet all
experimental conditions, including "No Infection" co-cultures, contributed cells (**Figure 5B**).
Cluster 2 was also enriched for infected cells as compared to the full dataset (95% versus
68%; p<2.2E-16; Chi-square test)(**Figure 5B**). Based on our previous observation that a
subset of astrocytes had particularly high RABV expression (**Figure 3A**), we compared viral
RNA load scores for cells in Cluster 1 and Cluster 2 (**Figure 5A**). On average, viral load scores
were 6.3-fold higher in Cluster 2 than in Cluster 1 (mean viral load: Cluster 1, 2.2%±0.04 sem;
Cluster 2, 13.8%±0.7; p < 2.2E-16, Kolmogorov-Smirnov test)(**Figure 5C**). We conclude that
a subpopulation of transcriptionally unique astrocytes supports very high levels of Tha RABV
RNA expression. Thus, we refer to Cluster 2 astrocytes as "pro-viral". While pro-viral Cluster 2
astrocytes were observed without infection (~5%), astrocytes tended to adopt this pro-viral

molecular state following Tha RABV infection, especially when the 2P4M mutations were present. These results demonstrate that wild-type Tha P and M proteins actively restrict the emergence of this pro-viral state during astrocyte infection. A corollary conclusion is that the pro-viral astrocyte molecular milieu promotes RABV transcription more so than in other cellular contexts.

To quantify the magnitude of transcriptional changes distinguishing Cluster 1 and pro-viral Cluster 2, we performed differential expression testing. Our analysis revealed significant alteration in the RNA levels of 8,862 genes, equating to changes in ~38% of all astrocyte expressed genes (Cluster 2 enriched: 2,343 genes; Cluster 2 depleted: 6,521 genes)(**Figure 5D**). To determine to what degree viral load contributed to these transcriptional differences, we downsampled scRNA profiles such that viral load distributions were equivalent across clusters and repeated differential expression testing (n=276 cells in each cluster; **Methods; Figure S5A,B**). Gene-specific fold change values were highly correlated across the full and downsampled analysis (r = 0.82), with 32% of significant genes shared in both comparisons. The vast majority of other genes passing the significance threshold were observed in the full dataset but had similar, non-significant directional changes in the downsampled data (**Figure 5E**), likely due to the drop in test sensitivity from far fewer cells in the analysis (n= 552 versus 3,975 scRNA profiles). These data suggest that the massive transcriptional changes in human genes observed in pro-viral Cluster 2 are largely independent of high viral load.

We next tested whether the molecular state in pro-viral Cluster 2 affects the transcriptional coupling between RABV and host cell genome during infection using *DYNNL1*. To do this, we focused on the positive relationship between *DYNNL1* RNA levels and viral load, clearly apparent when all Tha RABV-infected cells are stratified into low, medium and high viral RNA load groups (**Methods**). Further stratification of scRNA profiles by cell type revealed that *DYNNL1* RNA levels grew with viral load scores in neurons and Cluster 1 astrocytes but not in pro-viral Cluster 2 astrocytes (Neurons, $p < 2E-16$; Cluster 1 astrocytes, $p < 2E-16$; pro-viral Cluster 2 astrocytes, $p = 0.06$; Kruskal-wallis test)(**Figure 5F**). These results suggest that the molecular properties of pro-viral Cluster 2 astrocytes fundamentally alter the transcriptional coupling between RABV and host cell genome that occurs during infection of other cell types.

Identification of pro-viral Cluster 2-like astrocytes in the human brain

The presence of ~5% of uninfected astrocytes in Cluster 2, including from uninfected co-cultures, hinted that this pro-viral astrocytic transcriptional state might exist independent of RABV infection and motivated us to explore the possibility that Cluster 2-like astrocytes might be present in human brains independent of RABV infection. To evaluate this possibility, we took advantage of a snRNA-seq dataset acquired from flash-frozen cortical tissue resected during Normal Pressure Hydrocephalus (NPH) surgery[46], enabling analysis of *ex vivo* astrocyte RNA profiles from 52 living patients. Therefore, these cortical samples were collected without the confound of post-mortem interval nor acute central nervous system infection. To search for Cluster 2-like astrocytes in the 82,634 NPH snRNA-profiles from astrocytes, we developed an aggregate expression score approach, leveraging genes highly enriched (> 2 log2 fold-change) in pro-viral Cluster 2 astrocytes to create a "discovery" gene set (**Figure 5G-I**; **Methods**). As expected, aggregate expression of this Cluster 2 "discovery" gene set (n=268 genes) clearly distinguished Cluster 1 and Cluster 2 scRNA profiles in a manner independent from our original analysis, confirming the approach's sensitivity (**Figure 5G**). We then calculated aggregate expression scores for NPH astrocyte snRNA-seq profiles based on the 196 "discovery" genes

expressed in both datasets. To contextualize the distribution of "discovery" gene set scores and define a false-discovery threshold, we performed a similar analysis on n=1,000 permuted gene sets of 196 genes matched for expression level. We then calculated gene set-specific z-scores to directly compare the "discovery" and permutation results (**Figure 5H**; **Methods**). In support of Cluster 2-like astrocytes present in living human cortex, we observed a small number of snRNA profiles with very high "discovery" set z scores (up to 12.5 standard deviations above the mean) not observed in the permutations. Using a z-score threshold of 4.5 (corresponding to a p value cut off of 4.7E-7 based on the permutations), we identified n=38 Cluster 2-like astrocytes contributed by 21 of 52 total patients (n=1 to 4 Cluster 2-like NPH astrocytes per patient, ranging from 7 to 4,990 total astrocyte snRNA profiles per patients (median: 1,278). We reasoned that if these 38 single-nucleus RNA profiles were indeed Cluster 2-like, they should also be enriched for an independent gene set with enriched expression in pro-viral Cluster 2 astrocytes. Indeed, a "validation" gene set of 521 genes with RNAs 1-2 log2 fold-enriched in Cluster 2 astrocytes also had enriched expression in the 38 snRNA-profiles as compared to all other NPH astrocytes (n= 82,596: p < 2E-16, chi-square test). The degree of "discovery" and "validation" gene set enrichment in NPH astrocytes corresponded to the predictions from pro-viral Cluster 2 astrocytes (NPH expression enrichment: "discovery", 2.8; "validation", 1.2)(**Figure 5I**). Collectively, these analyses provide preliminary support for a rare (~1 in 2,200) population of pro-viral Cluster 2-like astrocytes in human cortex without acute infection of the central nervous system.

Transcriptional analysis identifies major cell-autonomous and nonautonomous functional changes of pro-viral astrocytes

We next sought to analyze how the massive transcriptional changes distinguishing Cluster 1 from pro-viral Cluster 2 astrocytes might alter both intercellular interactions with other cell types and cell-autonomous astrocyte function. Importantly, we found no evidence that the pro-viral transcriptional state we observed in Tha2P4M infected human astrocytes was previously documented in cultured or *ex vivo* rodent and human astrocytes experimentally driven into "reactive" states through interferon[47,48] or lipopolysaccharide exposure (**Figure S6A**).

To understand to what degree the pro-viral transcriptional state affects astrocyte signaling with other co-cultured brain cell types, we leveraged CellPhoneDB(v5.0), a database of pairwise-protein interactions that includes both secreted and extracellular ligands in relationship to receptor complexes. We focused our analysis on genes with > 1 log2 fold-enrichment in either Cluster 1 (n=2,186) or Cluster 2 (n=877). CellPhoneDB uses cell-type-assigned scRNA-seq data and a gene-shuffling permutations to identify "relevant" ligand-receptor interactions that are selectively enriched in target gene sets over background expression in other cell types (p < 0.05 based on permutations). CellPhoneDB analysis revealed that pro-viral Cluster 2 astrocytes tended to express fewer "relevant" ligand and receptor genes than Cluster 1 astrocytes, suggesting a global reduction in the capacity for intercellular signaling (**Figure 6A**). Interestingly, the more minor subset of ligands upregulated in pro-viral astrocytes include immune effectors that function as secreted chemokines (*IL34*, *LIF*, *EDN1*) or extracellular glycoproteins (*VCAM1* and I*CAM1*). In some cases, ligands or receptors from the same signaling family exhibited bi-directional changes in RNA levels. For example, *WNT3A* and *VEGFA* (ligands) and *EPHA4* (receptor) were enriched while *WNT7B* and *VEGFB* (ligands) and *EPHB1* (receptor) were reduced in pro-viral Cluster 2 Astrocytes. Analysis of "relevant"

ligands and receptors in the context of RNAs expressed by other co-cultured brain cell types
suggested that pro-viral Cluster 2 astrocytes (as compared to Cluster 1 astrocytes) exhibit
reduced signaling capacity to all major cell types to approximately the same degree. These
data also imply that pro-viral Cluster 2 astrocytes are cut-off from receiving interactions from
other cell types (save from other pro-viral and Cluster 1 astrocytes)(**Figure 6B**). These RNA-
based inferences suggest that pro-viral Cluster 2 astrocytes are poised to send and receive
fewer total cellular interactions yet highlight a small number of key signaling pathways through
which astrocytes in the pro-viral molecular state might "advertise" to other brain cell types.
476
We next leveraged gene expression changes to build testable hypotheses for how the pro-viral
transcriptional state might affect cell-autonomous function of human astrocytes. To find
themed structure in the ~38% of astrocyte-expressed genes differentially expressed across
Cluster 2 and Cluster 1 astrocytes, we performed hierarchical clustering of REACTOME
categories based on shared genes up regulated in Cluster 1 (n=6,521 genes; n=84 categories,
p <1E-6) or Cluster 2 (Cluster 2, 2,343 genes; n=32 categories, p<1E-3)(**Figure 6C**). These
results implicate a diverse set of cellular processes affected by the large-scale restructuring of
the pro-viral astrocyte transcriptome. Due to the number and complexity of these changes, we
focused further analysis on the following salient gene sets to more fully understand how
astrocytes in particular respond to infection: 1) genes controlled by "Toll-like receptor
cascades" (**Figure 6D**) and genes encoding machinery for 2) protein translation and 3)
mitochondrial respiration (**Figure 6E**). ("Toll-like receptor (TLR) cascades" is likely a proxy for
gene sets activated by the IRF3/IRF7/NF-κB transcription factor complex, which in the case of
RABV infection, is primarily driven through activation of viral sensors such as TLRs and RIG-
I-like receptors (RLRs)[49,50]).
492
To determine how the molecular milieu of Cluster 2 astrocytes is sculpted by RNA level
changes of genes controlled by "Toll-like receptor cascades", we ranked fold-changes for 108
associated genes (**Figure 6D**). This analysis highlighted the striking role for transcriptional
induction of both NF-κB and immediate early gene (IEG) transcription factors and regulators
(NF-κB: *NFKB1*, *NFKB2*, *NFKBIA*, *NFKBIB*; IEG: *JUN*, *FOS*) as well as induction of gene
targets controlled by both NF-κB and IEG transcriptional complexes (NF-κB: *BIRC3*, *BIRC2*,
NOD2, *RIPK2*, *IRAK1*, *TRAF2;* IEG: *DUSP4, DUSP6, DUSP3*). RNAs from this group depleted
in the pro-viral state encode MAP kinases and regulators (*MAP2K6*, *MAPK10*, *MAPK3*,
MAPK14, *MAPKAPK3*, *MAPK8*, *MAPK7*) as well as ubiquitin and ubiquitin regulators (*UBB*,
UBA52, *UBE2V1*, *UBC*, *UBE2D1*, *UBE2N*, *UBE2D2*). Thus IRF3/IRF7/NF-κB activation
downstream of viral sensor activation contributes to the pro-viral state through potent activation
of NF-κB genes and targets and depletions of RNAs that likely alter MAPK kinase and ubiquitin-
based protein degradation. Intriguingly, *BIRC3* and *RIPK2*, the two genes with the largest fold-
change, encode anti-apoptotic (BIRC3) and pro-necrotic (RIPK3) proteins, potentially
contributing to the fate of pro-viral astrocytes.
508
To determine how transcriptional alterations of genes encoding protein translation and
mitochondrial function might contribute to the function of pro-viral astrocytes, we assessed
expression-level changes of ribosomal subunits, tRNA synthetases and the COX and NDUF
gene families encoding Complex IV and Complex I of the electron transport chain, respectively
(**Figure 6E**). Pro-viral astrocytes exhibit potent reductions in RNAs encoding nearly all subunits
of the cytosolic ribosome (n=85 genes), and bi-directional regulation of mitochondrial ribosome
subunits (n=78) and tRNA synthetases (n=37 genes). Most members of the COX and NDUF

gene families had reduced expression in pro-viral astrocytes. These transcriptional changes
were highly-selective for pro-viral astrocytes, as RNA levels associated with these genes were
not different across No Infection and Tha(0.5) RABV infected astrocytes (**Figure 6E**). These
results suggest that pro-viral astrocytes likely have severely reduced or dysregulated capacity
for protein translation and oxidative phosphorylation, indicating a potential mechanism of "host
shut off" based on RNA level changes. Since RABV morphogenesis and infection viral particle
production relies on host cell translation and ATP production to produce infective virion, our
cell signaling and gene-set focused analyses suggest pro-viral astrocytes may create an
immune-stimulatory environment by fostering high levels of viral RNA while restricting
collateral infections. Tha RABV infection with wild-type P and M protein would efficiently inhibit
this theoretical outcome.

Microglia indirectly respond to infection of other cell types through interferon-
stimulated genes potentiated by 2P4M mutations
Lastly, we explored how RABV infection-resistant microglia indirectly respond to infection
properties of other susceptible co-cultured brain cell types and how these transcriptional
responses associate with Tha RABV titer or innate immune signaling disinhibited by 2P4M
mutations. To do this, we re-clustered microglia scRNA-seq profiles and tracked the
experimental origins of each library (**Figure 7A**). Three distinct analysis or visualization
approaches – including UMAP embeddings (**Figure 7A**), principal components analysis of
shared expression variance (**Figure 7B**) and differential expression analysis (**Figure S7C**) –
revealed that exposure to Tha RABV particles and the milieu of neighbouring infected cells
affect a graded transcriptional response of interferon-induced genes in microglia (e.g. *SNX10*,
GBP1, *IFIT2*, *ACSL1*) (**Figure 7C**). The number and degree of interferon-induced
transcriptional differences were largest in the Tha(5) condition, followed by Tha2P4M(0.5) and
then Tha(0.5)(**Figure 7D,E** and **Figure S7C**), as clearly evidenced by example gene RNA
levels (*ISG15, IDO1, and IFIT3*)(**Figure 7E**). Consistent with rapid induction and degradation[51],
RNAs encoding interferon proteins were not detected 48 hours after viral infection, obfuscating
the cellular source of interferons in our analysis. Importantly, in titer-matched experiments, the
interferon-related transcriptional response in microglia was larger with 2P4M-mutations
(**Figure 7C**), suggesting that disinhibited innate immune signaling and/or higher levels of viral
RNA in cells potentiate an interferon-stimulated gene responses in microglia.

Discussion

In this work, we characterized how the innate immune signaling inhibition conferred by RABV
P and M proteins shapes the transcriptional properties of the host and viral genomes across
human neurons and glia. While molecular mechanistic analyses in cell lines has described the
potent and synergistic ways that RABV M and P proteins inhibit the induction and response to
IFNs[18–20,25–28], the consequences of innate immune inhibition or disinhibition on host-virus
relationships were unknown. Here we used an experimental and analytical framework with
several key attributes to characterize these consequences in major human CNS cell types,
revealing important new insights into RABV-host cell interactions and how innate immune
antagonism shapes viral infection properties. These attributes include 1) the use of Tha RABV
derived from a field isolate (that exhibits profound innate immune inhibition as compared to
attenuated RABV strains more adapted to cell culture) and 2P4M mutations (that selectively
and potently strip away major RABV innate immune inhibitory mechanisms); 2) co-cultured
human stem-cell derived brain cell types, enabling human cell biology to be studied in a

relevant model of cross-cell type signaling; 3) single-cell RNA-seq phenotyping in which RNA
level across the RABV and cell-type identified human genomes are measured at cellular
resolution; and 4) novel analytical methods to qualitatively group infected and uninfected
scRNA-seq profiles across heterogenous infection states and the use of "viral RNA load" as a
quantitative proxy for infection state progression. (Viral RNA load varied considerably in
infected cells after 48 hours, from 0.4 to 65% viral mRNA, highlighting the importance of
tracking viral load when experimentally phenotyping individual cells).

Our results suggest two ways in which Tha RABV gene expression is not anticipated by the
accepted "start stop" transcriptional model. First, in both bulk mRNA and scRNA-seq based
datasets, Tha RABV RNA levels were not strictly explained by genome order, with *N*, *P* and *M*
levels high (~24-46% of viral mRNAs) and *G* and *L* levels much lower (~1-2%). While RNA
capture and library preparation methods can complicate cross-gene RNA level comparisons,
the lack of strict genome-ordered expression across independent methods suggests other
factors (such as post-transcriptional regulation) may need to be considered to fully understand
variable levels of RABV transcripts in infected cells. Second, scRNA-seq analysis suggests a
clear if subtle role for host cell type in shaping RABV gene expression. Most saliently, *L* RNAs
were observed on average at double the levels in neurons as compared to astrocytes,
differences that could be driven by either molecular or physiological differences in host cells.
Future experiments are warranted to fully validate and understand the functional
consequences of cell-type-specific RABV gene expression differences and to identify the
mechanisms driving these effects.

In Tha RABV-infected neurons and astrocytes, we discovered largely conserved bi-directional
transcriptional programs involving ~60 human genes that likely promote infection progression
by both boosting RNAs encoding known pro-viral proteins or reducing RNAs encoding anti-
viral transduces or effectors. For example, of the four genes robustly induced by Tha RABV
infection (*DYNLL1, DYNLL2, NRAV and HSPA8;* **Figure 4A***),* all have been shown to promote
viral replication in some contexts. Importantly, the products of the protein-coding genes
(DYNNL1, DYNLL2 and HSPA8) are bound and/or sequestered by RABV proteins during
infection. *DYNNL1/DYNNL2* encode light-chain dynein subunits targeted by RABV P[38,40,52] and
L[43] proteins. The long non-coding RNA *NRAV* spans exons 2 and 3 of *DYNLL1* gene locus in
the anti-sense orientation on chromosome 12 and promotes influenzae replication and
virulence[45] (the functional effects of *NRAV* on RABV pathogenesis are yet to be determined).
HSPA8 encodes a member of the HSP70 family, a host cell protein recruited to RABV Negri
Bodies (the specialized viral organelles in which viral transcriptional and replication occur) and
promotes RABV replication[44]. Our data thus suggest that RABV (and perhaps other viruses[37])
evolved to sequester host cell factors transcriptionally regulated by hijackable negative
feedback systems, enabling pro-viral host factor production to match viral demand as infection
proceeds. Indeed, *DYNLL1* levels positively scaled with viral RNA load in neurons and Cluster
1 astrocytes (**Figure 5F**) and previous work identified a potential mechanism: DYNLL1
sequestration by P and L might disinhibit DYNLL1-based negative regulation of the ASCIZ
transcription factor which promotes *DYNNL1* transcription[42]. More experiments are required to
mechanistically understand these transcriptional feedback systems, including how *HSPA8*
RNA levels might be induced by HSP70 recruitment to Negri Bodies. The genes potently
downregulated by Tha infection include RNAs encoding proteins with central roles in anti-viral
responses. These include anti-viral effectors IFIT1 and ISG15, as well as core components of
the ISGF3 transcriptional complex (STAT1 and IRF9) responsible for inducing interferon
expression[53]. These results offer insight into the mechanisms through which Tha RABV

infection completely blocks interferon-stimulated gene expression, even after exogenous IFNα
stimulation[14]. While more work is necessary to determine exactly how anti-viral RNAs are
reduced during Tha RABV infection, wild-type P and M proteins are likely involved, as an
overlapping anti-viral gene set is strikingly induced in neurons infected by Tha2P4M (**Figure**
4C).

One major observation of our study is that 2P4M-based disinhibition of innate immunity results
in a mean doubling of viral load across cell types (**Figure 3A** and **Figure S3C**). Three pieces
of evidence suggest that increased viral transcription is an indirect effect of the disinhibited
innate immune milieu rather than a direct effect of the 2P4M mutations on the RNA-dependent
RNA polymerase L. First, the 2P4M mutations sit at residues independent and distant from
those known to bind or modulate L function[14,16,54]. Second, Tha and Tha2P4M have
indistinguishable replication properties in BSR-T7 cells that lack an IFN response[14]. Third, P/M-
based restriction of RABV transcription is cell type and state-specific, as observed in the "pro-
viral" astrocyte subpopulation that had on average six-fold higher viral load scores than other
neurons and astrocytes (Cluster 2; **Figure 5A,C**). Therefore, one important consequence
RABV innate immune inhibition is likely to restrict viral transcription.

Our discovery and characterization of "pro-viral" human astrocytes deepens the growing
appreciation of how astrocytes contribute immune functions in the human CNS[11,55,56]. Our *in*
vitro analysis suggests that the "pro-viral" molecular state – distinguished by RNA level
differences in ~38% of astrocyte expressed genes – exists independently of RABV infection
and viral RNA load. This is supported by 1) the presence of 5% uninfected "pro-viral" astrocytes
(including those from uninfected culture wells); 2) the presence of pro-viral like single-nucleus
RNA profiles sampled from cortical biopsies of presumably RABV free NPH surgical patients
(~1 out of 2,200; observed in 21 of 52 patient samples); and 3) the observation that "pro-viral"
gene expression signatures are largely retained after controlling for viral load differences.
However, the proportion of astrocytes in the "pro-viral" state tends to increase after Tha RABV
infection, is further increased by higher Tha RABV titer and is dramatically increased when the
2P4M mutations are present (**Figure S5C**). These data may suggest that the pro-viral state is
not induced by infection exclusively, but is present in normal human brain tissue and can be
activated through signaling by other infected cells, especially when 2P4M mutations disinhibit
innate immune responses.

We leveraged gene expression data to draw a preliminary description of how the large-scale
"pro-viral" state might affect astrocyte function and cellular interactions. Our analysis suggests
that the "pro-viral" state tends to reduce the number of molecular opportunities for cell signaling
to other brain cell types and the only unique interactions "pro-viral" astrocytes are poised to
receive are from other astrocytes (in contrast to other infected astrocytes, which maintain
receptors to interact with all other cell types in our co-cultures). Our analysis highlights a
number of key signaling molecules including both ligands (*HBEGF4*, *VEGF4*, *IL34*, *VCAM1*,
ICAM1, *WNT3A* and *EDN1*) and receptors (*EPHA4*, *SSTR2*) that merit further investigation for
"pro-viral" astrocyte function. Cell autonomously, "pro-viral" gene expression changes indicate
a dramatic increase in NF-κB target gene expression, predicted to alter MAPK function and
protein ubiquitination. We also observed cellular RNA level changes consistent with potent
reductions in ribosomal machinery for protein translation and mitochondrial machinery for
oxidative phosphorylation; changes that may reflect an astrocyte-specific form of "host shut
off". (To our knowledge, "host shut off" molecular programs have not been previously described
either in astrocytes or for RABV infection of any cell type). The uncoupled transcriptional
feedback between *DYNNL1* levels and viral load observed in "pro-viral" astrocytes (but not in

other cell types) may be an important feature of this process (**Figure 5F**). Astrocyte-based
abortive infections occur at higher frequency in lab-attenuated versus field isolate RABVs[57],
suggesting the intriguing possibility that the "pro-viral" state we observed at higher rates
following Tha2P4M infection might represent a transcriptional snapshot of the abortive
infection process[58]. High levels of viral RNA and with reduced protein translation might suggest
that "pro-viral" astrocytes create an immune-stimulatory environment through viral RNA while
minimizing the generation of infective virions. Astrocyte infection fate-mapping experiments
could help clarify if the pro-viral state leads to abortive infections or other outcomes[58].

Our study also sheds a new light on the role of microglia. Our analysis suggests that microglia
are almost exclusively recalcitrant to RABV infection (~1% infected, n = 10 of 859; **Figure 7**).
The susceptibility of human microglia to RABV infection has been a topic of scientific
debate[35,59,60] . Our findings indicate that human microglia do not play major roles in the
replication and spread of canine RABV. The presence of viral RNAs in the 1% of microglia we
classified as infected may also be attributed phagocytosed material from infected cells.
Further, the degree of microglial interferon-induced transcriptional differences was largest in
the Tha RABV(5) condition, followed by Tha2P4M(0.5) and then Tha RABV(0.5) (**Figure 7D,E**
and **Figure S7C**), suggesting that Tha RABV is not able to actively infect microglia and
antagonize intracellular innate immune pathways via P and M proteins, as observed in
susceptible CNS cells such as neurons and astrocytes. Thus our data suggest that microglia
play an important bystander role and are capable of responding to the effects of innate immune
inhibition from other RABV infected cell types and/or extracellular RABV particles by mounting
a graded anti-viral interferon-stimulated gene response (**Figure 7**). Future experiments should
identify the sources and ligands responsible for these responses in microglia.

Our study has important limitations and follow-up studies are necessary to more fully
understand the biological results we reveal. For example, our genome-wide molecular
phenotyping was restricted to polyadenylated RNA levels, yet direct measurements of RABV
negative-stranded RNA genomes, host and viral RNA isoforms, non-coding RNAs (including
RABV leader and trailer RNAs) along with chromatin remodeling data would be necessary to
measure at cellular resolution to more fully understand the molecular consequences of isolate
RABV infection and "unmasked" innate immune signaling. Additionally, more work is required
to fully understand the function of "pro-viral" astrocytes. Future experiments should 1) locate
and quantify "pro-viral" astrocytes through molecular anatomical analysis of human brain
tissue; 2) characterize the temporal progression and fate of the "pro-viral" state across different
conditions (infection both other viruses, aging and neurodegeneration, for example) and 3)
functionally assess how the "pro-viral" state affects astrocyte physiology and cell signaling.

Another limitation stems from the sex differences in the karyotypes of the cell types used in
this study. The iPSC-derived microglia used had a male karyotype, whereas the neurons and
astrocytes derived from human neural stem cells (hNSCs) had a female karyotype[61] . These
sex-specific differences may influence cellular responses and contribute to some of the
observed outcomes. Future studies would benefit from a systematic examination of how sex-
linked genetic and epigenetic differences and genetic variation affect RABV infection dynamics
in human brain cell models.

Despite these limitations, our single-cell RNA-seq analysis using the Tha/Tha2P4M RABV
study system in human brain cell-type co-cultures provides a powerful approach to discover
key features of host-RABV interactions and a road map for building testable hypotheses

regarding the dynamics and key molecular interactions that drive neurotropic infection in the
brain.

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Author contributions

717 Conceptualization (LF, KY, HB, AS); Data Curation (ZG, JPC); Formal Analysis (KY, GC, LBA,
718 AS); Funding acquisition (HB, AS); Investigation (LF, TK, LK); Methodology (LF, KY, AS);
719 Project Administration (HB, AS); Resources (LF, VL, FG, MH); Software (ZG, AS); Supervision
720 (HB, AS); Validation (LF, AS); Visualization (KY, GC, AS); Writing – original draft (LF, AS);
721 Writing – review & editing (LF, KY, GC, HB, AS).

Declaration of interests

724 The authors declare no competing interests.

Figures

Figure 1. Experimental overview for unmasking the molecular effects of innate immune signaling inhibition across human brain cell types using field-isolate Tha RABV and single-cell RNA-seq analysis.

(A-B) Schematic illustrations of the RABV particle (A; modified from[2]) and genome (B) color-coded by the five RABV genes and encoded proteins.

(C) Schematic illustrating known mechanisms of RABV P and M inhibition of viral detection and response in Tha (*left*) or Tha2P4M (*right*) infection along with basic pathways (numbered

below) through which viral/host interactions and inhibited/disinhibited innate immune signaling
could affect viral and host cellular processes. Germline-encoded pattern recognition receptors
(PRRs) are viral sensors (such as toll-like receptors (TLRs); retinoic acid-inducible gene I (RIG-
I) like helicases (RLRs); and nucleotide-binding oligomerization domain-like receptors (NOD-
like receptors) that induce NF-kB and IFN pathways upon activation.

(D) Gene locations and amino acid alterations of six key point mutations that abolish innate
immune inhibition by P ("2P") and M ("4M") proteins.

(E) Protein structures of *lyssavirus* P (RABV CVS strain[62]) and M (Lagos bat virus[63]) highlight
the outward-facing locations of mutant residues in P and M (red). P mutations cluster around
the "W hole" (after[29]); M mutations affect three spatially-distinct interaction sites.

(F) Study system and scRNA-seq data generation overview. Human induced neural stem cells
(hiNSCs) or pluripotent stem cells (hiPSCs) were transformed into neurons/astrocytes or
macrophages and co-cultured, further inducing macrophage transformation into microglia.
Under Biohazard Safety Level 3 conditions, scRNA-seq analysis was performed on acutely
dissociated cells 48 hours after no viral infection (n=3 replicates) or bath application of Tha
virus at MOI 5 (Tha(5); n= 2 replicates) or MOI 0.5 Tha(0.5); n= 3 replicates) and Tha2P4M
virus at MOI 0.5 (Tha2P4M(0.5); n=2 replicates). After quality control, the final dataset
consisted of 23,457 RNA profiles and included 23,528 human and 5 RABV genes.
(G) Immunolabeling of cell type marker proteins on co-cultured cells after infection of Tha
RABV expressing eGFP, confirming the presence of infected human-induced neurons
(TUBB3), astrocytes (GLAST) and microglia (IBA1).

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Figure 2. Transcriptional identification of infected and uninfected cell types

(A) Density plot comparing the number of viral UMIs versus total (viral + human) UMIs for each scRNA profile in the analysis.

(B) Systematic identification of infected and uninfected scRNA profiles using an Expectation-Maximization modeling approach to distinguish two cell populations based on viral UMIs (regressed by total UMIs)(**Methods**). Example results of infected (magenta) and uninfected (gray) scRNA profiles at iteration 1 (random assignment), iteration 2 and 20 (after convergence) are shown.

(C) Density plots of "viral RNA load" (the percentage of total UMIs that are viral) for scRNA profiles called as infected (magenta) or uninfected (gray).

(D) UMAP plot showing two dimensional embeddings of scRNA profiles following Seurat-based clustering analysis using exclusively human genes (**Methods**). scRNA profiles colored by infection status (*right*) or cell type-based cluster assignments (*left*).

(E) Barplots of the percent infected cells stratified by experimental condition and cell type.

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Figure 3. Tha2P4M mutations double viral RNA load without major alterations to cell-type-specific viral gene expression.

(A) Density plots of viral RNA load stratified by neurons and astrocytes and color-coded by experimental condition (n cells: Neurons, Tha(0.05) = 2,711; Tha(5) = 1,877; Tha2P4M(0.05) = 2,080; Astrocytes, Tha(0.05) = 1,036; Tha(5) = 798; Tha2P4M(0.05) = 806). Arrowhead indicates high viral RNA load astrocytes. Both cell type and experimental condition explain differences in viral load distributions (p<2E-16, Kruskal-wallis tests).

(B) Density plots of viral RNA load stratified by experimental condition and color-coded by cell type. Arrowhead indicates high RNA viral load cells in astrocytes. Same cells as in A. (Tha(0.5), p=1.1E-7; Tha(5), p=1E-14; Tha2P4M(0.5), p=0.58).

(C) Schematic of the accepted model of *lyssavirus* transcription, in which a genome-ordered RNA expression gradient is achieved by the RNA-dependent RNA polymerase (L). This model does not account for differences based on host cell type (after[2]).

(D) Density plots of relative RNA levels for each of the five Tha RABV genes color-coded by cell type and stratified by both gene identity and experimental condition. P values for differences in Neuron versus Astrocyte expression distributions are reported for each gene and experimental condition in the figure panel (Kolmogorov-Smirnov tests).

Figure 4. Tha2P4M mutations unmask a large-scale astrocyte-specific transcriptional response to infection.

(A-D) Genome-wide differential expression comparisons between neurons and astrocytes across no infection and Tha(0.5) infected (**A,B**) or infected Tha(0.5) and infected Tha2P4M(0.5) experimental conditions (**B,C**).

(A,C) Volcano plots of gene expression differences with select genes labelled (red, p < 0.01).

(B,D) Scatter plots comparing log2 fold expression level changes for genes significantly altered (p < 0.01) in either neurons (orange), astrocytes (purple) or both cell types (blue). Circle size is proportional to expression level in uninfected neurons.

(E) Gene set enrichment analysis of Biological Process Gene Ontology categories for differentially expressed genes (p < 0.01) across astrocytes infected with Tha(0.5) versus Tha2P4M(0.5) RABV. Gene set Enrichment Scores are shown for the nine most significantly enriched Biological Processes.

Figure 5. A pro-viral human astrocyte subpopulation supports high viral RNA load and is decoupled from typical host cell transcriptional feedback through a massive alteration in RNA levels.

(A) UMAP embedding plot of astrocyte scRNA profiles clustered exclusively by human gene expression differences and stratified by experimental condition (**Methods**). *Top*, color-coded cluster identities. (Cluster 1, n=3,759 cells; Cluster 2, n=216 cells). *Bottom*, heat map of viral RNA load scores.

(B) Bar plots comparing the composition single astrocyte RNA profiles from the full dataset versus Cluster 1 or Cluster based on experimental identity (Cluster 1 versus All: p=0.006; Chi-square test; Cluster 2 versus All: p<2.2E-16) or by infection status (Cluster 1 versus All: p=0.14; Cluster 2 versus All: p<2.2E-16).

(C) Combined histogram and density plot comparing viral RNA load distributions for Cluster 1 and 2 (p<2.2E-16, Kolmogorov-Smirnov test).

(D) Volcano plots of gene expression differences across Cluster 1 and 2 with select genes labelled (red, p < 0.01).

(E) Scatter plots comparing log2 fold expression level changes for genes significantly altered (p < 0.01) across Cluster 1 or Cluster 2 in the full dataset or a dataset in which viral RNA load scores were down-sampled to an equivalent distribution in Cluster 1 and 2 (**Methods**; **Figure S5A,B**). Differentially expressed genes are color-coded by membership (shared, red; full dataset only, cyan; equivalent viral load, green).

(F) Violin plots of *DYNNL1* expression levels stratified by both cell type and viral RNA load groups (Neurons, p<2E-16; Astrocytes Cluster 1, p<2E-16; Astrocytes Cluster 2, p=0.05. Anova test).

(G-I) Identification of rare "Cluster 2-like" astrocytes from single-nuclei RNA profiles derived from *ex vivo* cortical resections of living human Normal pressure hydrocephalus (NPH) surgical patients[46].

(G) Scatterplot of Cluster 1 or 2 astrocyte single-cell RNA profiles based on aggregate expression scores for genes up regulated in Cluster 1 (n=144 genes) or Cluster 2 (n=268 genes) (p < 0.01 and log2 fold-change > 2). *Left*, heat map of point densities. *Right*, color-coded cluster identities.

(H) Analysis of Cluster 2 aggregate gene scores for n=82,634 single-nucleus RNA profiles of astrocytes from n=52 NPH patients (median nuclei profile per patient = 1,277). Density and boxplots show aggregate expression z-score distribution for the 196 genes shared across both datasets (*top*) versus 1000 permutations of expression-matched NPH gene sets (**Methods**). snRNA-seq profiles > 4.5 standard deviations above the mean were considered "Cluster 2 like" (n=38 profiles identified in 21 of 52 total patients; p=4.7E-7 based on permutations). In box plots, outlier nuclei profiles > 1.5 interquartile range are shown as dots color-coded by patient identity with size proportional to aggregate gene z-score.

(I) Scatterplots of normalized metacell expression values for the 196 genes used to identify "Cluster 2-like" profiles (Identification Gene Set: p < 0.01 and >2 log fold-change; *left*) and for an independent set of n=521 gene RNAs with enriched expression in Cluster 2 astrocytes (Validation Gene Set: p < 0.01 and 1-2 log fold-change; *right*)(**Methods**). Metacells are composed of n=38 "Cluster 2-like" nuclei RNA profiles versus all other astrocyte nuclei profiles in the NPH dataset (n=82,596). Total UMI counts for both NPH gene sets were significantly enriched in "Cluster 2-like" NPH astrocyte profiles at levels that matched expectation from Cluster 2 (Identification Gene Set, 2.8 fold enriched; Validation Gene Set, 1.2 fold enriched; p<2.2E-16, Chi Square Test).

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Figure 6. Gene expression changes in pro-viral human astrocytes imply reduced inter-
cellular interactions, activation of toll-like receptors and complex changes in protein
translation and mitochondrial respiration.

(A,B) Gene expression-based inference of alterations to inter-cell type interactions between
Cluster 1 and Cluster 2 astrocytes using CellPhoneDB (CPDB) v5.0[64], a database of 1,419
molecular interactors (**Methods**).

(A) Volcano plot-based visualizations of ligand (*left*) or receptor (*right*) gene expression changes between Cluster 1 and Cluster 2. Ligand or receptor genes significantly enriched in either cluster ($p<0.01$) and significantly "relevant" (after CPDB permutation; $p < 0.05$) are circled in red (Ligand genes: Cluster 1, n=46; Cluster 2, n=11; Receptor genes: Cluster 1, n=32; Cluster 2, n=5). Other ligand or receptor genes are shown in blue and all other genes in gray.

(B) Chord diagrams showing the number of CPDB relevant interactions from (*left*) or to (*right*) Cluster 1 or Cluster 2 astrocytes for other cell types.

(C) Tree plot clustering of enriched REACTOME gene categories (Cluster 1: $p < 0.000001$, n=84 categories; Cluster 2: $p < 0.01$, n=32 categories) based on genes upregulated in Cluster 1 (*left;* n=6,551) or Cluster 2 (*right;* n=2,347)($p<0.01$). Hierarchical clustering results reflect shared genes driving each REACTOME category association. Dot size scales with the gene number in each category. Heat map indicates p value of each included category.

(D) Heat map plot reflecting log2 fold-changes in Cluster 2 of each gene in the Toll-Like Receptor Cascade REACTOME category (n=104 genes). Dots indicate significant expression changes ($p < 0.01$).

(E) Combined violin and dot plots reflecting gene-specific log2 fold-changes for gene sets encoding proteins related to translation (*left* and *middle*) or mitochondrial respiratory complexes I and IV (*right*). *Top row*, Cluster 1 versus Cluster 2 astrocytes. *Bottom row,* No Infection versus Tha(0.5) RABV infected astrocytes. Ribosomal subunit genes are stratified by whether the encoded protein is a component of cytosolic (n=85 genes) or mitochondrial (n=78 genes) ribosomes. tRNA synthetase genes are stratified by whether the encoded enzyme aminoacyl-tRNAs used for translation in the cytosol (n=17 genes), mitochondria (n=17 genes) or both ribosome types (n=3 genes). Nuclear gene components or assembly factors of the cytochrome c oxidase (COX) family (n=23 genes), Complex IV. The NADH:ubiquinone oxidoreductase (*NDUF*) family (n=47 genes) encoding Complex I. Red outlines indicate significant expression changes ($p <0.01$).

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Figure 7. Uninfected microglia respond to Tha RABV infection through graded interferon stimulated gene transcription potentiated by higher viral titer and disinhibited innate immune signalling of other infected cell types.

(A) UMAP embedding plot of microglia scRNA profiles stratified by experimental condition (**Methods**)(n=1,218 cells).

(B) Principal component analysis of variably expressed microglia genes. *Left*, cell component loadings of PC 1 (contamination of neuronal RNAs; **Figure S7B**) versus PC 2 (interferon stimulated gene expression; **Figure S7B**). *Right*, n=15 genes with the highest gene loadings for PC 2.

(C). Scatter plots comparing log2 fold expression level changes of differentially expressed genes (p < 0.01) across No Infection microglia and microglia from various experimental conditions (*top*, Tha(0.5) versus Tha2P4M(0.5); *bottom*, Tha(5) versus Tha2P4M(0.5)). Color reflects significant genes shared across comparisons (pink) versus those unique to experimental conditions.

(D) REACTOME pathway analysis plot based on n=202 shared genes found differentially expressed in comparisons of both Tha2P4M(0.5) and Tha(5) to No Infection microglia.

(E) Normalized gene expression plots for three representative interferon stimulated genes plotted against principal component 2 scores and color-coded by experimental condition.

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A

P Protein

CVS 1 MSKIFVNPSAIRAGLADLEMAEETVDLINRNIEDNQAHLQGEPIEVDNLP 50
MSKIFVNPSAIRAGLADLEMAEETVDLINRNIEDNQAHLQGEPIEVDNLP
Tha 1 MSKIFVNPSAIRAGLADLEMAEETVDLINRNIEDNQAHLQGEPIEVDNLP 50

CVS 51 EDMKRLHLDDEKSSNLGEMVRVGEGKYREDFQMDEGEDPNLLFQSYLDNV 100
EDM+RL LDD K S L + E KYREDFQMDEGEDP+LLFQSYLDNV
Tha 51 EDMRRLQLDDRKPSGLSGIATAVESKYREDFQMDEGEDPSLLFQSYLDNV 100

CVS 101 GVQIVRQMRSGERFLKIWSQTVEEIVSYVTVNFPNPPRRSSEDKSTQTTG 150
GVQIVRQMRSGERFLKIWSQTVEEI+SYVTVNFPNP RS EDKSTQT G
Tha 101 GVQIVRQMRSGERFLKIWSQTVEEIISYVTVNFPNPSGRSLEDKSTQTAG 150

CVS 151 RELKKETTSAFSQRESQPSKARMVAQVAPGPPALEWSATNEEDDLSVEAE 200
RELKKE+ SA QRES+P KARM AQ A GPPALEWSATNEEDDLSVEAE
Tha 151 RELKKESPSAPLQRESKPLKARMEAQTASGPPALEWSATNEEDDLSVEAE 200

CVS 201 IAHQIAESFSKKYKFPSRSSGIFLYNFEQLKMNLDDIVKEAKNVPGVTRL 250
IAHQIAESFSKKYKFPSRSSGIFLYNFEQLKMNLDDIVKE+KNVPGVTRL
Tha 201 IAHQIAESFSKKYKFPSRSSGIFLYNFEQLKMNLDDIVKESKNVPGVTRL 250

CVS 251 AHDGSKIPLRCVLGWVALANSKKFQLLVEADKLSKIMQDDLNRYTS 296
A +GSK+PLRCVLGWVALANSKKFQLLVE +KL+KIMQDDLNRYTS
Tha 251 AREGSKLPLRCVLGWVALANSKKFQLLVEPEKLNKIMQDDLNRYTS 296
                  W265G   **M287V**

M Protein

LAG 1 MNFLRKIVKNCKDEEIPKPGTPSAPPDDDDLWMPPPEYVP 40
MNFLRKIVKNC+DE+ KP SAPPDDDDLW+PPPEYVP
Tha 11 MNFLRKIVKNCRDEDTQKPSPVSAPPDDDDLWLPPPEYVP 50

LAG 41 LTQIKGKENVRNFCINGEIKICSPNGYSFRILRHILKSFD 80
L ++ GK+N+RNFC+NGE+K+CSPNGYSFRILRHIL+SFD
Tha 51 LKELTGKKNMRNFCVNGEVKVCSPNGYSFRILRHILRSFD 90
                                           R77K

LAG 81 NVYSGNRRLIGVVKVVIGLVLSASPVPEGMNWVYKLRRTL 120
+YSGN R+IG+VKVVIGL LS +PVPEGMNWVYKLRRTL
Tha 91 EIYSGNHRMIGLVKVVIGLDLSGAPVPEGMNWVYKLRRTL 130
                        D100A A104S M110L

LAG 121 IFQWAESHGPLEGEELEYSQEITWDDEAEFVSLQIRVSAK 160
IFQWA+S GPLEGEELEYSQEITWDD+ EFV LQIRVSA+
Tha 131 IFQWADSRGPLEGEELEYSQEITWDDDTEFVGLQIRVSAR 170

LAG 161 QCHIQGRLWCINMNSKACQLWADMGLKTQQSQEDENTSLL 200
QCHIQGR+WCINMNS+ACQLW+DM L+TQ+S+ED+++SLL
Tha 171 QCHIQGRVWCINMNSRACQLWSDMSLQTQRSEEDKDSSLL 210

LAG 201 LE 202
LE
Tha 211 LE 212

Supplemental Figure 1. RABV P and M protein alignments and locations of 2P4M mutations.

(A) Amino acid-based protein alignments comparing Tha RABV P and M proteins versus those protein sequences from the solved structures shown in **Figure 1E** (CVS P[62] (PDB Accession 1vyi) and Lagos Bat M[63] (PDB Accession 2w2s). The sites of the "2P" and "4M" mutations are shown in red.

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Condition	No Infection	Tha (MOI 0.5)	Tha2P4M (MOI 0.5)	Tha (MOI 5)	Total
Experimental Replicates	3	3	2	2	10
Passing Cells	7,324	7,026	5,064	4,043	23,457

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Supplemental Figure 2. Identifying molecular cell types and Tha RABV infection states using single-cell RNA-seq.

(A) Quality-control metrics for inclusion of scRNA profiles. Density scatter plots compare the size of RNA libraries (based on total human UMI counts) versus the fraction of RNA derived from the mitochondrial genome. The red polygons define high-quality RNA libraries included for downstream analysis. Colored heat map indicates point density.

(B) Table summarizing the number of RNA profiles and biological replicates for each experimental condition.

(C) Heat map depiction of expression levels of select marker genes for transcriptional clusters
associated with major human brain cell types. Colored heat map indicates expression level.
Cells are downsampled by cell type for visualization.

(**D**) Density plot-based comparison of the real versus simulated data of viral versus total UMI
counts, demonstrating the accuracy of the model used for Expectation-Maximization
identification of RABV infected versus uninfected cells (**Methods**).

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Supplemental Figure 3. RNA expression analysis of Tha RABV genes

(A) Comparison of normalized sequencing read coverage across the Tha RABV genome for

bulk RNA sequencing (*top*) following poly A capture and enrichment[30] versus subsets of n=10

scRNA-profiles associated with Neurons and Cluster 1 and Cluster 2 Astrocytes (*bottom*)(Fig.

5; **Methods**). A schematic of the Tha RABV genome is shown at bottom and the locations of

polyadenylation signals are shown with arrows.

(B) Comparison of relative expression levels for each Tha RABV gene based on bulk RNA

sequencing (red; three biological replicates) versus the scRNA-seq analysis used in this study

(blue; five total biological replicates, n=3 Tha(0.5) and n=2 Tha(5) aggregated across all cell
types).

(C) Density plots of viral RNA load stratified by brain cell types and color-coded by
experimental condition. P values reporting differences in distributions by experimental
condition are reported in each panel (Kruskal-wallis tests).
(D) Density plots of relative RNA levels for each of the five Tha RABV genes color-coded by
experimental condition and stratified by both gene and neuron or astrocyte identity. P values
reporting differences in gene expression distributions by experimental condition are reported
for neurons and astrocytes in each panel (Kruskal-wallis tests).

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Supplemental Figure 4. Host cell gene expression responses to Tha versus Tha2P4M RABV infection.

(A) Volcano plots of genome-wide expression differences stratified by cell type and experimental condition (*top row*, No Infection versus Tha(0.5); *middle row*, Tha(0.5) versus Tha2P-4M(0.5); *bottom row*, Tha(0.5) versus Tha(5)). Select genes with significant differences (red, $p < 0.01$) are labelled for clarity.

(B) Combined violin dot plots stratified by neurons or astrocytes illustrating RNA expression levels for key genes stratified by experimental condition. (RNA levels are shown as after log-normalization and centering following the default Seurat workflow; **Methods**).

Supplemental Figure 5. Large-scale gene expression changes driving pro-viral Cluster 2 astrocytes occur independently of viral RNA load.

(A) Combined histogram and density plot of viral RNA load distributions for Cluster 1 and 2 after downsampling each cluster to n=276 scRNA profiles with equivalent viral load distributions (**Methods**).

(B) Volcano plots of gene expression differences across viral RNA load downsampled Cluster 1 and 2 with select genes labelled (red, p < 0.01).

(C) Schematic approximating the abundance of astrocytes in the Cluster 2 (or Cluster 2-like) pro-viral state across experimental conditions estimated from the NPH and Tha datasets. Circles representing 2,200 astrocytes are shown. The experimental state is indicated by the dot fill, while the Cluster 2/Cluster 2-like state is indicated by a purple outline (beginning at top left, as indicated by the arrow).

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Supplemental Figure 6. Gene expression signatures observed in pro-viral Cluster 2
astrocytes are not observed in previous descriptions of "reactive" rodent or human
astrocytes.

(A) Plots of differentially expressed RNAs or proteins from previous studies plotted on volcano
plot of depicting expression differences across Cluster 1 and Cluster 2 astrocytes. The size
and color of dots represents the intersection of differentially expressed RNAs or proteins from
previous studies with those RNAs differentially expressed across Cluster 1 or Cluster 2. Large
blue dots correspond to previously described as differentially expressed gene/protein sets (p ,
0.01); those with red outlines are also significant in the Cluster 1 versus Cluster 2 comparison
(p < 0.01). Smaller dots correspond to those genes observed as differentially expressed across
Cluster 1 and Cluster 2 (red, p < 0.01; grey, p >= 0.01) but are not observed as differentially
expressed in previous studies. *Left*, 46 genes differentially expressed following scRNA-seq
analysis of mouse cortical astrocytes *ex vivo* with an IFN activated gene signature following
Lipopolysaccharides (LPS) stimulation. Primary rat (*middle*) or iPSC-derived human (*right*)
astrocytes cultured *in vitro* and stimulated with TNF, IL1α, C1Q and IFNβ to induce an
interferon-responsive state. The 63 rat genes show concordant changes from bulk RNA-seq
and proteomic analysis; the 7 human genes showed alterations based on proteomic analysis
only (bulk RNA-seq was not performed).

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Supplemental Figure 7. Microglia transcriptional response to Tha RABV infection of other cell types.

(A) UMAP embedding plot of microglia scRNA profiles color-coded by experimental condition (*left*) and infection status (*right*).

(B) Gene principal component loading scores for the top and bottom n=15 genes for PC 1 and PC 2. PC 1 genes suggest contamination of neuronal transcripts, while PC 2 genes represent genes transcriptionally regulated by interferon signalling.

(C) Volcano plots of gene expression differences with select genes labelled (red, p < 0.01). The corresponding fold-change values for these analyses are shown in **Figure 7C**.

Supplemental Table

Supplemental Table S1 contains all differential gene expression testing results reported in the manuscript.

Supplemental information

STAR Methods

KEY RESOURCES TABLE

REAGENT or RESOURCE	SOURCE	IDENTIFIER
Antibodies		
Mouse anti-TUBB3	Sigma	Cat# T858
Rabbit anti-GLAST	Invitrogen	Cat# PA5-111080
Rabbit anti-IBA1	Proteintech	Cat# 10904-1-AP
Goat Anti-mouse DYLIGHT 549	KPL	Cat# 072-04-18-06
Goat anti-rabbit Alexa Fluor 549	Invitrogen	Cat# A11035
Virus strains		
Tha RABV (8743THA)	Delmas et al.[65]	GenBank No. EU293121
Tha-eGFP RABV (based on 8743THA)	Besson et al. [66]	Ref-SKU: 014V-03195
Tha2P4M RABV (based on 8743THA)	Sonthonnax et al.[14]	N/A
Chemicals, peptides, and recombinant proteins		
Ascorbid acid	Sigma-Aldrich	Cat# A4403
BMP-4	R&D Systems	Cat# 314-BP-050
B-27 serum free supplement	Thermo Fisher	Cat#17504044
CHIR99021	TOCRIS	Cat# 4423
CSF-1	R&D Systems	Cat# 216-MC-01M
Dead Cell Removal Kit	Miltenyi Biotec	Cat# 130-090-101
DKK-1	R&D Systems	Cat# 5439-DK-500
EGF	Thermo Fisher	Cat# PHG0311
fetal bovine serum (heat inactivated)	Eurobio	Cat# S182H-500
FGF	Thermo Fisher	Cat# PHG0026
FGF-2	R&D Systems	Cat# 223-FB-500
Geltrex	Invitrogen	Cat# A1413201
Glutamax	Thermo Fisher	Cat# 35050038
Hoescht 33342	Thermo Fisher	Cat# H1399
IL-3	R&D Systems	Cat# 203-IL-050
IL-6	R&D Systems	Cat# 206-IL-050
IL-34	R&D Systems	Cat# 5265-IL-010
Knock-out D-MEM/F-12	Thermo Fisher	Cat# A1370801
Laminin	Sigma-Aldrich	Cat# L2020
Neurobasal medium	Thermo Fisher	Cat# 10888022
Papain	Sigma-Aldrich	Cat# P4762
PBS	Thermo Scientific	Cat# 10010023
Penicillin/Streptomycin	Thermo Fisher	Cat# 15140148
Poly-ornithine	Sigma-Aldrich	Cat# P4957
ROCK inhibitor Y-27632	Stemcell Technologies	Cat# ACS-3030
SCF	R&D Systems	Cat# 255-SC-01M
StemPro Accutase	Thermo Scientific	Cat# A1110501
StemPro Neural Supplement	Thermo Fisher	Cat# A1050801

Triton-X	Millipore	Cat# 648463
VEGF	R&D Systems	Cat# 293-VE-500

Critical commercial assays

Chromium Next GEM Single Cell 3' Kit v3.1	10x Genomics	Cat#: 1000121
Single Index Kit T Set A, 96 rxn	10x Genomics	Cat#: PN-2000240
NovaSeq 6000 S4 Reagent Kit v1.5 (300 cycles)	Illumina	Cat#: 20028312

Deposited data

scRNA-seq data (raw)	This paper	GEO: GSE284262
scRNA-seq data (processed)	This paper	https://drive.google.com/drive/folders/1Qnv4TorlnZ5z_Z6yzBMwJAlleGyXP9x9?usp=drive_link
Tha bulk mRNA seq data (raw)	Kim et al.	GEO: GSE178583
NPH snRNA sequencing data (processed)	Gazestani et al.	https://zenodo.org/records/8319719
Mouse astrocyte scRNA-seq (processed)	Hasel et al.	PMID: 34413515 (Supp. Table 5)
Rat astrocyte RNA-seq/proteomics (processed)	Prakash et al.	PMID: 8031883 (Supp. Table 5)
Human astrocyte proteomics (processed)	Prakash et al.	PMID: 8031883 (Supp. Table 5)

Experimental models: Cell lines

Human neural stem cells (EnStem-A™)	Millipore	Cat#: SCC003
XCL-1 iPSC	XCell Science	Cat#: IP-001-1V

Software and algorithms

R programming language (v4.3.0)	N/A	https://cran.r-project.org/
Python programming language (v3.8.19)	N/A	https://www.python.org/
STAR (v2.7.9a)	Dobin et al.[67]	https://github.com/alexdobin/STAR
RSEM (v1.3.1)	Li et al.[68]	https://github.com/deweylab/RSEM
CellRanger (v5.0.1)	10x Genomics	https://github.com/10XGenomics/cellranger
Seurat (v4.4.0)	Hao et al.[69]	https://cran.r-project.org/
tidyverse (v2.0.0)	Wickham et al.[70]	https://cran.r-project.org/
dplyr (v1.1.4)	Wickham et al.[71]	https://cran.r-project.org/
ggplot2 (v3.5.1)	Wickham[72]	https://cran.r-project.org/
Matrix (v1.6-4)	N/A	https://cran.r-project.org/
viridis (v0.6.5)	N/A	https://cran.r-project.org/
Libra (v1.0.0)	N/A	https://github.com/neurorestore/Libra
clusterProfiler (v4.8.3)	Xu et al.[73]	https://bioconductor.org/
enrichplot (v1.2.3)	Yu[74]	https://bioconductor.org/
ReactomePA (v1.44.0)	Yu et al.[75]	https://bioconductor.org/
ggrepel (v0.9.5)	Slowikowski[76]	https://cran.r-project.org/
ggtree (v3.8.2)	Yu et al.[77]	https://cran.r-project.org/
smplot2 (v0.2.4)	Min et al.[78]	https://bioconductor.org/
qs (v0.26.3)	N/A	https://cran.r-project.org/
data.table (v1.15.4)	Barrett et al.[79]	https://cran.r-project.org/
cowplot(v.1.1.3)	N/A	https://cran.r-project.org/
CellPhoneDB (v5.0)	Troulé et al.[64]	
circlize (v0.4.16)	Gu et al.[80]	https://cran.r-project.org/
PupillometryR (v0.0.5)	Forbes et al.[81]	https://cran.r-project.org/
Snapgene (v7.2.1)	Dotmatics	www.snapgene.com

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RESOURCE AVAILABILITY
Lead contact
Further information and viral reagent requests will be fulfilled by lead contacts Dr. Arpiar Saunders and Dr. Herve Bourhy.

Materials availability
Tha RABV reagents are available from Dr. Herve Bourhy with a completed MTA and appropriate lab safety and import restrictions.

Data and code availability
The scRNA-seq datasets generate for this study are available from Gene Expression Omnibus Accession GSE284262. All analysis scripts are available from the Saunders Lab Github () and processed data are also available (https://drive.google.com/drive/folders/1Qnv4TorlnZ5z_Z6yzBMwJAIIeGyXP9x9?usp=drive_link).

EXPERIMENTAL MODEL AND SUBJECT DETAILS
Ethics Statement
All Tha RABV *in vitro* infections were performed under BSL3 containment in accordance with the biosafety protocols developed and approved by the Pasteur Institute.

Human brain cell type co-culture
Human neural stem cell culture and differentiation
Human neuronal stem cells (hNSC, EnStem-A™ SCC003, Millipore) were amplified on plates previously cultured with geltrex (A1413201, Invitrogen) in complete neural stem cell (CNSC) medium containing Knock-out D-MEM/F-12 (A1370801, Thermo Fisher), 2 mM Glutamax (35050038, Thermo Fisher), 2% StemPro Neural Supplement (A1050801, ThermoFisher), 20 ng/ml human FGF (PHG0026, Thermo Fisher), and 20 ng/mL human EGF (PHG0311, Thermo Fisher) at 37°C and 5% CO_2. For differentiation, hNSC cells were seeded at a density of 1.5×10^5 cells/cm^2 on plates previously coated with poly-ornithine (P4957, Sigma-Aldrich) and laminin (L2020, Sigma-Aldrich). One day after seeding, the medium was changed to differentiation medium containing neurobasal medium (10888022, Thermo Fisher), 2 mM Glutamax (35050038, Thermo Fisher), 2% B-27 serum free supplement (17504044, Thermo Fisher), 200 μM Ascorbid acid (A4403, Sigma-Aldrich) and 1x Penicillin/Streptomycin (15140148, Thermo Fisher). Human NSC were differentiated for one week before hiMacs were added to the culture. Half of the medium was changed every third day.

Differentiation of hiPSCs to hiMacs
Human induced macrophage-like cells (hiMacs) were generated from iPSCs according to a published method described by Takata *et al*[82]. In short, 5 ng/mL BMP-4 (314-BP-050, R&D Systems), 50 ng/mL VEGF (293-VE-500, R&D Systems), 2 μM CHIR99021 (4423, TOCRIS) induced mesoderm specification of human iPSC colonies (XCL-1) and hemangioblast-like cell formation (36). Replacement of CHIR99021 by 20 ng/mL FGF-2 (223-FB-500, R&D Systems), followed by maintenance in 15 ng/mL VEGF and 5 ng/mL FGF-2 induced differentiation into the hematopoietic lineage according to a modified protocol from Grigoriadis *et al.* (37). Wnt signalling was inhibited and hematopoietic stem cells were matured by incubation with 50 ng/ml SCF (255-SC-01M), 10 ng/mL FGF-2, 20 ng/mL IL-3 (203-IL-050, R&D Systems), 10 ng/mL

IL-6 (206-IL-050, R&D Systems), 10 ng/mL VEGF and 30 ng/mL DKK-1 (5439-DK-500) for 6
days and with 50 ng/mL SCF, 10 ng/mL FGF-2, 20 ng/mL IL-3 and 10 ng/mL IL-6 for 4 days.
To promote terminal differentiation of hiMacs, cells were cultured with 50 ng/mL CSF-1 (216-
MC-01M, R&D Systems) for 14 days (38–40).

Differentiation of hiMacs to hiMicros
After hiMacs generation, hiMacs were co-cultured with 70 – 80 % confluent one week old (day
0 = induction of neural induction) hiNeurons and hiAstrocytes for three consecutive weeks. In
detail, 7 days after the induction of neural differentiation, $1x10^4$ cells/cm^2 hiMacs were added
to the $1.5x10^5$ cells/cm^2 hiNeurons and hiAstrocytes. Half of the culture medium was changed
every third day supplemented with 50 ng/mL recombinant human CSF-1 (216-MC-010, R&D
Systems) and 50 ng/mL human IL-34 (5265-IL-010, R&D Systems). Cells were co-cultured for
three consecutive weeks before infection experiments were started.

Tha RABVs
Thailand virus, referred to as 8764THA (Genbank No. EU293111) is a field strain of RABV
isolated from the brain of a Thai patient who died of RABV after being bitten by a rabid dog
(EVAg collection, Ref-SKU: 014V-02106) (29). This virus was further adapted to cell culture
on BSR cells (a BHK-21 clone, kindly provided by Monique Lafon, Institute Pasteur, Paris)
(32), consequently called 8743THA (Genbank No. EU293121) (29) and in this manuscript
referred to as "Tha". The recombinant Tha2P4M RABV harbors the same genetic background
as Tha apart from bearing two point mutations in the viral P-protein (W265G, M287V) and four
mutations in the viral M-protein (R77K, D100A, A104S, M110L) which were previously
described (15,21,33). To validate viral infection, recombinant viral Tha-eGFP and Th2P4M-
eGFP constructs were used which were generated by cloning sequences of eGFP (recovered
from pEGFP-C1 plasmid, Promega) into the genetic sequence of Tha (34) and Th2P4M,
respectively. Viral strains were sequenced before used for infection experiments. Viral titers
were determined by virus titration on BSR cells via staining of the viral nucleoprotein (5100,
Sigma-Aldrich).
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METHOD DETAILS
Visualizing 2P4M mutations on P and M protein structures
ChimeraX (v1.8)[83] was used to highlight the P protein (W265G, M287V) substitutions on the
structure of the P protein from RABV CVS-11 strain (Protein Data Bank Accession: 1vyi) and
four mutations in the M protein (R77K, D100A, A104S, M110L) on the M protein from Lagos
bat virus (Protein Data Bank Accession: 2W2S). Amino acid alignments (using the CLUSTALW
algorithm implemented in SnapGene (v7.2.1)) confirmed the conserved site positions of each
mutation across *lyssavirus* species and strains (**Figure S1B**).
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Tha RABV infection conditions
After four weeks of differentiation *in vitro*, co-cultured human brain cells were subject to Tha
RABV infection through bath-application of Tha RABV (diluted in 500 ul of differentiation
media) versus mock infections (500 ul of differentiation media alone) for two hours at 37°C and
5% CO_2. To visualize infected cells and confirm identities of infected cell types, Tha RABV
expressing GFP (Tha-eGFP, MOI 0.5) was used following post-hoc immunofluorescence
analysis. To generate co-cultures upstream of single-cell RNA sequencing, infections were
performed with Tha (MOI 0.5 or 5.0), Tha2P-4M (MOI 0.5) or "No Infection" (mock infection)
were performed.

Immunofluorescence-based identification of Tha RABV infected cell types

Forty-eight hours post-infection, co-cultures were fixed using 4% PFA for 15 minutes at room temperature. After fixation, cells were then washed with PBS (10010023, Thermo Scientific) and permeabilized using 0.5% triton X-100 (648463, Millipore) for 10 minutes. Immunolabeling was performed with primary and secondary antibodies (Key resources table) using the following staining conditions: Cells were stained with the primary antibody diluted in PBS (10010023, Thermo Scientific) supplemented with 5% heat-inactivated fetal bovine serum (S182H-500, Eurobio) overnight at 4°C according to the manufacturer's instructions. Subsequently, cells were washed using PBS (10010023, Thermo Scientific), followed by staining with the secondary antibody for 30 minutes at 37°C according to the manufacturer's instructions. Immunolabeled cultures were washed using PBS (10010023, Thermo Scientific) and imaged using the Opera Phenix™ High Content Screening System (Perkin Elmer) using standard conditions.

Single-cell RNA sequencing data generation and processing

Forty-eight hours after infection, cells were dissociated using StemPro Accutase (A1110501, Thermo Scientific) supplemented with 50 U/mL papain (P4762, Sigma Aldrich). In detail, cells were incubated in 400 μl dissociation solution for 10 minutes at 37°C. After 10 minutes, cells were resuspended in neurobasal medium (10888022, Thermo Fisher) supplemented with 2% heat-inactivated fetal bovine serum (S182H-500, Eurobio) and 10 μM ROCK inhibitor Y-27632 (ACS-3030, Stemcell Technologies). Cells were centrifuged at 1000 *rpm* for 5 minutes at 4°C. Viability was increased by removing dead cells via the Dead Cell Removal Kit (130-090-101, Miltenyi Biotec). In short, cells were resuspended in 100 μl of dead cell removal beads. After 15 minutes of incubation, 400 μl of binding buffer was added to each sample. Samples were added to the freshly washed LS columns (130-042-401, Miltenyi Biotec). Columns were washed with 4.5 mL binding buffer (Miltenyi Biotec) and the flow-through was collected. After the collection of viable cells, cells were centrifuged at 1000 *rpm* for 5 minutes at 4°C. Meanwhile, viable cells were counted and diluted to a final concentration of 1000 cells/μl. 10,000 cells were loaded per condition using the Chromium Next GEM Single Cell 3' Reagent Kit v3.1 (PN-1000128, 10x Genomics). The 10x libraries were sequenced at a depth of 40,000 reads per cell using the Illumina NovaSeq Instrument (Novogene). CellRanger (10x Genomics; v5.0.1) was used to align reads against a composite human (GRCh38) and Tha RABV genome. Digital Gene Expression (DGE) matrices were generated using reads mapped to gene exons.

scRNA-seq workflow for analysis of Tha RABV and human gene expression

Single-cell RNA-seq data was analyzed in two distinct ways to study human and viral gene expression in an independent manner and in a synergistic manner in which viral and human RNAs were associated with the same RNA profiles using experiment-specific cell barcodes. First, to study human gene expression patterns without the influence of Tha RABV RNAs, Tha RABV genes were removed to create human-specific DGEs. Human-specific DGEs across all experimental conditions were filtered based on quality control metrics (described below) and then processed using a standard workflow in Seurat (v4.4.0)[69] to clustering RNA profiles, revealing cell type identities. Specifically, scRNA libraries were filtered to include those libraries with >2,500 UMIs and % of mitochondrial RNAs meeting custom thresholds based on library size (**Figure S2A**; range: 1-19.9 %). UMI counts in each library were then log-normalized (*NormalizeData(normalization.method = "LogNormalize", scale.factor = 10000)*) and expression values for each gene were centered (*ScaleData()*). Clustering was then performed after variable gene selection (*FindVariableFeatures()* and *RunPCA()*), using n=15 principal

components as input for shared nearest-neighbor graph construction
(*FindNeighbors(dims=1:15)*). Clustering was then performed with the smart local moving
algorithm (*FindClusters(resolution=0.12)*) and a UMAP embedding was generated
(*RunUMAP(dims=1:15, min.dist=0.4))* for visualization. Cell type identities for each cluster
were assigned by evaluating the expression patterns of well-established cell-type-specific
marker genes for neurons, astrocytes, microglia, neural stem cells and mitotic cell (**Figure**
S2B). Second, an "infection summary" file was generated to study Tha RABV gene expression
at single-cell resolution. The summary infection file includes UMI counts for each Tha RABV
gene as well as total Tha RABV and grand total UMIs (human + Tha). Cell type and infection-
status identities (see below) were then assigned to the Tha infection file using experiment-
specific cell barcodes for downstream analysis. Importantly, to avoid confounds of low-quality
libraries, only those RNA profiles passing the quality-control metrics and included in the final
Seurat analysis were included for analyses of Tha gene expression. After global clustering
analysis, astrocyte and microglia cellular RNA profiles were independently analyzed in Seurat
using a similar workflow. In each case, subclustering revealed minor groups of RNA profiles
that exhibited gene expression signatures of other cell types or high-levels of nuclear lncRNAs
and thus were removed as candidate "doublets" or low-quality cellular RNA profiles.
1521
Identification of infected and uninfected cells using expectation-maximization
The observed Tha RABV viral RNA UMI counts were modelled as a mixture of two compound
log-normal-binomial distributions, one for each of the populations of infected and uninfected
cells. These compound distributions were also regressed by the total UMIs for each profile (i.e.
library size), allowing the model to account for differences infectivity across cell type
populations with varying library sizes. Specifically, letting *LS = library size (total Tha + human*
UMIs), *VL = viral load (% of UMIs from Tha)*, and *VC = viral counts (total Tha UMIs)*, for a
given cell with index *i* we draw:
*VL_i ~ logNormal (mu_offset + mu_coef * log (LS_i), sigma_offset + sigma_coef * log(LS_i))*
and then:
VC_i ~ Binom (VL_i, LS_i)
where the parameters *mu_offset*, *mu_coef*, *sigma_offset*, and *sigma_coef* are learned
separately for the populations of infected and uninfected cells. The conjugate prior distribution
for the binomial distribution is the beta distribution, but we found the beta distribution to fit the
expression data poorly, which we hypothesize is due to numerical instability arising from the
extreme skew towards low viral load in our data. We chose instead to use a log-normal
distribution as the prior distribution for VL, with the additional restriction 0 <= VL <= 1. (In
practice, the missing/erroneous probability density from VL > 1 is negligible). Parameter
learning was accomplished with a standard expectation-maximization algorithm, first randomly
assigning each cell to one of two groups, which we will later categorize as infected or
uninfected. For the maximization step, we fit a log-normal-binomial compound distribution (via
maximum likelihood estimation) for each population of cells, as well as estimating the priors
for each cell belonging to either group. To find maximum likelihood estimates for the log-
normal-binomial distributions, we computed and maximized likelihood using the R language
optimizer "optim" function, with "method = 'Nelder-Mead'" and starting parameters `mu_off = -
4, mu_coef = -0.1, sigma_off = 1.5, sigma_coef = 0`. The probability density for the log-normal-
binomial distribution was computed by grid approximation (using 200 points evenly spaced
between [-15, 0] and exponentiated). For the expectation step, each cell was assigned to the
fitted model from the previous step that maximized its posterior probability. Then new

compound log-normal-binomial distributions were fit to the reassigned groups of cells, and the
cells recategorized, repeating this process until convergence (n=20 iterations).
1553

1554   **Gene expression plotting**
1555   Gene expression levels were plotted using normalized, gene-centered data using functions
1556   from Seurat or custom plotting functions using the "ggplot2" (v3.5.1)[72] R package.
1557

Bulk and scRNA-seq analysis of Tha read alignment and gene expression
We re-analyzed bulk mRNA expression data from Tha RABV infection of BSR cells (Gene
Expression Omnibus accession GSE178583) in addition to Tha RABV scRNA-seq data from
human brain cell type co-cultures to compare Tha RABV gene expression levels and read
alignment locations across sequencing modalities (**Figure S3A,B**). Bulk mRNA sequencing
data was generated with the TruSeq Stranded mRNA library kit (Illumina). In the previous
publication[30], bulk mRNA data were aligned and analyzed with respect to only the human
genome (reference GRCh38). Thus STAR (v2.7.9a)[67] was used to realign the bulk mRNA fastq
files to both the human and Tha genomes followed by RSEM (v1.3.1)[68] to quantify Tha RABV
gene expression levels using transcripts per million reads (TPM) values. Sequencing read
coverage against the Tha genome was assessed for the bulk mRNA data and ten randomly
selected cell barcodes from the scRNA-seq associated with the neurons, cluster 1 and pro-
viral cluster 2 astrocytes. To do this, BAM files associated with these specific read sets were
converted to bigwig files then read alignment coordinates were exported to csv files for analysis
in R.
1573

Tha RABV gene expression analysis from scRNA-seq data
Viral RNA load scores were calculated for each cell's RNA profile as the percentage of total
UMIs (human + Tha) attributed to the five genes in Tha RABV genome (*N, P, M, G* and *L*).
Relative expression of each Tha RABV gene was calculated based on the UMIs associated
with each gene versus the total Tha RABV UMIs for each cellular RNA profile. To avoid biases
driven by insensitive mRNA detection, analysis was limited to cellular RNA profiles with > 0
UMIs for *G* and *L* (the Tha genes with the lowest expression levels; **Figure S3B**). A one-way
ANOVA was used to test for differences in Tha gene expression levels, while a two-way
ANOVA was used to evaluate if cell type and experimental condition affected relative
expression of each Tha gene. Pairwise testing of differences Tha gene expression by cell type
and experimental condition was performed using the Kolmogorov–Smirnov test. P values are
reported as uncorrected.
1586

1587   **Differential expression testing**
1588   Human gene differential expression testing across experimental conditions or cell types was
1589   implemented in the "Libra" (v1.0.0) R package using the DESeq2 likelihood ratio test method
1590   (*Libra::run_de(de_method="DESeq2", de_type="LRT")*). All reported and analyzed p values
1591   are corrected for multiple hypothesis testing using the Benjamini-Hochberg method.
1592

Gene Set Enrichment and REACTOME analysis
Gene Set Enrichment Analysis (GSEA) and REACTOME Analysis were performed using the
"clusterProfiler" (v4.8.3)[73] and the ReactomePA(v1.44)[75] R packages, respectively. GSEA
assessed the "Biological Pathways" ontology using a gene-specific score based on multiplying
the -log10(p value) * log2FC for each gene across Tha2P4M(0.5) versus Tha(0.5) astrocytes
(*clusterProfiler::gseGO(ont = 'BP',OrgDb = 'org.Hs.eg.db', eps=1e-300)*). The ten Biological

Pathways with strongest enrichment scores visualized using the enrichplot (v1.20.3) R
package (*enrichplot::gseaplot2(= 1:10, ES_geom = "line"*). REACTOME analysis was
performed on differentially expressed gene sets (p < 0.01) enriched in either Cluster 1 (n=2,137
genes) or Cluster 2 (n=5,887 genes) Astrocytes (p <0.01)
(ReactomePA::enrichPathway(pvalueCutoff = 0.01). To discern structure within complex
REACTOME results, hierarchical clustering was performed for the most enriched REACTOME
categories Cluster 1 (p < 0.000001; n = 32 categories) and Cluster 2 (p < 0.01; n = 84
categories) based on similarities of gene driving each categorical enrichment. These results
were visualized using the treeplot() function from the enrichplot (v1.20.3) R package.
REACTOME p values are computed from the hypergeometric distribution using a one-sided
Fisher's exact test and corrected for multiple comparisons using the Benjamini–
Hochberg method.
1611
Analysis of cell-cell interaction using CellPhoneDB
"CellPhoneDB"[64] (v5.0; implemented in Python v3.8.19) was used to infer "relevant"
differences in cell-cell interactions between Cluster 1 and pro-viral Cluster 2 astrocytes across
the scRNA-seq dataset. Specifically, "relevant" interactions were identified from the list of
differentially expressed genes comparing Cluster 1 and pro-viral Cluster 2 (p < 0.01; LFC > 1;
n= 2,186 enriched in Cluster 1; n= 877 enriched in Cluster 2), a subset of which encode ligands
(n=427) or receptors (n=341). "Relevant" interactions were those that were selectively enriched
in either astrocyte cluster following the CellPhoneDB gene shuffling approach across all cell-
type clusters (neurons, microglia, hNSC and mitotic) from full scRNA-seq dataset (p < 0.05).
The "relevant_interactions" CellPhoneDB output file was used for downstream analysis,
visualization and plotting in R including, the R package "circlize" (v0.4.16)[80].
1623
Identification of pro-viral Cluster 2-like Astrocytes in the NPH snRNA-seq dataset
To test for evidence of pro-viral Cluster 2-like astrocytes in the human brain without confounds
of post-mortem interval, we took advantage of a published snRNA-seq dataset profiled from
flash-frozen cortical tissue acquired during surgical treatment of Normal Pressure
Hydrocephalus[46]. We used RNA count data and associated patient-specific metadata from the
subset of snRNA-seq profiles belonging to astrocytes (n= 82,634 profiles;
https://zenodo.org/records/8319719). The RNA count data were cell-normalized and gene-
centered using the standard Seurat workflow (equivalent to the processing performed on the
Tha scRNA-seq dataset). To identify potential Cluster 2-like astrocytes from these NPH data,
we generated an aggregate expression score based on the n=196 genes observed in the NPH
data and enriched in Cluster 2 (p <0.01 and 2 > log2 fold-change). To critically evaluate the
biological significance of these aggregate expression scores, we generated 1,000 expression-
matched sets of 196 genes. Expression-matching was performed by rank-ordering the NPH
genes by expression level; dividing these expression-ranked genes into ten bins from low to
high expression; and randomly sampling (without replacement) each bin by the number of
instances of each of the 196 Cluster 2 enriched genes. To facilitate comparison of the real and
permuted aggregate gene score distributions, each of 82,634 scores were z-scored by gene
list and z-score distributions were then analyzed (**Figure 5H**). A z-score threshold of 4.5
standard deviations was used to identify n=38 Cluster 2-like NPH astrocytes contributed by
n=21 of 52 total patients (n=1 to 4 Cluster 2-like NPH astrocytes in each of those 21 patients;
z-score range: 4.5 – 12.5). The cut-off of 4.5 standard deviations corresponds to a p-value of
< 4.7E-7 based on the permuted data. To validate these 38 astrocyte RNA profiles resembled
those of Cluster 2, we tested whether gene counts associated with the 196 "discovery" gene

set and an independent "validation" gene set of RNAs enriched in Cluster 2 (p <0.01 and 1-2
log2 fold-change; n=521 genes) were enriched in the 38 Cluster 2-like astrocytes versus all
other NPH astrocyte RNA profiles (n=82,596). The discovery and validation gene counts were
2.8 and 1.2 enriched respectively in the 38 Cluster 2-like NPH astrocytes and highly significant
(chi-square test of expected versus observed UMIs; p < 1E-16).

1652

Comparing "reactive" astrocyte gene signatures from other datasets to pro-viral Cluster
2 astrocytes
To assess the similarity of previously reported rodent and human reactive astrocyte gene
expression signatures to those observed in pro-viral Cluster 2 astrocytes, we re-analyzed data
from *ex vivo* mouse astrocytes stimulated with lipopolysaccharides (Hasel et al; scRNA-seq
data)[48] or cultured rat and human astrocytes stimulated with TNF, IL1α, C1Q, and IFNβ, a
cocktail that induces an interferon-responsive reactive state (Prakash et al; RNA and proteomic
profiling)[47]. Specifically, for Hasel et al, gene enrichment data from the ten scRNA-seq-defined
astrocyte clusters were downloaded (Supplementary Table 5). Analysis focused on those
genes enriched in cluster 8 (n=70 genes), an astrocyte sub-population described by Hasel et
al as "interferon reactive"[48]. For Prakash et al, RNA and protein enrichments associated with
rat and human interferon-responsive state were downloaded (Supplementary Tables 3 and 5).
Analysis focused on the n=67 rat genes with concordant, statistically-significant enrichments
in both RNA and protein; for human astrocytes, analysis focused on the n=8 genes enriched
via proteomic analysis (RNA expression data was not acquired). The genes from these three
lists were visualized on volcano plots describing Cluster 1 versus pro-viral Cluster 2
differentially expressed genes. In all three cases, RNAs from the published gene set showed
no obvious enrichments for those genes differentially expressed in Cluster 1 or pro-viral Cluster
2 and thus no statistical test was performed.

1672

1673 **Analysis of single-cell RNA sequencing data**
1674 Statistical testing and plot generation was performed in R (v4.3.0; R packages are provided in
1675 the Key Resources table). All p-values are reported as adjusted for multiple-hypothesis testing
1676 unless otherwise stated. Test-specific information is included the relevant STAR Methods
1677 sections.

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