Stress-Responsive Transcriptomic Signatures in Human iPSC-Derived Microglia

Reveal Links to Alzheimer's Disease Risk Genes

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Keywords: iPSC-derived Microglia; Cellular Stress Responses; Alzheimer's Disease; Single-Cell

RNA Sequencing; CRISPR Interference

Abstract

Cellular stress responses are essential for maintaining homeostasis in the face of environmental or internal challenges. In the central nervous system, microglia serve as key stress sensors and immune responders, shaping neuroinflammatory processes and disease progression. However, the molecular programs engaged by distinct stressors and their impact on microglial viability remain incompletely understood.

In this study, we used human induced pluripotent stem cell-derived microglia-like cells to investigate stress responses to amyloid beta (Aβ), a chronic Alzheimer's disease–related stressor, and lipopolysaccharide (LPS), a classical acute inflammatory stimulus. Using single-cell RNA sequencing, we mapped the transcriptional programs activated by each condition and benchmarked these states against reference microglial datasets from mouse and human brains. In parallel, we performed a pooled CRISPR interference screen targeting Alzheimer's disease-associated microglial genes to identify genetic determinants of microglial survival.

We found that Aβ and LPS elicit partially overlapping but distinct transcriptional responses. Aβ induced more focused and disease-associated gene expression changes, while LPS triggered broad inflammatory activation and stronger cell death signatures. A subset of genes activated by stress overlapped with Alzheimer's disease risk genes and with hits from the survival screen, suggesting that disease-associated microglial genes may contribute to stress adaptation and cellular fitness.

These results demonstrate that iPSC-derived microglia-like cells can recapitulate in vivo–like stress-responsive states and offer a tractable platform to investigate genetic and environmental influences on microglial behavior. Together, our findings reveal transcriptional programs that link stress sensing, survival regulation, and Alzheimer's disease–associated gene networks, providing a foundation for future efforts to enhance microglial resilience in neurodegenerative disease contexts.

Introduction

Stress responses are fundamental cellular programs that maintain homeostasis in the face of internal or external challenges. In the central nervous system, microglia—the brain's resident immune cells—play a key role as stress sensors and responders (1,2). They integrate a wide range of environmental cues, including pathogen exposure, injury, and neurodegenerative insults(3). Disruption of microglial homeostasis by persistent stressors is increasingly recognized as a contributor to disease progression in neurodegenerative conditions such as Alzheimer's disease (AD)(4–7)

Among the stressors implicated in AD, the amyloid-β (Aβ) peptide represents a chronic, disease-relevant signal that may trigger innate immune responses and engage microglia in maladaptive ways. In contrast, lipopolysaccharide (LPS) is a potent exogenous inflammatory stimulus that models acute innate immune activation and systemic inflammation. While both Aβ and LPS are widely used to interrogate microglial responses, the extent to which they elicit shared or distinct molecular, phenotypic, and survival programs in human microglia remains incompletely defined.

To address this, we employed a multi-modal approach using human induced pluripotent stem cell-derived microglia-like cells (iMGLs) exposed to either Aβ or LPS. We performed single-cell RNA sequencing to characterize transcriptional responses and benchmarked iMGL states against human and mouse brain microglia. We further assessed morphological and functional changes associated with stress exposure and leveraged a pooled CRISPR interference (CRISPRi) screen targeting 168 AD-associated genes to identify regulators of microglial survival during differentiation.

Integrating these data, we found that Aβ and LPS induce partially overlapping but distinct stress response programs, with Aβ eliciting a more specific transcriptional signature and LPS driving a broader inflammatory phenotype. Importantly, we identified subsets of stress-responsive genes that overlap with AD risk genes and with survival regulators identified by our CRISPRi screen, providing

mechanistic insight into how microglia respond to distinct stressors. These findings underscore the

utility of iPSC-derived microglia as a disease-relevant model for studying microglial stress response

and reveal new candidate pathways for promoting microglial resilience in neurodegenerative disease

contexts.

Methods

Maintenance of iPSCs

All stem cell work was performed in compliance with the Rush University Medical Center IBC

committee. Cells were incubated at 37 °C, 5% CO2 under normoxic conditions during all experiments

and stimulations unless otherwise specified. Two iPSC lines (BR9 and BR28) were previously

generated from white blood cells collected from participants in the Rush Memory and Aging Project

(MAP) by the New York Stem Cell Foundation and banked in house (8,9), The dCas9-KRAB iPSC

iPSC line was developed at the Allen Institute for Cell Science (allencell.org/cell-catalog) and

available through the Coriell Institute for Medical Research (AICS-0090-391). This Allen Cell line was

derived from the WTC parental line released by the Conklin Laboratory at the J. David Gladstone

Institute. iPSCs were maintained on hESC-qualified Matrigel (Fisher, 8774552) coated 10cm dishes

in mTESR Plus (StemCell Technologies, 5825) and passaged every 3-4 days with ReLeSR (StemCell

Technologies, 5872) according to the manufacturer's protocol.

Generation of iPSC-derived microglia like cells (iMGLs)

iMGLs were generated according to previously published protocols(10,11) with the following minor

adjustments. iPSCs were seeded in hESC-qualified Matrigel-coated plates in mTESR Plus

supplemented with Y-27632 ROCK Inhibitor (RI,10mM; Stem Cell Technologies, 72304) and cultured

for 24-48 hours. On d0, colonies were switched to iPSC-derived hematopoietic progenitor (iHPC)

basal media supplemented with FGF2, BMP4, Activin-A, and LiCl. On d2, cultures were fed with iHPC

basal media supplemented with FGF2 and VEGF. On d4, cultures were fed with iHPC basal media

supplemented with FGF2, VEGF, TPO, SCF, IL-6, and IL-3. Cultures were given a half media change

every two days until d12. On d12, iHPCs were collected, washed, and resuspended in iMGL basal

media supplemented with M-CSF, IL-34, and TGFβ-1. Without removing the conditioned media, cells

were fed with complete iMGL differentiation media every two days until d30 and expanded as

needed. From d30 – d40, cells were fed with iMGL basal media supplemented with M-CSF, IL-34,

TGFβ-1, plus maturation factors CD200 and CX3CL1. Media formulations and concentrations can be

found in Table S1.

Aβ preparation and labeling

Amyloid-beta ($Aβ_{1-42}$) was reconstituted and aggregated according to Labeling Amyloid Beta with

pHrodo Red protocol from Fujifilm Cellular Dynamics Inc. All reagents required to reconstitute Aβ

were provided in the aggregation kit (rPeptide, A-1170-2). Briefly, lyophilized Aβ was reconstituted in

250 uL 10 mM NaOH and transferred to a 1.5 mL microcentrifuge tube. 250 uL of HPLC water was

added, followed by 56 uL 10x TBS (pH 7.4). The reconstituted AB was allowed to aggregate in an

incubator overnight under normoxic conditions. After overnight incubation, the aggregates were

collected by centrifugation at 16,000 x g for 1 min at room temperature. Supernatant was removed

and aggregates were washed with 200 μL fresh 0.1 M NaHCO3 (Sigma, 144-55-8) in water. 1 mg of

pHrodo Red, Succinimidyl Ester (ThermoFisher, P36600) was reconstituted in dimethylsulfoxide

(DMSO; Sigma, D2650) to a final concentration of 10 mM/mL immediately before use. pHrodo

labeling dye was added to supernatant-free AB aggregates and mixed well. The reaction was

incubated in the dark at room temperature for 1 h. The reaction tube was centrifuged as described

and supernatant removed. To remove excess dye, 1 mL of cold methanol was added to the

aggregates and vortexed on high for 10 s. The reaction tube was centrifuged again, and the

supernatant removed. Aggregates were washed with 1 mL of Hank's Balanced Salt Solution (HBSS;

ThermoFisher, 14175095), vortexed on high for 10 seconds, and centrifuged before removing the

supernatant. The aggregates were washed an additional 3 times with HBSS as described. Finally, the

aggregates were resuspended in 200 uL HBSS, sonicated for 10 minutes, and stored at -20 C in

individual aliquots.

Aβ phagocytosis assay

iMGLs were collected between d40 – d42 of the differentiation and counted. iMGLs were then re-

plated in a minimum of 2 mL of conditioned maturation media on Matrigel hESC-qualified coated 6-

well plates and allowed to incubate overnight. pHrodo-labelled Aβ was thawed to room temperature

and resuspended by vortexing. Aβ was added at a dilution of 1:200 and incubated for 2 h. Plates

were then incubated on ice for 5 – 10 min to promote cell detachment of adherent cells. Cells were

collected and used for downstream applications.

LPS stimulation

iMGLs were collected between d38 – d39 of the differentiation and counted. iMGLs were then re-

plated in a minimum of 2 mL of conditioned maturation media on hESC-qualified Matrigel coated 6-

well plates and allowed to incubate overnight. iMGLs were treated with LPS (1 ug/mL; Thermo, 00-

4976-93) for 24 h. At the end of the 24 h incubation, plates were incubated on ice for 5 – 10 min to

promote cell detachment of adherent cells. iMGLs were collected and used for downstream

applications.

Flow cytometry

Extracellular protein staining: After stimulation, iMGL were collected for extracellular flow cytometry

(FC) as described above. The buffer for fluorescence-activated cell sorting (FACS) was prepared by

diluting 30% BSA (Fisher Scientific, 50-203-6474) in DPBS to a final 2% solution. The buffer was

filtered through a 0.22 um filter system (Fisher, 09-761-107) and kept on ice. Cells were collected into

136 5 mL round-bottom tubes (Fisher, 14-959-1A) and the wells were washed once with DPBS and once

137 with 2% FACS buffer to collect any remaining cells. Cells were pelleted by centrifugation at 300 x g

138 for 5 min at 4 °C and supernatant was removed. Pelleted cells were washed twice with FACS buffer.

139 Supernatant was removed and the pelleted cells were resuspend in 100-200 uL FACS buffer. Cells

140 were then simultaneously treated with Human TruStain FcX according to the manufacturer's

141 instructions (Biologend; 422302) and stained with a live/dead dye (1:2500 in DPBS) on ice for 15 min.

142 Fluorophore-conjugated antibodies or their isotype controls were added to the cells and incubated in

143 the dark on ice for 30 min. Cells were washed twice with FACS buffer and centrifuged as described.

144 Stained cells were fixed with Fixation Buffer (Biolegend, 420801) according to the manufacturer's

145 instructions and washed twice with FACS buffer. Cells were either stained for intracellular (ICFC)

146 markers as described below or resuspended in 100-200 uL FACS buffer and immediately analyzed.

147 *Intracellular protein staining*: If applicable, iMGLs were stained for intracellular flow cytometry

148 (ICFC) after FC staining. Fixed cells were washed twice with 5 mL FACS buffer followed by

149 permeabilization with Intracellular Staining Permeabilization Wash Buffer (Biolegend, 421002)

150 according to the manufacturer's instructions. Cells were stained with conjugated antibodies or their

151 isotype controls for 30 min in the dark at room temperature and washed twice with FACS buffer. Cells

152 were resuspended in the 100-200uL FACS buffer and immediately analyzed. All FC and ICFC data

153 were collected using the Sony SH800 Cell Sorter and flow cytometry data was analyzed using FlowJo

154 (v10). Compensation metrics were set using unstained and single-color compensation controls and

155 gating was determined using Fluorescence Minus One (FMOs) controls. All live/dead dyes,

156 conjugated antibodies, isotypes and their dilutions are listed in Table S1.

157 **Immunostaining**

158 iMGLs were collected between d40 – d42 of the differentiation and replated overnight on Matrigel-

159 coated Ibidi μ-Slide 8 Well [high] chamber slides (Ibidi, 80806) at a density of 50,000 – 75,000 iMGLs

per chamber. iMGLs were stimulated with LPS for 24 h or AB for 2 h and fixed with 4%

paraformaldehyde (PFA; Electron Microscopy Sciences, 15714-S) for 15 min at room temperature.

After washing three times with DPBS, iMGLs were permeabilized and blocked using 5% normal

donkey serum (Jackson Immuno Research, 017-000-121) with 0.02% Triton X-100 (Fisher,

BP151100) in PBS for 1 h at room temperature. iMGLs were then incubated with primary antibodies

diluted in blocking buffer at room temperature for 2 h. iMGLs were then washed three times with

DPBS and incubated with secondary antibodies diluted in a blocking buffer at room temperature for

45 min in the dark. If applicable, in staining panels containing two primary antibodies produced in

mouse or rabbit, the second primary antibody was conjugated to a 647 secondary using the Flexible

CoraLite Plus 647 Antibody Labeling Kit for Rabbit IgG (Proteintech, KFA003), Mouse IgG1

(Proteintech, KFA023), or Mouse IgG2a (Proteintech, KFA043) according to the manufacturer's

protocol. Following the last washing step after secondary incubation, iMGLs were stained with 674-

conjugated primaries for 2 h at room temperature in the dark. Cells were washed three times with

DPBS and then stained with Hoechst 33342 diluted 1:2000 in PBS before use (ThermoFisher; 62249)

for 3 min at room temperature in the dark. Cells were washed one final time and imaged using a

Nikon AX/AX R with NSPARC confocal microscope using Nikon NIS-Elements Imaging Software.

Primary antibodies used for immunofluorescence and dilutions are listed in Table S1. All secondary

antibodies were all used at a 1:1000 dilution in the blocking buffer and are listed in Table S1.

Intracellular stress assays

iMGLs were stimulated with LPS for 24 h or AB for 2 h using concentrations described above.

Staining for MitoSOX red (Thermo, M36008) and LipidTOX red (Thermo, H34476) was completed

according to the manufacturer's instructions. iMGLs were then fixed with 4% PFA for 15 min at room

temperature. iMGLs were washed three times with DPBS and then stained with Hoechst 33342

(ThermoFisher; 62249) diluted 1:2000 in PBS before use for 3 min at room temperature in the dark.

iMGLs were washed one final time and imaged using a Nikon AX/AX R with NSPARC confocal

microscope using Nikon NIS-Elements Imaging Software.

Mesoscale multiplex biomarker assay

iMGLs were replated in 2 mL of conditioned maturation media overnight prior to stimulation with LPS

for 24 h or Aβ for 2 h as described above. To assess multiple biomarkers, conditioned media from

each treatment condition was prepared and analyzed using the V-plex Human Biomarker 39-Plex Kit

(Mesoscale Discovery; K15209D-1) according to the manufacturer's protocol.

Sample preparation, library construction, single-cell RNA sequencing, and data processing

After stimulation with Aβ or LPS, single-cell suspensions were processed into sequencing-ready

libraries using the 10x Genomics Chromium Single Cell 3′ Platform. Libraries were sequenced on a

NovaSeq 6000 (Illumina) at a depth of 50k reads/cell. Following sequencing and FASTQ generation,

raw count matrices were produced using CellRanger v6.0.1. RNAs were mapped to the GRCh38

reference genome via STAR. Transcripts were assigned to individual cells and duplicate reads

removed. The resulting count matrices were processed using the Seurat (v5.3.0) package in R. We

applied quality controls metrics to the single-cell RNA sequencing results to remove cells with poor

transcriptomic quality (nCount_RNA >7500 & < 70,000; nFeatures_RNA >2500 & < 8,000; percent.mt

<10%; percent.rb to <30%). Seurat SCTransform function was used to normalize and scale the UMI

counts for each individual library based on regularized negative binomial regression. Principal

component analysis (PCA) was performed, followed by the FindNeighbors (dims = 1:10) and

FindClusters (res = 0.75) functions to identify clusters based on a shared nearest neighbor (SNN)

clustering algorithm. Finally, we performed UMAP dimension reduction (dims = 1:15). The data was

inspected for cell doublets using DoubletFinder (v2.0.4) and those containing mixed cluster

signatures were removed. Cell clusters were reprocessed using the functions described above prior

to in-depth analysis.

208   Marker gene identification and cluster annotation

We identified the top 200 differentially expressed genes (DEGs) for each of our 4 main clusters (padj

≤ 0.05) using the FindAllMarkers function in Seurat (logfc.threshold = 1, min.cells.feature = 0.15, only

positive). We annotated each cluster based on the top 10 DEGs, sorted by descending order of log2

fold change. The Gene Ontology (GO) network for our 4 clusters was constructed using ClueGO

(v2.5.10) plugin in Cytoscape (v3.10.3). The analysis was performed using the

GO_BiologicalProcess-EBI-UniProt-GOA-ACAP-ARAP database (release 25.05.2022, 00:00). A two-

sided enrichment/depletion test was used to determine ontology enrichment with Bonferroni stepdown

correction ($p ≤ 0.01$) Parameters for network constructions were as follows: GO levels 3 – 8 with GO

term fusion to reduce redundant terms; Kappa score = 0.4; minimum genes included in term = 3;

minimum percentage of genes included in term = 4%. We also identified unique DEGs for our 13

subclsuters (padj ≤ 0.05) using the FindAllMarkers function in Seurat (logfc.threshold = 1,

min.cells.feature = 0.05).

221   Gene ontology network analysis

We compared Aβ and LPS-specific genes against the Unstimulated cluster using FindMarkers

(logfc.threshold = 0.1, min.cells.feature = 0.05) to identify treatment-specific DEGs. Genes with an

adjusted p value ≤ 0.05 were retained, and up- (avg_log2FC > 1) and down-regulated genes

(avg_log2FC < -1) were defined. ggplot2 was used to generate volcano plots. We identified enriched

GO networks (Biological Processes, Molecular Function, and Cellular Component using enrichGO

(v4.14.3) with the human reference annotation database (Org.Hs.eg.db).. Enrichment was performed

(maxGSSize = 500), and results were filtered for pathwayswith pval < 0.05. The top 20enriched and

underrepresented pathways were used to generate plots and scale set by Fold Enrichment.

Prioritization of Alzheimer's Disease-associated genes expressed in microglia

The prioritization of candidate genes was conducted using multiple criteria. These included the

selection of representative genes from each AD GWAS loci, as reported in the EADB GWAS, along

with genes with colocalization posterior probabilities (PP4) higher than 0.7, calculated using coloc,

against multiple eQTL/sQTL, including bulk RNA-seq across various brain tissues (MSBB, ROSMAP,

and Mayo Clinic), LCL RNA-seq, and sorted microglia RNA-seq[12,13]. Genes reported in another

AD GWAS, with prioritization model probability higher than 0.5, and coloc results higher than 0.7

(across multiple eQTL datasets)[14]. Genes identified in the colocalization results reported in the

MiGA study[15], which included four AD GWAS datasets[16–19] , along with transcriptome data

from in-vivo microglia eQTL[20] and ex-vivo microglia eQLT/sQTL from 4 brain regions (plus meta-

analysis). And finally, genes reported by the microglia-specific eQTL and caQTL study[21] that

applied multiple prioritization methods, including coloc, moloc[22], ABC model [23], and overlap with

microglia ATAC-seq peaks.

Comparison to mouse and human microglia sets

We applied SEURAT FindAllMarkers (logfc_threshold = -Inf, min.pct = 0.15) to contrast the

expression of cells in one iMGL subcluster vs. cells in remaining iMGL subclusters. This produced a

log2FC value and a p-value for each gene of MGLs. We then multiplied sign(log2FC) to -log10(p) for

each gene of each iMGL subcluster and applied GSEA with the 7 sets of rodent MG state markers

(2,24–30)and 12 sets of human MG state markers[31] as gene sets. Plotted is the sign (NES)*-

log10(p) from GSEA.

Single-guide RNA (sgRNA) design, cloning and lentiviral library generation

For each identified gene, three sgRNA targets were chosen between -50 and +300bp of the

transcriptional start site. Targets were chosen from top hits identified by CRISPick (Broad Institute)

and E-crisp (Boutros lab). In addition to 165 genes prioritized for analysis, sgRNAs targeting control

genes, CSF1R, CSF2RB, CDK8, and TGFBR2, previously identified as regulators of survival, as well

as non-targeting controls were included. The vector pCRISPRia-v2 was a gift from Jonathan

Weissman (Addgene 84832)(32). This was modified to express eGFP amplified from pXR001, a gift

from Patrick Hsu (Addgene 109049), in place of BFP by restriction digestion at the EcoRI and CsiI

sites and T4 ligation (NEB). Guide RNA sequences were appended with appropriate 5' and 3'

sequences, and a pool of oligonucleotides was synthesized (Twist Bioscience). The vector was

digested with BstXI and BlpI, and oligonucleotides were amplified by PCR and subsequently cloned

by Gibson assembly as previously described to generate an sgRNA library (33). Plasmids were

amplified and prepared by MaxiPrep for lentiviral generation as previously described(34). Lentivirus

was prepared by transfecting 293T cells in T75 flasks with the plasmid pool as well as psPAX2 and

pVSVg (Gifts from the Trono and Reya labs, Addgene 12260 and 14888, respectively) helper

plasmids using FuGene HD (Fisher, NC2132803).

CRISPRi survival screen

Human iPSCs constitutively expressing the CRISPRi construct dCas9-TagBFP-KRAB were

dissociated in Accutase and seeded into 6 well tissue culture-treated plates coated with Matrigel.

Cells were transduced with lentivirus at low MOI to generate cultures with 30% positive eGFP signal

and an average of at least 1000x sgRNA coverage. Cells were cultured overnight in the presence of

10µM Y-27632 and mTeSR Plus. Media was changed the following day. Cells were selected with

2µg/ml puromycin the next day for a duration of four days and allowed to recover without selection.

Cells were then seeded as small colonies in 15cm dishes for HPC differentiation and subsequent

iMGL differentiation as described above. Cells were collected and pelleted at days 0, 24, 36 and 45 of

differentiation. Pellets were subjected to gDNA extraction (Zymo).

Sequencing and analysis of sgRNA distribution

Genomic DNA was amplified with barcoded NGS primers as modified from (34) to include unique

indices on both forward and reverse primers as well as a 10nt variable region just upstream of the 5'

vector binding sequence. PCR reactions from each sample were pooled, and DNA was purified with

dual size selection with SPRI beads and analyzed on Fragment Analyzer. Sequencing libraries were

diluted and loaded onto Illumina iSeq 100. For CRISPR screening analysis, BCL files were converted

to FASTQ format. Raw reads were aligned to the reference with seqtk. Counts were then converted

to phenotype scores with MAGeCK-iNC pipeline modified so that two of the top three sgRNA

sequences per gene were analyzed(32). With this pipeline, comparisons between adjacent time

points day 12, day 24, day 36 and day 45 were made to assess the effect of gene knockdown at

different stages of iMGL differentiation and maturation. Heatmap displaying genes with significant

changes in abundance in at least one of these three intervals was made with ggplot2 in R. Epsilon

reflects abundance phenotype such that positive numbers reflect a reduction in corresponding gene-

targeting cell enrichment.

Results

Benchmarking iMGL differentiation of dCas9-KRAB iPSC line against control ROSMAP iPSC lines

293 To ensure that the dCas9-KRAB iPSC line is suitable for downstream experiments, we first

294 benchmarked its microglial differentiation potential by comparing it to two in-house ROSMAP control

295 iPSC lines, BR09 and BR28 (8). All three iPSC lines were subjected to microglial differentiation using

296 published protocols (10,11), and quality control was performed at day 12 and day 40. Flow cytometry

analysis demonstrated comparable expression of CD43 and CD45 at both time points across all three lines (sFig.1A), indicating similar differentiation trajectories.

We then further characterized the dCas9-KRAB line—the primary experimental line for this study— using immunocytochemistry. The resulting iMGLs expressed key microglial markers, including PU.1, IBA1, TREM2, P2RY2 and TREM119 (sFig.1B). qRT-PCR analysis validated the temporal expression of microglia-relevant genes such as CD33, APOE, and TREM2 during differentiation (sFig.1C). Functionally, these iMGLs exhibited Aβ phagocytosis upon exposure to pHrodo Red-labeled Aβ, which was further enhanced upon LPS stimulation (sFig. 1D).

Together, these results demonstrate that the dCas9-KRAB iPSC line differentiates into functional iMGLs with phenotypic and functional characteristics comparable to the control lines. This supports its use for subsequent stimulation experiments, single-cell RNA sequencing, and the CRISPR-based genetic screen.

Aβ and LPS induce distinct morphological and marker expression changes in iMGLs

To evaluate iMGL activation states in response to pathological stimuli, we treated cells with Aβ or LPS and assessed morphological and marker expression changes using phase-contrast imaging and immunostaining. Both Aβ and LPS treatments resulted in pronounced morphological changes characterized by increased cellular processes and a transition to a multipolar morphology (Fig.1B). These changes were particularly prominent under LPS treatment, which produced hypertrophic cells with cytoplasmic granularity typical of classical microglial activation (Fig. 1B).

Immunostaining for IBA1 and CD45 confirmed activation-induced morphological changes. Notably, in unstimulated iMGs, CD45 expression appeared localized to a small perinuclear cluster. Upon Aβ or LPS stimulation, CD45 redistributed along the cell membrane, consistent with a shift in activation status. We further quantified these morphological changes by measuring the proportion of cells

320 bearing processes longer than 3μm. Both Aβ- and LPS-treated conditions showed a significant

321 increase in the number of such cells compared to control, with the LPS condition exhibiting the

322 strongest effect (Fig. 1B).

323 **Single-cell RNA sequencing reveals stimulus-related iMGLs states**

324 To investigate how distinct stimuli shape the transcriptional landscape of human iMGLs, we

325 performed single-cell RNA sequencing (scRNA-seq) using the 10x Genomics Chromium platform on

326 control, Aβ-treated, and LPS-treated iMGLs. After quality control and filtering (sFig.2A), unsupervised

327 clustering revealed four major transcriptional clusters (Table S2), largely segregated by treatment

328 condition, yet all expressing core microglial identity genes such as *IRF1*, *PTPRC*, and *SPI1*,

329 confirming their microglial lineage (Fig. 1E, sFig2. B-C,).

330 Clusters 0 and 1 were predominantly composed of cells from the control and Aβ-treated conditions,

331 respectively. Cluster 0 expressed canonical microglial markers such as *P2RY12*, *FFAR4*, and

332 *CEBPA*, which are known markers of quiescent microglia and are typically downregulated under

333 neuroinflammatory stress. Cluster 1, which was enriched in Aβ-treated cells, showed elevated

334 expression of genes involved in lipid metabolism and tissue remodeling (*SCD4*, *CLDN1*, *PDGFB*), as

335 well as transcriptional regulators linked to immune adaptation and neuroinflammation, such as

336 *NR4A1*, *NR4A3*, and *IL23A (35–38)*. Cluster 2 was dominated by LPS-treated cells and characterized

337 by high expression of classical inflammatory and interferon-stimulated genes, including *CCL7*,

338 *MMP13*, and *MARCO*, suggesting a strong immune-activated state. Cluster 3 was composed of

339 proliferative iMGLs from both unstimulated and Aβconditions, marked by genes involved in cell cycle

340 and proliferation including *E2F8*, *TOP2A*, and *UBE2C*.

341 Gene Ontology (GO) enrichment analysis of the top 200 genes per cluster further supported the

342 functional divergence between clusters (Table S2). Cluster 1 (Aβ-enriched) showed enrichment for

pathways related to antigen processing, cell adhesion, and T-cell activation and differentiation.

Cluster 2 (LPS-enriched) was significantly enriched for immune response, chemotaxis, cytokine

production, and defense response pathways. Cluster 3 was strongly associated with cell cycle

transition and DNA repair processes. Although Cluster 0, which represents primarily unstimulated

iMGLs, does not dominate any single GO category, it nonetheless shows modest yet consistent

contributions across multiple biological processes, including defense response, cell proliferation, and

cellular activation. This pattern suggests that in the absence of external stimulation, iMGLs retain a

basal level of transcriptional activity related to homeostatic surveillance and immune readiness,

consistent with their physiological role as sentinels of the brain environment

These data demonstrate that Aβ and LPS elicit distinct transcriptional programs in iMGLs, with

partially overlapping yet stimulus-enriched activation states. This transcriptional diversity reflects the

capacity of iMGLs to mount tailored responses to different pathological cues and provides a

foundation for downstream integration with genetic perturbation data.

Mapping iMGL states to mouse and human microglial states

To contextualize our in vitro model with known in vivo iMGL diversity, we subclustered the four major

IMGL transcriptional clusters into 13 subclusters (Fig. 2A–B; Table S3) and systematically compared

them to reference microglial states from both mouse models (2,24–30). Among the reported mouse

microglia states, Aβ-associated subclusters were enriched for disease-associated microglia (DAM)

(10), neurodegeneration-associated microglia (MGnD) (30), and white matter-associated microglia

(WAM)(28). In contrast, LPS-associated subclusters showed strong alignment with interferon-

responsive microglia (RM) (25) and proliferative-region-associated microglia (PAM)(29), consistent

with pathways related to innate immune activation and cellular proliferation.

Mapping to published single-nucleus RNA-seq datasets from the human postmortem brain (31)

further supported stimulus-specific transcriptional signatures. Unstimulated clusters were primarily

aligned with ribosome biogenesis (MG3) and homeostatic microglia (MG0). Aβ-treated clusters

mapped to ribosome biogenesis (MG3), lipid processing (MG4), phagocytic (MG5), stress signature

(MG6), glycolytic (MG7), and inflammatory III (MG10) microglia. LPS clusters were mapped to

inflammatory I (MG2), glycolytic (MG7), inflammatory III (MG10), and cycling (MG12) microglia.

Clusters 12 and 13, which were derived from the major proliferative cluster (Cluster 3), also aligned

with cycling (MG12) microglia.

Together, these cross-species and cross-platform comparisons highlight that iMGLs are capable of

recapitulating disease-relevant microglial subtypes and preserving transcriptional heterogeneity in

response to distinct pathological stimuli.

To gain insight into the functional impact of Aβ and LPS exposure, we performed module score

analysis using curated gene sets from the Molecular Signatures Database (MSigDB)(39–42) related

to inflammation, stress response, and cell death (Table S3). Both Aβ and LPS increased cell death

(apoptosis, necroptosis, ferroptosis, pyroptosis), stress response (oxidative stress, integrated stress

response) and inflammatory phenotypes (IL6/IL10/IL27 signaling, INFɣ signaling and TGFβ signaling)

across multiple subclusters; however, the LPS condition showed a more pronounced increase in

those pathways. Interestingly, these cell stress, cell death and inflammatory pathways co-localized in

Aβ and LPS specific subclusters, suggesting a tightly coupled relationship between inflammatory

activation and cytotoxicity. The unstimulated and proliferative subclusters also demonstrated minimal

stress, inflammation, and cell death–related enrichment. These findings raise key mechanistic

questions about how microglia balance activation, stress adaptation, and survival in response to

pathologic insults such as Aβ and LPS.

388 **Differential gene expression analysis reveals shared and divergent molecular programs in Aβ-**

389 **and LPS-stimulated iMGLs**

To delineate the transcriptional responses of iMGLs to pathological stimuli, we performed differential

gene expression analysis comparing Aβ- and LPS-treated cells to unstimulated controls. Both

treatments induced substantial shifts in microglial identity, highlighted by the downregulation of key

homeostatic markers. Notably, *P2RY12* and *TREM2*, genes critical for maintaining homeostatic and

DAM-associated functions(43,44), were markedly suppressed in Aβ-treated cells and nearly

abolished under LPS stimulation (Fig. 3A). These findings indicate a profound reprogramming of

microglial state, with LPS eliciting a more extensive departure from the homeostatic transcriptome.

We next identified genes either commonly dysregulated across both stimuli or uniquely responsive to

Aβ or LPS (Fig. 3A; Table S4). GO term enrichment of shared upregulated genes revealed activation

of ferroptosis, lipid storage and transport, and inflammatory signaling pathways, including Toll-like

receptor (TLR) and NOD-like receptor (NLR) pathways—highlighting a convergent innate immune

and metabolic stress response. Conversely, shared downregulated genes were enriched for G-

protein-coupled receptor (GPCR) signaling, suggesting broad suppression of membrane signaling

and proteostasis (Fig. 3B; Table S4).

Aβ-specific transcriptional changes included upregulation of MAPK signaling, apoptotic processes,

interferon-γ and TNF response, cyclic AMP activity, and Golgi lumen acidification. These features

suggest a regulated stress response that may involve inflammatory signaling and enhanced

intracellular trafficking (Fig. 3C; Table S4). Interestingly, Aβ stimulation also led to upregulation of

pathways related to phagocytosis, suggesting engagement of clearance mechanisms potentially

relevant to Aβ processing (Fig. 3C; Table S4). By contrast, LPS-specific responses were

characterized by robust induction of cytokine signaling (e.g., IL-27, IL-15), detoxification, metal ion

sequestration, and apoptosis-related pathways (Fig. 3D, Table S4). Downregulated LPS-specific

pathways included MHC class II-mediated antigen presentation and T-cell activation (Fig. 3D, Table

S4), indicative of an innate-dominant inflammatory profile with suppressed adaptive immune features.

We further investigated the expression of key genes associated with distinct forms of programmed

cell death (PCD). Aβ or/and LPS stimulation induced upregulation of *CASP1, CASP4*, and *CASP5*,

consistent with activation of pyroptosis. However, the magnitude of upregulation varied:

CASP5 showed minimal expression in unstimulated and Aβ-treated cells but was strongly induced in

the LPS condition. Similarly, *CASP1* and *CASP4* were modestly upregulated in Aβ-treated iMGLs and

more robustly elevated under LPS stimulation (Figure 3E). These caspases are central to

inflammasome activation and cytokine processing, a hallmark of pyroptotic cell death(45–49) . We

also observed differential activation of apoptotic pathways. *CASP3* was mildly upregulated in both Aβ-

and LPS-treated cells but *CASP7* exhibited a pronounced increase exclusively in LPS-treated cells.

These executioner caspases mediate downstream apoptotic processes including DNA fragmentation

and membrane blebbing (50,51). Regarding ferroptosis, we detected significant upregulation of

ACSL4, *TFRC*, *FTH1*, and *PTGS2* in both Aβ- and LPS-treated conditions, but again with stronger

induction under LPS stimulation. These genes are involved in lipid metabolism and iron homeostasis,

which sensitize cells to ferroptosis(52–55). *GPX4*, a central negative regulator of ferroptosis that

detoxifies lipid hydroperoxides(56,57), was downregulated under both conditions, but the suppression

was more modest in the Aβ-treated cells. This expression pattern supports activation of ferroptotic

stress, particularly in the LPS condition. In addition, we observed increased expression of *RIPK1* and

MLKL, key mediators of necroptosis(58,59), in LPS-treated cells, with a mild elevation of *RIPK1* also

noted in Aβ-treated cells. Altogether, these findings suggest coordinated activation of multiple PCD

mechanisms, with LPS inducing a more potent and multifaceted response than Aβ.

Together, these findings demonstrate that Aβ and LPS induce overlapping but distinct molecular

programs in iMGLs. While both stimuli activate inflammatory and PCD pathways, Aβ elicits a more

controlled response involving MAPK signaling, vesicular trafficking, and phagocytosis, whereas LPS

drives widespread innate immune activation with suppression of adaptive immune signaling. This

divergence highlights the context-specific nature of microglial responses to different pathological

insults.

Cellular assays confirmed Aβ- and LPS-induced cellular stress and inflammatory responses

To validate the transcriptional phenotypes identified in our single-cell analysis, we performed a series

of cellular and molecular assays in iMGLs under unstimulated, Aβ-, and LPS-treated conditions.

Immunofluorescence staining for cleaved caspase-3, a marker of apoptosis, revealed increased

staining in both Aβ- and LPS-treated cells compared to controls, aligning with the upregulation of

apoptotic genes and gene modules. LPS treatment induced a more robust apoptotic response than

Aβ, which showed a modest, non-significant increase (Fig. 4A).

To assess oxidative stress, we used MitoSOX staining to detect mitochondrial superoxide production.

MitoSOX is a mitochondrial-targeted fluorogenic dye that selectively reacts with superoxide,

generating red fluorescence that serves as a readout of mitochondrial oxidative stress. While

unstimulated cells showed minimal signal, Aβ-treated cells exhibited diffuse cytoplasmic staining with

some perinuclear accumulation (Fig. 4A). By contrast, LPS-treated cells showed punctate signals

concentrated in the soma and processes (Fig. 4A). Both treatments led to an increased proportion of

MitoSOX$^+$ cells, which was more pronounced with LPS (Fig. 4A), indicating elevated mitochondrial

ROS production.

Similarly, we applied LipidTOX staining to assess lipid peroxidation. LipidTOX dyes detect neutral

lipids and are commonly used to monitor lipid droplet accumulation and oxidative lipid damage.

Elevated LipidTOX signal reflects increased lipid peroxidation, a hallmark of ferroptosis(60). Indeed,

LipidTOX staining revealed enhanced lipid peroxidation in both Aβ- and LPS-treated iMGLs (Fig. 4A),

consistent with transcriptional signatures indicative of ferroptosis activation.

We next examined lysosomal activation using CD68 immunostaining and flow cytometry. Both

treatments increased CD68 expression relative to controls, suggesting enhanced lysosomal stress.

Flow cytometry further confirmed this elevation and revealed differential expression patterns of

activation markers (Fig. 4A, 4B). Aβ-treated microglia upregulated TREM2, while LPS treatment

reduced its expression (Fig. 4B). CD38, in contrast, was specifically upregulated by LPS, with no

notable change in Aβ-treated cells (Fig. 4B), indicating stimulus-specific immune activation states.

Finally, multiplex cytokine profiling confirmed the distinct inflammatory responses triggered by each

condition. Aβ stimulation led to the selective secretion of chemokines such as CCL3 and CCL4, while

LPS induced a broader pro-inflammatory signature, including elevated levels of multiple cytokines

and chemokines (Fig. 4C; Table S5).

Together, these findings confirm that Aβ and LPS induce overlapping yet distinct stress and

inflammatory responses in iMGLs. Both stimuli activate oxidative, lysosomal, and immune pathways,

with LPS driving a more extensive cytotoxic and inflammatory program.

CRISPRi functional screening reveals partial overlap between AD-risk genes and microglial

stress response genes

To build on our finding that Aβ and LPS induce microglial PCD through multiple stress programs—

including apoptosis, pyroptosis, ferroptosis, and necroptosis —we sought to identify genetic

regulators of microglial survival under baseline differentiation conditions. We focused on 168

microglial genes implicated in Alzheimer's disease risk by GWAS and fine-mapping studies (16–19).

We first examined their expression across unstimulated, Aβ-, and LPS-treated iMGLs in our single-

cell dataset. A distinct pattern of transcriptional responses emerged, with 127 AD-associated genes

differentially expressed in a condition-specific manner (Fig. 5B). This suggested that a subset of

these genes might contribute to the microglial stress response and cell viability.

To functionally assess knockdown impact, we first targeted the AD risk gene CD33 using individual

lentiviral constructs. CD33 expression was significantly reduced at both the transcript and protein

levels, confirming effective targeting by two independent sgRNAs (Fig. 5C–E). We then proceeded to

clone all sgRNAs targeting the 168 genes into pooled lentiviral vectors (Table S6). These pooled

libraries were transduced into iPSCs prior to iMGLs differentiation, and sgRNA representation was

quantified at four key timepoints (D0, D12, D24, D36, and D45) via PCR amplification and next-

generation sequencing (Fig. 5A). Initial distribution analysis confirmed an appropriate sgRNA

distribution at the iPSC stage as described [32] (Fig. 5G). To reduce the confounding effects of

differentiation-associated gene expression changes, we compared sgRNA abundance between two

consecutive timepoints (D24 vs D12, d36 vs d24, and D45 vs d36). This strategy minimizes temporal

bias and enables more accurate identification of genes involved in iMGL survival. We identified 38

genes regulating iMGL survival (Fig. 5G; Table S6), 31 of which were also expressed in the scRNA-

seq dataset. These genes were classified into pro-survival, anti-survival, and dynamic

regulators based on temporal and directional effects (Fig. 5I-J).

To explore the relationship between transcriptional stress responses and survival, we compared

differentially expressed genes in Aβ- and LPS-treated iMGLs with the 31 candidate survival regulators

identified from our genetic screen. Among 127 genes differentially expressed under either treatment,

27 overlapped with survival-related genes, and 17 were shared across Aβ-responsive, LPS-

responsive, and survival-linked categories. (Fig. 5H, Table S6). Interestingly, LPS treatment led to a

general downregulation of both pro-survival and anti-survival genes, except for *TREM1*, which was

strongly upregulated and classified as anti-survival. By contrast, Aβ treatment induced moderate

upregulation of several pro-survival (*COX7C*, *CSF2RB*, *PLEKHA1*), anti-survival (*PHB, PICALM*) and

dynamic-expression (*FIBP, SPI1*) genes (Fig. 5I–J). These patterns align with the more pronounced

cytotoxicity seen in LPS-treated cells and suggest that Aβ may activate compensatory survival

programs.

his intersection supports the idea that a fraction of AD-associated microglial genes influence stress

response and survival, highlighting key candidates for future mechanistic studies aiming to connect

AD genetics to microglial viability under disease-relevant conditions.

Discussion

Our study reveals that human iPSC-derived microglia like cells (iMGLs) exhibit distinct and

overlapping transcriptional and functional responses to two key stressors—Aβ and LPS—which

represent Alzheimer's disease-associated and classical inflammatory insults, respectively. Both

treatments induce pronounced cellular stress, immune activation, and features of programmed cell

death (PCD), including apoptosis, pyroptosis, and ferroptosis. However, LPS treatment elicits a

broader pro-inflammatory and cytotoxic response, whereas Aβ triggers a more specific set of gene

programs. This distinction is supported by module score analysis using curated gene sets (Fig.s 2E),

differential gene expression and pathway analysis (Fig. 3) and cellular assays (Fig. 4).

Through a pooled CRISPRi screen targeting 168 AD-associated microglial genes, we identified 31

genes that regulate iMGL survival during differentiation. Notably, 27 of these 31 genes were also

differentially expressed in response to Aβ or LPS treatment, revealing a partial overlap between

stress-induced transcriptional changes and intrinsic pro-survival and anti-survival programs (Fig. 5).

These findings suggest that the transcriptional stress response may either promote adaptive survival

or drive degeneration depending on the context and specific genes engaged.

The overlap between stress-responsive and survival-regulating genes also aligns with the emerging

literature on microglial PCD as a critical regulatory mechanism in the CNS. Apoptosis, pyroptosis,

necroptosis and ferroptosis have all been observed in microglia under various pathological conditions,

including neurodegeneration and CNS injury (61,62) . Dysregulation of these pathways can result in

excessive inflammation and tissue damage, contributing to disease progression in a feedforward

manner (62–64). Our data reinforce this concept by demonstrating that microglial stress responses,

when unresolved, may trigger programmed cell death pathways that could exacerbate

neurodegeneration.

Importantly, our results build on prior studies using iMGLs as models of human disease. Notably,

Dolan et al. demonstrated that iMGLs recapitulate key transcriptional states of disease-associated

microglia (DAM) under stress conditions, including Aβ exposure (65). Our findings are consistent with

and extend this work by adding functional dimensions—specifically cell survival regulation—and

highlighting the utility of iMGLs for genetic perturbation studies. Compared to previous CRISPR

screens(32) that focused on druggable genes, our approach integrates disease-relevant gene

selection with developmental timing, offering new insights into microglial vulnerabilities and resilience

mechanisms.

Collectively, these data position iPSC-derived iMGLs as a powerful and tractable model to interrogate

human microglial states under disease-relevant stressors. They also point to new directions for

therapeutic discovery, particularly targeting stress-modulated survival pathways to enhance microglial

fitness and slow neurodegenerative progression.

Conclusion

This study provides a multifaceted view of how iMGLs respond to stressors relevant to AD and

inflammation. By integrating single-cell transcriptomics, cellular assays, and a pooled CRISPRi

survival screen, we show that Aβ and LPS induce both shared and distinct molecular responses,

including stress, immune and PCD pathways. These responses are functionally linked to a subset of

AD-associated microglial genes, some of which regulate microglial viability. Our findings underscore

the dual role of microglia as stress sensors and effectors of cell fate and demonstrate that adaptive

versus degenerative responses are driven by distinct transcriptional programs. This work not only

advances our understanding of microglial biology in neurodegeneration but also lays a foundation for

identifying and modulating gene pathways that promote microglial resilience. Future efforts should

aim to mechanistically dissect pro-survival versus pro-death modules and explore therapeutic

strategies that fine-tune microglial adaptation under stress.

Limitations

While our findings provide valuable insights into microglial stress responses and survival programs,

several limitations should be noted. First, the CRISPRi screen was performed under baseline

differentiation conditions without exposure to Aβ or LPS, limiting our ability to identify condition-

specific survival regulators. Future context-dependent screens could more precisely map genes

involved in stress-specific adaptation. Second, although iPSC-derived iMGLs recapitulate many

transcriptional and functional aspects of primary human microglia—including disease-associated

states—they do not fully mimic the CNS environment, lacking interactions with neurons, astrocytes,

and vasculature. This may impact the generalizability of observed responses. Third, the gene set

used in the screen was focused on AD-associated genes and may not capture broader regulators of

microglial homeostasis or stress resilience. Finally, while gene expression and functional overlap

suggest possible regulatory roles, transcriptional induction does not confirm causality. Future

mechanistic studies will be necessary to validate the direct contribution of candidate genes to

microglial stress handling and survival.

List of abbreviations

Aβ: amyloid beta

LPS: lipopolysaccharide

AD: Alzheimer's Disease

iMGLs: human induced pluripotent stem cell-derived microglia-like cells

MAP: Rush Memory and Aging Project

sgRNAs: singe-guide RNAs

CRISPRi: CRISPR interference

scRNA-seq: single-cell RNA sequencing

GO: Gene Ontology

DAM: disease-associated microglia

MGnD: neurodegeneration-associated microglia

WAM: white matter-associated microglia

IRM: interferon-responsive microglia

PAM: proliferative-region-associated microglia

MSigDB: Molecular Signatures Database

TLR: Toll-like receptor

NLR: NOD-like receptor

GPCR: G-protein-coupled receptor

PCD: programmed cell death

FC: flow cytometry

FACS: fluorescence-activated cell sorting

Declarations

Ethics approval and consent to participate

Two iPSC lines (BR09 and BR28) were obtained through the Rush Memory and Aging Project (MAP)

cohort study at the Rush Alzheimer's Disease Center, Rush University Medical Center (RUMC),

Chicago, IL., in compliance with national ethical guidelines. All MAP participants agreed to annual

clinical evaluation, blood draw, and brain donation. MAP was approved by the Institutional Review

Board of RUMC. All participants signed an informed and repository consent and an Anatomic Gift Act

for brain donation.

Availability of data and materials

We generated raw and normalized count matrices of the single-cell RNA sequencing and CRISPR

interference screen datasets from the dCas9-KRAB line. These data are available at GEO under

accession code GSE306200 & GSE306202.

Competing interest

The authors declare that they have no competing interests

Funding

This study was supported by NIA grants R01AG074082 and R01AG079223 (to Y.W.), P30AG10161,

P30AG72975, R01AG015819, R01AG017917, U01AG61356 and the Paul M Angell Family

Foundation (to D. A. B.).

Author contributions

E.M.C established the iMGL differentiation protocol in-house based on published methods. D.S.

performed cellular assay validation experiments and conducted single-cell RNA sequencing data

analysis. F.S. carried out the CRISPR interference screen and performed subsequent data analysis.

R.A.V. selected AD-associated microglial genes for CRISPR screening. B.N. contributed to microglial

state mapping analysis. N.A.K. and H.V. assisted with assay development. D.S., N.A.K. and S.D.T.

conducted single-cell RNA sequencing experiments, and J.X. performed data processing. D.S.

drafted the initial version of the manuscript and Y.W. substantially revised and finalized the

manuscript. D.A.B. provided insightful and critical feedback and input. Y.W. conceived and directed

the study, led the research activities, and supervised manuscript preparation. All authors reviewed

and approved the final manuscript.

Acknowledgments

We thank the thesis committee of Dr. Devin Saunders, including Dr. Jeffrey H. Kordower, Dr.

Jennillee Wallace, Dr. Xiu-Ti Hu, and Dr. David Bennett, for their insightful feedback and input. We

also acknowledge the support of all RADC staff for their assistance throughout this project. This

research was made possible through the Allen Cell Collection, available from the Coriell Institute for

Medical Research.

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Materials Availability

This study did not generate new unique reagents.

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Figure 1. Aβ and LPS drive distinct morphological and transcriptional activation states in iMGLs. (**A**) Schematic of Aβ and LPS stimulation protocol and scRNA-seq analysis pipeline. (**B**) Representative phase-contrast and IBA1/CD45 immunofluorescence images showing distinct morphological phenotypes in unstimulated, Aβ-treated, and LPS-treated iMGLs. Quantification of cells bearing at least one process >3 μm revealed that unstimulated cells display small somas with fine processes (61.21 ± 10.3%); Aβ-treated cells exhibit elongated, polarized processes with minimal soma enlargement (61.06 ± 11.3%); whereas LPS-treated cells show hypertrophic morphologies characterized by enlarged somas, thickened highly branched processes, and occasional granular morphologies (75.92 ± 6.8%, $p < 0.05$ vs. unstimulated and Aβ). Fixed/stained cultures confirmed a significant increase in process-bearing cells for Aβ ($p < 0.05$ vs. unstimulated) and highly significant elevations for LPS ($p < 0.0001$ vs. unstimulated and Aβ) in both IBA1$^+$ and CD45$^+$ populations. Data represent mean ± SD; significance determined by one-way ANOVA with Tukey's multiple comparisons test. (**C–D**) UMAP visualization of 12,231 high-quality iMGLs by scRNA-seq, showing segregation into four transcriptional clusters, largely categorized by treatment condition. (**E**) Dimensional feature plots showing expression of canonical microglial identity genes (*AIF1, PTPRC,* and *SPI1*) across all clusters. (**F**) Dot plot showing the top 10 differentially expressed genes for each cluster. (G) Gene ontology (GO) enrichment analysis performed in Cytoscape ClueGO (v3) highlighting stimulus-responsive enrichment of biological process (BP), molecular function (MF), and cellular component (CC) pathways for each cluster.

Figure 2. Subclustering Analysis reveals stimulus-specific microglial heterogeneity and links Aβ- and LPS-responsive states to in vivo microglia signatures. (**A**) UMAP visualization of subclustering results, showing 13 transcriptionally distinct microglial subclusters derived from the four major clusters identified in Figure 1. (**B**) Dot plot showing the top 4 differentially expressed genes for each subcluster. (**C**) Heatmap comparing subcluster gene sets to published rodent microglial signatures (Stage 1 and 2 Disease-associated microglia (DAM), neurodegenerative microglia

(MGnD), white matter-associated microglia (WAM), interferon response microglia (IRM), lipid droplet-
associated microglia (LDAM), and proliferative region-associated microglia (PAM). Gene set
enrichment analysis (GSEA) was performed on subcluster-specific ranked gene lists (log$_2$FC-
weighted – log10 adjusted p) and results were considered significant at adjusted $p < 0.05$. (**D**)
Heatmap showing enrichment of reported human AD-associated microglial states (MG0 – MG12)
across subclusters. GSEA was performed using the 12 microglial state signatures and the plotted
values represent sign (NES) x -log10(adjusted p) for each signature. (**E**) Module scoring was
performed using gene sets from the Molecular Signature Database (MSigDB) related to cell death,
cellular stress, and inflammatory signaling. per-cell scores were calculated s using Seurat's
AddModuleScore function, averaged across subclusters, and z-scored for visualization.

Figure 3. Aβ and LPS induce shared and distinct transcriptional stress responses. (**A**) Differential gene expression profiles in Aβ- and LPS-treated microglia compared to unstimulated controls reveal shared and stimulus-specific responses, and stimulus-responsive markers. Feature plots on the right show expression of *TREM2* and *P2RY12*. (**B**) GO term enrichment of shared upregulated and downregulated genes. (**C**) GO term enrichment of upregulated genes upon Aβ treatment. (**D**) GO term enrichment of upregulated and downregulated genes upon LPS treatment. (**E**) Violin plots showing expression of genes related to pyroptosis *(CASP1*, *CASP4*, and *CASP5*), apoptosis (*CASP3* and *CASP7*)*, ferroptosis (*GPX4, ACSL4, TFRC, FTH1*, and *PTGS2*) and necroptosis (*RIPK1, MLKL*), each of which exhibited significantly increased or decreased expression in Aβ- or/and LPS-treated microglia relative to unstimulated controls (adjusted $p < 0.0001$).

Figure 4. Cellular assays confirmed Aβ- and LPS-induced cellular stress and inflammatory responses. (**A**) Quantification of cleaved caspase-3 (positive nuclei), MitoSOX and LipidTOX (stained area normalized to nuclei count), and CD68 (positive cells) across three conditions. Data represent mean ± SD. *p < 0.05 (ANOVA with Tukey's multiple comparisons). (**B**) Flow cytometry analysis of TREM2, CD68 and CD38 expression across three conditions. Data represent mean ± SD. Significance: *p < 0.05 (ANOVA with Tukey's multiple comparisons) (**C**) Cytokine profiling reveals Aβ- and LPS-induced cytokine/chemokine responses, normalized by log2 transformation.

Figure 5. CRISPRi functional screening reveals partial overlap between AD-risk genes and microglial stress response genes. (**A**) Schematic of the CRISPRi screen targeting 168 AD-associated microglia genes. (**B**) Expression analysis identified 127 genes expressed in iMGLs across three conditions, showing distinct expression patterns. (**C**) Representative image of iMGLs infected with lentiviral sgRNA targeting CD33 at day 40 (10 days post-infection). (**D-E**) Knockdown validation of CD33 by qRT-PCR (fold-change expression) and flow cytometry (mean ± SD; significant by Welch's t-test, $p < 0.0001$). (**F**) sgRNA distribution in iPSCs infected with the pooled lentiviral library targeting 168 AD-associated microglia genes. (**G**) Survival screen identifies 31 genes regulating iMGL survival that were also expressed in scRNA-seq data; these genes were categorized as pro-survival, anti-survival, or dynamic regulators. (**H**) Venn diagram showing 27 genes overlapping between survival hits and 127 DEGs induced by Aβ or LPS; 17 genes were shared across Aβ-responsive, LPS-responsive, and survival-linked categories. (**I-J**) Heatmap showing fold changes in gene expression relative to unstimulated controls under Aβ or LPS stimulation, grouped by pro-survival, anti-survival, or dynamic regulators.

Supplementary Figures

Supplementary Figure 1. Benchmarking iMGL differentiation of dCas9-KRAB iPSC line against control ROSMAP iPSC lines. (**A**) Flow cytometry analysis of CD43 and CD45 expression at day 12 and day 40 of differentiation across three iPSC lines. Representative histograms and quantification illustrate robust expression of myeloid markers during iMGL differentiation. (**B**) Immunocytochemistry (ICC) images and corresponding quantification showing dCas9-KRAB iPSC-derived iMGLs express canonical microglial markers including PU.1, IBA1, TREM2, P2RY12, and TMEM119. (**C**) Quantitative RT-PCR analysis of APOE, CD33, and TREM2 expression across multiple differentiation stages, demonstrating transcriptional maturation of iMGLs. (**D**) Phagocytosis assay showing dCas9-KRAB iPSC-derived iMGLs respond to Aβ stimulation, with enhanced phagocytic uptake upon LPS or cytokine treatment, as evidenced by flow cytometry and quantification.

Supplementary Figure 2. Single-cell RNA-seq quality control and microglial marker gene expression. (**A**) Boxplots showing quality control metrics across individual clusters, including number of detected genes (nGene), number of UMIs (nUMI), percentage of mitochondrial reads (percent.mt), and percentage of ribosomal reads (percent.RB). (**B**) Heatmap displaying the top 50 differentially expressed genes defining each cluster. (**C**) Feature plots illustrating the expression of microglial marker genes across clusters.

Supplementary Tables

Table S1. Media and Assay Reagents

Table S2. iMGL Markers by Cluster and ClueGO Pathways

Table S3. iMGL Markers by Subcluster and MSigDB Gene Sets

Table S4. Stimulus Specific DEGs and GO Terms

Table S5. MesoScale Cytokine Concentrations

Table S6. Candidate Survival Genes from CRISPRi Screens