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Single-nucleus chromatin accessibility and transcriptomic characterization of Alzheimer's Disease

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Abstract

The gene-regulatory landscape of the brain is highly dynamic in health and disease, coordinating a menagerie of biological processes across distinct cell-types. Here, we present a multi-omic single-nucleus study of 191,890 nuclei in late-stage Alzheimer's Disease (AD), accessible through our web portal, profiling chromatin accessibility and gene expression in the same biological samples and uncovering vast cellular heterogeneity. We identified cell-type specific, disease-associated candidate cis-regulatory elements and their candidate target genes, including an oligodendrocyte-associated regulatory module containing links to *APOE* and *CLU*. We describe cis-regulatory relationships in specific cell-types at a subset of AD risk loci defined by genome wide association studies (GWAS), demonstrating the utility of this multi-omic single-nucleus approach. Trajectory analysis of glial populations identified disease-relevant transcription factors, like *SREBF1*, and their regulatory targets. Finally, we introduce scWGCNA, a co-expression network analysis strategy robust to sparse single-cell data, and perform a systems-level analysis of the AD transcriptome.

The human brain is composed of multiple heterogeneous subsets of cells; both neuronal and nonneuronal cells work in concert to perform simple and higher-order tasks. Recent studies have provided more precise molecular characterization and identification of

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Author Contributions

SM, EM, NM and VS planned and directed all experiments and analyses and wrote the manuscript with assistance from all authors. NM, EM and VS performed all dissections and sequencing experiments, and SM, EM and VS performed all bioinformatic analyses. ACM, EH, JS, KL, MPR, EM, NM and VS reviewed clinical information. EM performed RNAscope validation, and NM, SS, and ACM performed immunofluorescence/immunohistochemistry.

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neuronal and nonneuronal cell populations in the cognitively normal brain¹⁻⁴. However, our understanding of heterogeneous cell populations within the diseased brain is still largely limited, hindering our understanding of the biological processes underlying disease. Neurodegenerative disorders, like Alzheimer's disease (AD), are marked with massive neuronal loss, accompanied by gliosis, and the role of specific neuronal and glial cell populations in AD pathophysiology remains unclear. Several single-cell and single-nucleus RNA-sequencing (snRNA-seq) studies have been performed on both mouse and human tissue to study AD, revealing cell-type specific transcriptional changes⁵⁻⁹, but the regulators of these disease-associated cell subtypes have yet to be defined.

Moreover, a slew of genetic studies have been performed on AD, identifying multiple associated genetic risk variants¹⁰⁻¹⁶. Genome-wide association studies (GWAS) of complex diseases such as AD show that a substantial proportion of genetic risk from common variants partitions to distal regulatory elements, which are often cell-type specific regions in disease-relevant tissues. While much work has gone into intersecting GWAS signals with functional genomics assays, including bulk-tissue RNA-seq and assay for transposase accessible-chromatin with high-throughput sequencing (ATAC-seq)¹⁷, the resolution of such studies is noticeably limited by cell-type heterogeneity. A prerequisite for linking GWAS hits to cell-types is a map that links distal regulatory elements with their target genes.

ATAC-seq profiles the open chromatin regions within a tissue and has recently been adapted for single cell resolution¹⁸. To date, single-cell chromatin accessibility techniques, such as single-nucleus ATAC-seq (snATAC-seq) have been seldom used in primary samples of diseased tissues, with only two published studies of single-cell chromatin accessibility in the cognitively normal human brain^{19,20}. Therefore, we performed snATAC-seq and snRNA-seq in the same AD postmortem human brain tissue samples to define AD-associated gene regulatory programs at the epigenomic and transcriptomic level, providing a powerful lens into the cellular heterogeneity of the brain and allowing us to unravel novel biological pathways underlying neurodegeneration in specific cell populations.

Here, we present a multi-omic analysis of 191,890 nuclei from postmortem human brain tissue of AD and cognitively healthy controls at the single-nucleus resolution, in which we directly integrated snRNA-seq and snATAC-seq datasets, thus providing a more complete understanding of the molecular changes in AD. We identified cell-type specific candidate cis-regulatory elements (cCREs) based on chromatin accessibility and found disease-associated cell subpopulation-specific transcriptomic changes. We identified transcription factors (TFs) that may be regulating AD gene expression changes. Further, we applied pseudotime trajectory analysis on our integrated dataset to extensively characterize disease-associated glial cell states at the epigenomic and transcriptomic level, expanding on previous work exploring gene expression in diverse glial subtypes. We integrated fine-mapped GWAS signals at selected AD risk loci with our snATAC-seq data to link AD risk signals to the specific cell-types in which they are accessible and defined the cis-regulatory chromatin accessibility networks at these loci. Moreover, since network analysis has been effective at clarifying disease transcriptomic signatures in tissue-level RNA-seq data, we designed a co-expression network analysis pipeline, integrating single-cell and bulk-tissue RNA-seq datasets, that robustly identified AD-associated co-expression networks within each cell-

type. Altogether, we have clarified the gene regulatory landscape of AD, highlighting the role of glia in AD pathophysiology and identify several genes, namely SREBF1 in oligodendrocytes, for further study in the context of AD. Finally, we provide an online interface for exploration of these datasets (<https://swaruplab.bio.uci.edu/singlenucleiAD>).

Results

Multi-omic analysis of the human prefrontal cortex

We performed both snATAC-seq (10x Genomics; n=12 late-stage AD; n=8 control) and snRNA-seq (10x Genomics v3; n=11 late-stage AD; n=7 control) on nuclei isolated from the prefrontal cortex (PFC) using postmortem human tissue from late-stage AD and age-matched cognitively healthy controls (74-90+ years old, Fig. 1a). We defined late-stage AD and controls based on both Braak and plaque staging (Supplementary Tables 1-2). We specifically aimed to generate both transcriptomic and epigenetic data from the same tissue sample (aliquots of samples from the same dissection, see Methods) to minimize differences in cell-type composition between the two methods, thus allowing for meaningful downstream integrated analysis. After quality control filtering, we retained a total of 130,418 nuclei for snATAC-seq and 61,472 nuclei for snRNA-seq (Methods, Supplementary Fig. 1-2, Supplementary Table 3, Supplementary Note). To ensure the rigor of our study, we applied batch correction methods to the data from both assays, since library preparation limitations required multiple batches. For snATAC-seq, we used mutual nearest neighbors (MNN)²¹ to correct the Latent Semantic Indexing (LSI) reduced chromatin accessibility matrix, and for snRNA-seq we used integrative Non-negative Matrix Factorization (iNMF)²² to reduce dimensionality while simultaneously eliminating batch effects (Methods, Extended Data Fig. 1, Supplementary Note). We applied Uniform Manifold Approximation and Projection (UMAP)²³ dimensionality reduction and Leiden clustering²⁴ to the batch-corrected epigenomic and transcriptomic datasets, identifying distinct cell-type clusters in snATAC-seq (35) and snRNA-seq (34, Fig. 1b-c). With snATAC-seq, we profiled all major cell-types of the brain—excitatory neurons (24,076 nuclei, EX.a-e), inhibitory neurons (9,644 nuclei, INH.a-d), astrocytes (15,399 nuclei, ASC.a-f), microglia (12,232 nuclei, MG.a-e), oligodendrocytes (62,253 nuclei, ODC.a-m), and oligodendrocyte progenitor cells (4,869 nuclei, OPC.a)—annotated based on chromatin accessibility at the promoter regions of known marker genes (Fig. 1d, Extended Data Fig. 2). We used chromVAR²⁵ to compute TF motif variability in single nuclei by estimating the enrichment of TF binding motifs in accessible chromatin regions (Methods) and examined the enrichment of TF motifs by cell-type in respect to diagnosis, identifying several TF motifs with increased enrichment with disease in astrocytes, excitatory neurons, and microglia (Supplementary Fig. 3, Supplementary Data 1). Moreover, we performed TF footprinting analysis to further clarify cell-type-specific TF regulation, highlighting the SOX9 TF footprint in oligodendrocytes. Interestingly, we noticed TF motif enrichment of oligodendrocyte-related TFs in excitatory neurons. Likewise, we detected similar cell-types using snRNA-seq—excitatory neurons (6,369 nuclei, EX1-5), inhibitory neurons (5,962 nuclei, INH1-4), astrocytes (4,756 nuclei, ASC1-4), microglia (4,126 nuclei, MG1-3), oligodendrocytes (37,052 nuclei, ODC1-13), and oligodendrocyte progenitor cells (2,740 nuclei, OPC1-2)—classified by the gene expression of cell-type markers (Fig. 1e). In both

assays, oligodendrocytes were the most commonly profiled cell-type (Supplementary Fig. 3). Additionally, while many differentially expressed genes (DEGs) in each major cell-type agreed with previous literature, we also found cluster-specific genes previously established as neuronal or glial subtype markers, such as *LINC00507* for L2-3 excitatory neurons (EX1)⁴, *SV2C* for L3 interneurons (INH4)¹, and *CX3CR1* for homeostatic microglia (MG2)²⁶ (Fig. 1h, Supplementary Fig. 3-4, Supplementary Data 1).

Since the epigenomic landscape is deeply intertwined with downstream gene expression signatures, we integrated our snATAC-seq and snRNA-seq datasets using Seurat's integration platform^{27,28} (Methods, Fig. 1f, Extended Data Fig. 3, Supplementary Fig. 3). Cell-types that were independently classified using chromatin data or transcriptome data overwhelmingly grouped together in the integrated UMAP space (Fig. 1g, Supplementary Fig. 3). Using the same biological samples in snATAC-seq and snRNA-seq resulted in a high degree of overlap between nuclei from these two data modalities in the jointly constructed space. Additionally, we confirmed cell-type identities by gene activity and gene expression in a panel of canonical cell-type marker genes (Supplementary Fig. 3) and used Seurat's label transfer algorithm to verify cell-type annotations in the snATAC-seq dataset using the snRNA-seq dataset as a reference (Supplementary Fig. 5).

Multi-omic characterization of AD cellular heterogeneity

In both snATAC-seq and snRNA-seq, we discovered multiple neuronal and glial subpopulations, and we annotated the subpopulations from snRNA-seq based on previously identified marker genes^{1,4} (Fig. 2, Supplementary Fig. 6-7, Supplementary Note). For our snATAC-seq clusters, we used Seurat label transfer to calculate cluster prediction scores allowing for supervised annotation of our cell clusters, in which we mapped EX.a to EX1 and ASC.b to ASC2, for example (Supplementary Fig. 6-7). We examined the composition of each cluster in the context of disease and found several that are significantly over- or under-represented in late-stage AD compared to control, in both data modalities (Fig. 2d-g, Methods). ASC3 (*GFA^{high}/CHI3L⁺*) significantly increased in proportion with disease (bootstrapped cluster proportion analysis using a two-sided Wilcoxon rank sum test, FDR = 8.63×10^{-5}), whereas ASC4 (*GFA^{low}/WIFI⁺/ADAMTS17⁺*) significantly decreased (FDR = 4.68×10^{-7}), consistent with a recent snRNA-seq study of the 5XFAD mouse model of AD²⁹. We also found that the proportion of MG.a. and MG.b was increased in late-stage AD (FDR = 9.82×10^{-7} , 8.88×10^{-10}), both of which mapped to the activated snRNA-seq cluster MG1 (*SPP^{high}/CD163⁺*), which was also increased with disease (FDR = 6.32×10^{-7}). Additionally, we found that immune oligodendrocyte cluster ODC13 was significantly increased in late-stage AD (FDR = 1.62×10^{-4}).

Further, we identified both differentially accessible chromatin regions (DARs) and differentially expressed genes (DEGs) in late-stage AD for each cell cluster and found high cluster specificity for GO term enrichment of distal and proximal DARs, as well as DEGs (Methods, Supplementary Fig. 7-9, Supplementary Data 1-6, Supplementary Note). For example, we identified *NEAT1* as upregulated in astrocytes and oligodendrocytes, in agreement with previous findings in the entorhinal cortex⁷, and we confirmed AD upregulation of *NEAT1* with *in situ* hybridization (Extended Data Fig. 4). Altogether, we

found cluster-specific epigenetic and transcriptomic changes in late-stage AD, which may underlie the dysregulation of distinct biological pathways in different cell subpopulations in neurodegeneration.

Cell-type-specific cis-gene regulation in late-stage AD

Based on our experimental design utilizing both snATAC-seq and snRNA-seq in the same samples, we reasoned that we could identify the target genes of cCREs in specific cell populations (Extended Data Fig. 5a, Methods). To this end, we sought to elucidate the cis-regulatory architecture of the PFC in late-stage AD by constructing cis co-accessibility networks³⁰ (CCANs) separately for late-stage AD and control in each cell-type (Methods). To identify target genes of cCREs, we focused on the subset of co-accessible peaks where one of the peaks lies in a promoter element, yielding a set of cCREs and candidate target genes. For this set of co-accessible links, we correlated the expression of the candidate target gene to the chromatin accessibility of the cCRE, strengthening the evidence of a potential regulatory relationship beyond co-accessibility alone. Finally, we used NMF to analyze and cluster these gene-linked cCREs (gl-cCREs) based on their chromatin accessibility in each cell cluster. In sum, this process results in a set of candidate enhancer elements (gl-cCREs) grouped into functional modules, as well as a set of cCRE-linked genes, for each major cell-type in late-stage AD and control.

In total, using this approach we identified 56,552 gl-cCREs and 11,440 cCRE-linked genes, with a median of 4 cCREs linked to each of these genes (Fig. 3a, Supplementary Tables 4-5). By examining the overlap between sets of cCRE-linked genes identified in each cell-type, we observed a substantial number of genes with linked cCREs that are shared across multiple cell-types, in addition to those that are cell-type specific (Fig. 3b). For several cell-types, we found a significant overlap between the set of cCRE-linked genes and cell-type marker DEGs, as well as genes that are upregulated in AD within that cell-type, highlighting a critical role of cCREs in disease-related gene expression changes (Fig. 3c). We also investigated the chromatin accessibility in each snATAC-seq cluster for these gl-cCREs and noted a high degree of cell-type and cluster specificity (Fig. 3d). The majority of the gl-cCREs mapped to intronic regions (58.35%) (Fig. 3e). Moreover, by inspecting the NMF coefficient matrix (H), we were able to identify which cluster or cell-type each NMF module corresponds to, and we annotated several modules that are specific to control or late-stage AD nuclei within a given cluster (Fig. 3f-g, Supplementary Note). Additionally, we found that some of the cCRE target genes that are common to more than one cell-type are regulated by different cCREs in each cell-type.

Cell-type-specific transcription factors in late-stage AD

To complement our analysis of cis-regulatory elements, we sought to identify cell-type specific trans-regulatory elements in late-stage AD. TFs tightly control cell fate in neurodevelopment and have been implicated in neurodegenerative processes. We examined the regulatory role of microglial TF SPI1 (also known as PU.1) and nuclear respiratory factor 1 (NRF1) in oligodendrocytes (Figure 4a-f, Supplementary Fig. 10, Supplementary Note). SPI1 motif variability in our snATAC-seq microglia clusters was significantly increased in only upregulated clusters MG.a and MG.b, but SPI1's targets were significantly

downregulated in only MG1 (Fig. 4a-b, Supplementary Fig. 10). We also identified NRF1 is dysregulated in select oligodendrocyte clusters (Fig. 4d-f, Supplementary Fig. 10). These results indicate that SPI1 acts as a transcriptional repressor in late-stage AD, providing insight into how SPI1 contributes to AD pathophysiology. Additionally, NRF1 has previously been associated with mitochondrial function, and impaired mitochondrial function³¹, mediated by NRF1 dysregulation, may contribute to neuronal dysfunction in late-stage AD through the disruption of myelination. TF analyses in neuronal populations and Fos related antigen 2 (FOSL2) in astrocytes are shown in Extended Data Fig. 4 and Supplementary Fig. 10.

To gain further insight into TF-mediated gene regulation in late-stage AD, we constructed cell-type specific TF regulatory networks. For a given TF, we identified candidate target genes as those whose promoters or linked cCREs are accessible and contain the TF's binding motif in the cell-type of interest, and we repeated this for several select TFs, generating microglia-specific and oligodendrocyte-specific TF regulatory networks (Fig. 4g-h, Extended Data Fig. 5b, Supplementary Note). Within these networks we identified multiple AD DEGs, in addition to genes located at known AD GWAS loci, regulated by SPI1 in microglia and NRF1 in oligodendrocytes.

Integrated trajectory analysis of disease-associated glia

To further uncover molecular mechanisms driving glial heterogeneity in AD, we performed pseudotime trajectory analysis using monocle³²⁻³⁴ on the integrated snATAC-seq and snRNA-seq data in oligodendrocytes, microglia, and astrocytes (Supplementary Note). Multi-omic trajectory analysis allows us to investigate the dynamics of gene expression, chromatin accessibility, and TF motif variability throughout a continuum of cell-state transitions. We modeled gene expression and chromatin accessibility dynamics using a recurrent variational autoencoder (RVAE)³⁵. Briefly, RVAE is an encoder-decoder neural network framework that uses long short-term memory (LSTM) units to effectively model temporal biological data, yielding a two-dimensional latent representation of the input features as well as a de-noised reconstructed version of the original input (Supplementary Note). For each cell-type, we identified genes that are differentially expressed along the trajectory (t-DEGs, Supplementary Data 7) and used these genes as features to train the RVAE until the loss function converged (Supplementary Note, Extended Data Fig. 6).

Oligodendrocyte trajectory reveals SREBF1 dysregulation

We constructed an integrated oligodendrocyte trajectory using 58,221 nuclei from snATAC-seq and 36,773 nuclei from snRNA-seq (Fig. 5a), noting that the proportion of nuclei from late-stage AD samples appears to increase along the trajectory (Fig. 5b, Pearson correlation $R = 0.32$, $p\text{-value} = 0.022$). To clarify the functional state of oligodendrocytes associated with late-stage AD, we examined the gene expression signatures^{36,37} of newly formed oligodendrocytes (NF-ODC), myelin-forming oligodendrocytes (MF-ODC), and mature oligodendrocytes (mature ODC) (Fig. 5c, see Supplementary Note for gene signature lists). Interestingly, we found that the mature oligodendrocyte gene expression signature increased at the end of the trajectory, whereas the myelin-forming oligodendrocyte gene signature decreased. In addition, the newly formed oligodendrocyte gene signature decreased

throughout the trajectory, altogether suggesting that the oligodendrocyte pseudotime trajectory appears to recapitulate oligodendrocyte maturation. Chromatin accessibility of 9,231 oligodendrocyte gl-cCREs and gene expression of 1,563 oligodendrocyte t-DEGs reconstructed with RVAE showcases the vast amount of chromatin remodeling and transcriptional reprogramming that may be underlying oligodendrocyte maturation (Fig. 5d).

Additionally, the latent feature space (Z) learned by the RVAE provides further biological insight into the pseudotime trajectory and gene regulation in disease (Fig. 5e). Here, each dot represents a single feature (gene or chromatin region), and they are organized in 2D space based on their pseudotemporal dynamics learned by the RVAE. We ranked each feature based on the point in the trajectory that it reaches 75% of its maximum value, which we termed as the feature's "trajectory rank". We then correlated the reconstructed feature trajectories, as in Fig. 5d, to the proportion of late-stage AD nuclei, as in Fig. 5b, to see which features consistently change with AD. For both genes (t-DEGs) and chromatin regions (gl-cCREs), the latent space clearly groups features together that are positively or negatively correlated with the proportion of late-stage AD nuclei and groups features together with similar trajectory ranks, demonstrating the power of this RVAE model for the analysis and interpretation of multi-omic pseudotemporal dynamics.

We showcase two key TFs in oligodendrocytes: NRF1 and sterol regulatory element binding transcription factor 1 (SREBF1). SREBF1 is critical in regulating the expression of genes involved in cholesterol and fatty acid homeostasis³⁸, and it is proposed that A β inhibits SREBF1 activation³⁹. We found that NRF1 motif variability is upregulated in oligodendrocytes in late-stage AD (Bonferroni adjusted p-value = 5.13×10^{-20} , Fig. 4g), and SREBF1 motif variability is downregulated with disease in oligodendrocytes (Bonferroni adjusted p-value = 2.67×10^{-191} , Extended Data Fig. 4). We correlated TF motif variability trajectories (Extended Data Fig. 6) with the reconstructed t-DEG expression trajectories and visualized the correlation between the TF and each gene within the 2D latent space, identifying candidate target genes activated or repressed by TF binding events (positive or negative trajectory correlation, respectively) (Fig. 5f, Supplementary Note). We found that NRF1 is negatively correlated with target genes at the end of the trajectory, while SREBF1 is positively correlated with target genes at both the beginning and the end of the trajectory, indicating that SREBF1 acts as a transcriptional activator throughout the trajectory.

Microglia trajectory to define disease-associated microglia

Using the same analytical approach as our oligodendrocyte trajectory analysis, we constructed an integrated microglia trajectory using 10,768 nuclei from snATAC-seq and 4,119 nuclei from snRNA-seq (Fig. 6a). The proportion of nuclei from late-stage AD samples significantly increased throughout the microglia trajectory (Fig. 6b, Pearson correlation $R = 0.53$, p-value = 6.9×10^{-5}). We next sought to investigate gene signatures of disease-associated microglia (DAMs), which were introduced in Keren-Shaul *et al.*'s single-cell transcriptomic study⁴⁰ of 5XFAD mice and are highly debated in the field of AD genomics. DAMs are described as AD associated phagocytic microglia that are sequentially activated in *TREM2*-independent and -dependent stages (stage 1 and stage 2, respectively). We found that the integrated microglia trajectory follows a decrease in the homeostatic

signature, an increase in the stage 1 DAM signature, and a distinct global depletion of the stage 2 *TREM2*-dependent DAM signature (Fig. 6c, see Supplementary Note for gene signature lists), suggesting that this microglia trajectory describes the transcriptional and epigenetic changes during the transition from a homeostatic to disease-associated cell-state.

To further dissect the microglia trajectory, we modeled the chromatin accessibility and gene expression dynamics of 9,163 microglia gl-cCREs and 2,138 microglia t-DEGs, respectively, using RVAE (Fig. 6d-e). We highlight two ETS family TFs, SPI1 and ETS variant 5 (ETV5), both of which showing upregulated motif variability in late-stage AD (Bonferroni adjusted p-values 1.19×10^{-20} , 6.68×10^{-19} respectively), and their candidate target genes along the trajectory (Fig. 6f, Supplementary Note). We observed that the SPI1 motif trajectory is negatively correlated with genes at the end of the trajectory, supporting our previous findings that SPI1 acts as a repressor in late-stage AD

Disease-associated astrocytes in human AD

We also constructed an integrated astrocyte trajectory using 12,112 nuclei from snATAC-seq and 4,704 nuclei from snRNA-seq (Fig. 6g), and we again found that the proportion of late-stage AD nuclei significantly increases throughout the trajectory (Fig. 6h, Pearson correlation $R = 0.57$, p-value = 1.9×10^{-5}). In a similar fashion to our analysis of the DAM signature in the microglia trajectory, we investigated the gene signature of disease-associated astrocytes (DAAs), described in a recent snRNA-seq study of the hippocampus in 5XFAD mice²⁹ as an AD-specific *GFAP*^{high} astrocyte subpopulation that is distinct from another *GFAP*^{high} astrocyte subpopulation found in aged wild-type and 5XFAD (*GFAP*-high). Based on DAA gene signature analysis, we reasoned that this trajectory follows a trend from a *GFAP*-low state to *GFAP*-high and DAA-like states (Fig. 6i, see Supplementary Note for gene signature lists).

RVAE modeling of 12,487 astrocyte gl-cCREs and 1,797 astrocyte t-DEGs revealed rich gene-regulatory dynamics across the trajectory (Fig. 6j-k). We investigated the relationship between astrocyte t-DEGs and two TFs: CCCTC-binding factor (CTCF) and FOSL2, whose motif variability we have found to be downregulated and upregulated in late-stage AD, respectively (Bonferroni adjusted p-values 6.45×10^{-17} , 5.65×10^{-99} respectively). CTCF is known as a master chromatin regulator^{41,42}, and we observed that the CTCF motif variability trajectory is anti-correlated with the DAA and *GFAP*-high signatures (end of the trajectory, Extended Data Fig. 6) and positively correlated with t-DEGs in the *GFAP*-low phase of the trajectory (Fig. 6l). Alternatively, we found a positive correlation between the motif variability trajectory of FOSL2 with the *GFAP*-high and DAA gene signatures and a positive correlation with genes at the end of the trajectory (Fig. 6l, Supplementary Note). These findings suggest that FOSL2 may be an activator of the disease-associated astrocyte signature, whereas CTCF may promote a more homeostatic or non-diseased astrocyte state. By relating gene expression with TF motif enrichment, TF binding site accessibility, and using the temporal information learned by the RVAE, we begin to unravel the role of TFs in regulating cell states, such as disease-associated astrocytes.

Cell-type-specific cis-regulation at AD genetic risk loci

To further our understanding of AD genetic risk signals, we performed cell-type-specific linkage-disequilibrium score regression⁴³ (LDSC) analysis in our snATAC-seq clusters using GWAS summary statistics in AD^{10,11} and other relevant traits⁴⁴⁻⁵⁰ (Methods, Supplementary Table 6, Supplementary Note). Microglia clusters MG.b and MG.c showed a significant enrichment (FDR < 0.05) for AD GWAS SNPs from the Kunkle *et al.* study, and all five microglia clusters showed a significant enrichment (MG.a, MG.e FDR < 0.005; MG.b, MG.c, MG.d FDR < 0.0005) for GWAS SNPs from the Jansen *et al.* study, which included familial AD-by-proxy samples in addition to AD patient data (Fig. 7a). The results of this GWAS heritability analysis supports previous findings in non-diseased human²⁰ and mouse⁵¹ snATAC-seq data. We further investigated AD risk signals in microglia using gchromVAR⁵² to compute the enrichment of fine-mapped AD-associated polymorphisms from Jansen *et al.* along the microglia pseudotime trajectory and observed a significant increase (Pearson correlation, p-value = 0.0048, Methods, Fig. 7b-c) in the gchromVAR deviation score in distal peaks throughout the microglia trajectory, in stark contrast with a significant decrease in the deviation score for the analogous gene-proximal peak analysis (Pearson correlation, p-value = 0.0053), highlighting AD-associated SNPs at distal enhancers in disease-associated microglia. By overlaying the co-accessibility map with chromatin accessibility signal and GWAS statistics along the genomic axis, we unraveled the potential cis-regulatory relationships disrupted by causal disease variants in GWAS genes, such as *BINI*, *ADAM10*, *APOE* and *SCL24A4* (Fig. 7d-i). We found that the *APOE* locus, which harbors the main determinants of AD heritability and is one of the best studied AD risk loci, has cis-regulatory chromatin networks altered in disease in microglia and astrocytes, highlighting cCREs that are prime candidates for further study using genome editing technologies.

Single-cell co-expression networks using scWGCNA

To recontextualize snRNA-seq data in systems-level framework, we sought to develop a gene co-expression network analysis approach for single-cell data based on weighted gene co-expression analysis (WGCNA)^{53,54}, a powerful analytical approach for identifying disease-associated gene modules^{55,56} originally designed for bulk gene expression data. Our revised approach uses aggregated expression profiles in place of potentially sparse single cells, where *metacells* are constructed from specific cell populations by computing the mean expression from 50 neighboring cells using k-nearest neighbors (Methods, Extended Data Fig. 7, Supplementary Note). We re-processed published AD snRNA-seq data from Mathys *et al.*⁵ and used iNMF to integrate with our snRNA-seq data (Methods, Extended Data Fig. 8). Additionally, we performed bulk RNA-seq in early- and late-stage AD cases, as well as pathological controls and curated additional AD bulk-tissue RNA-seq samples from ROSMAP⁵⁷. Finally, we used consensus WGCNA⁵⁸, a meta-analytical approach, to jointly form co-expression networks in *metacells* constructed from the integrated snRNA-seq dataset and bulk-tissue RNA-seq data of the human PFC from two distinct cohorts. We call this approach Single-nucleus Consensus WGCNA (scWGCNA; Extended Data Fig. 1,7,9,10; Supplementary Data 7), performed iteratively for each cell-type, where each edge in a co-expressed module is supported by both bulk-tissue RNA-seq data (this study and ROSMAP⁵⁷) and aggregated snRNA-seq data (this study and Mathys *et al.*).

We specifically highlight our scWGCNA analysis for oligodendrocytes; we found four co-expression modules significantly correlated with AD diagnosis—OM1, OM2, OM4, and OM5 (Fig. 8a-b, Supplementary Data 7). For example, hub genes of the AD-downregulated module OM1 encode ribosomal subunits (*RPS15A*, *RPL30*, *RPL23A*, etc.), consistent with its enrichment of GO terms related to protein synthesis and sorting (Supplementary Fig. 11). OM2 gene members *MAG*, *CNP*, and *PLP1* are known to be involved in myelination, and unsurprisingly we found OM2 downregulated with disease.

Additionally, we examined SREBF1's downstream regulatory targets in the context of co-expression networks (Methods). Notably, we found that three of the oligodendrocyte modules were significantly enriched for targets of SREBF1, indicating the importance of SREBF1 in regulating gene expression in these modules (Fig. 8c). Using a multi-scale dataset of bulk-tissue RNA-seq, high-throughput proteomics⁵⁹, and SREBF1 ChIP-seq data (ENCODE), we defined a protein-protein interaction (PPI) network of SREBF1 target genes (Extended Data Fig. 7). Additionally, we found module eigengene expression of SREBF1 targets downregulated in early- and late-pathology AD cases at the level of proteins⁵⁹ and RNA (Fig. 8d), corroborated by downregulation of SREBF1 motif variability in snATAC-seq data (Extended Data Fig. 4). We also validated the downregulation of SREBF1 in late-stage AD through RNA *in situ* hybridization and immunohistochemistry and found a decrease in *ACSL4* expression, one of SREBF1's targets identified in ENCODE ChIP-seq data, in late-stage AD (Fig. 8e-g, Extended Data Fig. 7). Overall, our co-expression network analysis approach facilitates the identification of cell-type-specific disease biology, and we have highlighted TF SREBF1, largely unstudied in the context of AD, in oligodendrocytes to demonstrate our approach's ability to yield novel disease insights.

Discussion

Our integrated multi-omic analysis of late-stage AD provides a unique lens into the continuum of cellular heterogeneity underlying disease pathogenesis. Pinpointing causal mechanisms of complex diseases requires a rigorous understanding of cell population specific gene regulatory systems at both the epigenomic and transcriptomic level. While single-cell chromatin accessibility can provide important insights into disease, it is a challenging data modality to work with due to its inherent sparsity. We circumvented the issue of sparsity by integrating single-nucleus open-chromatin and single-nucleus transcriptomes from the same samples, in addition to using aggregation methods for pseudo-bulk accessibility profiling and co-accessibility analysis. Taking these considerations into account, our multi-omic analysis enabled us to analyze cell-type-specific epigenomic dysregulation in neurodegeneration and expands on previous work to decipher the transcriptomes of single nuclei in human AD.

A major contribution of our study is that we identified cell-type specific gl-cCREs, which may be mediating gene regulatory changes in late-stage AD, along with TFs that may be binding to these gl-cCREs within the given cell-type. While cCREs can be identified with epigenetic data alone, our analysis is substantiated by integrating single-nucleus transcriptomic data, as we link the gene expression of candidate target genes with cCRE chromatin accessibility. Previous studies of AD have not explored cis-gene regulation at a

cell-type or cell subpopulation level. We have highlighted both cis- and trans-gene regulation disrupted in late-stage AD, providing potential targets for further study into AD, like *NRF1* in oligodendrocytes and *FOSL2* in astrocytes and their corresponding gl-cCREs. Further, we examined cis-regulatory interactions in our multi-omic dataset to elucidate cell-type and disease specific patterns of genes implicated in inherited AD risk by GWAS, which are of particular interest as candidate therapeutic targets. For a subset of AD GWAS loci, we compared cis-regulatory networks between AD and control cell populations to identify interactions that are uniquely found in disease. Thus, this study serves as a resource for the broader AD community to explore cell-type and cell-state-specific regulatory landscapes of genes and genomic regions that may be of particular interest, such as AD GWAS loci.

Moreover, independent and joint analyses of the transcriptome and chromatin profiles of oligodendrocytes revealed disrupted gene regulation and biological pathways in AD (Supplementary Note). We described a multi-omic oligodendrocyte trajectory and evaluated gene expression signatures in the transition from newly formed to mature oligodendrocytes, observing that the trajectory seemed to follow oligodendrocyte maturation. Notably, we analyzed the trajectory dynamics of *SREBF1*, a TF involved in regulation of cholesterol and lipid metabolism that has been shown to be involved in A β -related processes³⁹. We found that *SREBF1* motif variability was decreased in late-stage AD, indicating that fewer *SREBF1* binding sites are accessible in disease, and *SREBF1* gene expression is also downregulated in AD oligodendrocytes. Trajectory analysis revealed that *SREBF1* motif variability is positively correlated with t-DEGs throughout the trajectory, suggesting that it acts as a transcriptional activator in oligodendrocytes.

Co-expression network analysis methods like WGCNA have been widely used for discovery of disease-associated gene modules in bulk gene expression data^{60,61}; however, these approaches are rarely used in single-cell transcriptomics, with some exceptions⁶² due to challenges in network construction from noisy data. Here we introduced scWGCNA, a method for interrogation of cell population-specific co-expression networks that leverages aggregated *metacells* to combat the sparsity of single-cell gene expression. Using scWGCNA, we found gene co-expression networks in human AD by jointly analyzing our snRNA-seq and bulk RNA-seq with additional snRNA-seq and bulk RNA-seq samples from the ROSMAP cohort^{5,57}. This meta-analytical approach ensured robustness of our network analysis and allowed us to evaluate the resulting gene modules in early-stage AD (Supplementary Note). Notably, scWGCNA identified three oligodendrocyte modules that were enriched for target genes of *SREBF1* and showed that the gene and protein expression of these targets were decreased in late-stage AD. With our co-expression and trajectory analysis of *SREBF1* in oligodendrocytes, *SREBF1* is clearly a gene to prioritize for follow-up studies as a candidate target for AD therapeutics, demonstrating the utility of our approach in identifying novel gene targets for disease.

While the causative molecular mechanisms of sporadic AD remain unknown, our work offers new insights which assist in unraveling the nature of gene regulation in AD, especially in regard to genomic loci with well-described heritable disease risk. Additional work is needed to spatially resolve the complexity of gene expression and epigenomics in AD and neurodegeneration in general. The data presented here are a valuable resource for

understanding regulatory relationships in the diseased brain, and our analysis framework serves as a blueprint for making discoveries in complex traits using single-cell multi-omic data. Finally, our intuitive web portal for exploring single nuclei in the human brain allows for the accessibility of our results to anyone with an internet-equipped device.

Methods

Human Samples

Human prefrontal cortex brain samples were obtained from UCI MIND's Alzheimer's Disease Research Center (ADRC) tissue repository and under UCI's Institutional Review Board (IRB). Postmortem human brain tissue from the Religious Orders Study and Memory and Aging Project (ROSMAP) study was obtained under the IRB of Rush University Medical Center. Informed consent was obtained for all human participants. Samples were dissected, homogenized on a dry ice pre-chilled isolating platform and aliquoted for snRNA- and snATAC-seq. For details on human samples used in this study (AD n = 6 males and 6 females, controls n = 5 males and 3 females, all 74-90+ years old), please see Supplementary Tables 1-2. ROSMAP RNA-seq data and details can be found on synapse.org website using corresponding synapse (syn) ID syn3219045.

Bulk RNA-seq

Total RNA was isolated from human prefrontal cortex using Mini Nucleospin RNA kit (Cat #740955.250, Takarabio). RNA integrity was assessed using 2100 Bioanalyzer (Agilent). Total RNA was quantified using Qubit RNA HS assay kit (Cat# Q32852, Invitrogen). ~500ng total RNA was used to prepare the cDNA library using SMARTer Stranded Total RNA Sample Prep kit-HI Mammalian (Cat#634874, Takarabio). cDNA library concentration was calculated using Qubit dsDNA HS assay kit (Cat#Q32851, Invitrogen). Library quality was assessed using either High sensitivity DNA assay kit (Cat# 5067-4626) on 2100 Bioanalyzer or D5000 HS kit (Cat#5067-5589, 5067-5588) on 4200 TapeStation (Agilent). Libraries were multiplexed with 96 and 95 samples in 2 lanes on an Illumina Novaseq S4 for 100-bp paired-end reads.

Single-nucleus RNA-seq

Single nucleus suspensions were isolated from ~ 50mg frozen human prefrontal cortex. Samples were homogenized in Nuclei EZ Lysis buffer (Cat#NUC101-1KT, Sigma-Aldrich) and incubated for 5 min. Samples were passed through a 70µm filter and incubated in additional lysis buffer for 5 min and centrifuged at 500 *g* for 5 min at 4°C before two washes in Nuclei Wash and Resuspension buffer (1xPBS, 1% BSA, 0.2U/µl RNase inhibitor). Nuclei were FACS sorted with DAPI (NucBlue Fixed Cell ReadyProbe Reagent, Cat#R37606, Thermo) before running on the 10x Chromium™ Single Cell 3' v3 platform. cDNA library quantification and quality were assessed as in bulk RNA-seq. Libraries were sequenced using Illumina Novaseq 6000 S4 platform at the New York Genome Centre, using 100bp paired-end sequencing.

Single-nucleus ATAC-seq

Single nucleus suspensions were isolated from ~ 50mg frozen human prefrontal cortex according to the 10x Genomics Nuclei Isolation from Mouse Brain Tissue protocol (CG000212, Rev A) with an additional sucrose purification step. Before resuspending our nuclei in Diluted Nuclei Buffer, we removed cellular debris by preparing a sucrose gradient (Nuclei PURE Prep Nuclei Isolation Kit, Cat#NUC201-1KT, Sigma). Nuclei were spun at 13,000 *g* for 45 minutes at 4°C and then washed once and filtered before running on the 10x Chromium™ Single Cell ATAC platform. Library quantification and quality check were performed according to manufacturer's recommendations. Libraries were sequenced using Illumina Novaseq 6000 S4 platform at the UCI Genomics core facility, using 100bp paired-end sequencing.

RNAscope (fluorescent *in situ* hybridization)

Fresh frozen human postmortem tissue was sectioned at 20µm on a cryostat at -20°C. Slides were stored airtight at -80°C until use. Immediately after removing from -80°C, slides were dried for 20 minutes at room temperature and then fixed in 4% paraformaldehyde/PBS for 15 minutes at 4°C. Slides were then washed in RNase-free PBS for 5 minutes at room temperature 3 times. For single labeling experiments, slides were incubated in PBS with an LED light for 96 hours at 4°C to quench autofluorescence⁶³, and for dual labeling, autofluorescence was quenched with TrueBlack (Biotium) for 30 seconds before coverslipping. Slides were processed following the RNAscope Multiplex Fluorescent Reagent Kit v2 Assay (ACD) instructions for fresh frozen tissue, except protease IV incubation was 15 minutes. Probes used were NEAT1 (Cat#411531), PLP1 (Cat#499271), CNP (Cat#509131-C2), SREBF1 (Cat#469871), ACSL4 (Cat#408301), MOG (Cat#543181-C2), and AQP4 (Cat#482441-C2). Fluorophores used were TSA Plus Cy5 (1:200, Perkin Elmer) and Opal 570 (1:200, Perkin Elmer) to avoid autofluorescence. Images were taken on ZEISS Axio Scan.Z1 at 20x magnification. Four regions per section were analyzed using QuPath. We used a trained object classifier to identify MOG+ or AQP4+ nuclei, except for ACSL4/MOG dual staining, which required manual assignment of MOG+ nuclei due to high background. Subcellular detection was used to count RNA punctae. We used linear mixed effects model to account for random effects (age, sex) and fixed effects (multiple regions from the same individual).

Immunofluorescence

Fixed and cryoprotected human postmortem tissue was sectioned at 40µm using a cryotome (Leica). For 6E10, Iba-1, MAP2, and GFAP, brain sections were treated with 90% formic acid for 4 min. For PDGFRA and Olig2, sections in sodium citrate buffer were heated at 80°C in a bead bath for 30 min. Sections were then washed before blocking (PBS with 5% goat or donkey normal serum, respective to the antibodies, and 0.2% TritonX-100) for 1 hour at room temperature. Primary antibodies were incubated at 4°C overnight (6E10-1:1000, Cat#803001, Biolegend; Iba-1-1:1000, Cat#019-19741, Wako; MAP2-1:500, Cat#ab32454, Abcam; GFAP-1:500, Cat#G3893, Sigma; PDGFRA-1:50, Cat#AF-307, R&D Systems; Olig2-1:200, Cat#ab109186, Abcam). Secondary antibodies (Goat anti-mouse 555, Cat#A-21422; Goat anti-rabbit 488, Cat#A11034; Goat anti-rabbit 488,

Cat#A11034; Goat anti-mouse 555, Cat#A-21422; Donkey anti-goat 488, Cat#A-11055; Donkey anti rabbit 555, Cat#A31572; all from ThermoFisher) were diluted 1:200 and incubated for 1 hour. Slides were treated with 0.3% Sudan Black in 70% EtOH for 4 min to reduce autofluorescence and imaged on a confocal microscope (Leica). Images from 3 randomly selected areas were used for volume analysis of amyloid plaques using IMARIS. We used linear mixed effects model as previously stated.

Annotation of major cell-types

Major cell-type annotations were assigned to UMAP partitions and initial clusters in snATAC-seq and snRNA-seq datasets respectively through manual inspection of canonical marker gene signals. ‘Pseudo-bulk’ chromatin accessibility coverage profiles of gene body and upstream promoter regions were visualized using the Signac⁶⁴ (v0.2.0) function CoveragePlot, while gene expression signals were visualized using Seurat^{27,28} (v3.1.2) snRNA-seq cell type assignments were further validated by integration with the Mathys *et al.*⁵ dataset.

Integrated analysis of snRNA-seq and snATAC-seq data

A unified dataset of both chromatin accessibility and gene expression was constructed using Seurat’s integration framework. Canonical Correlation Analysis (CCA) was used to generate a shared dimensionality reduction of the ‘query’ snATAC-seq gene activity and the ‘reference’ snRNA-seq gene expression. MNNs were then identified in this shared space, effectively identifying pairs of corresponding cells that anchor the two datasets together. To confirm major cell-type annotations in snATAC-seq cell populations, we used Seurat’s label transfer algorithm, which leverages these anchors to predict cell-types in snATAC-seq data, with cell type annotations in snRNA-seq cells as the reference and LSI reduced chromatin accessibility as the weights. We achieved a max prediction score ≥ 0.5 in 94% of cells, demonstrating high correspondence between the two data modalities. Next, we used these shared anchors to impute gene expression signals in snATAC-seq data. Following imputation, we merged gene expression in cells from the snRNA-seq dataset with snATAC-seq cells whose max prediction score ≥ 0.5 . The merged dataset was then centered, dimensionally reduced with PCA using 30 dimensions, batch corrected with MNN (monocle3, v0.2.0) and embedded with UMAP. Clusters and UMAP partitions were identified using Leiden clustering (monocle3). We visualized correspondence of major cell-types from their dataset of origin to their joint UMAP partitions using ggalluvial (v 0.11.1).

Cell-type specific dimensionality reduction and cluster analysis

Cell-type specific analyses were performed for snATAC-seq and snRNA-seq by subsetting each major cell-type from the fully processed dataset followed by re-embedding with UMAP. Subpopulations of each cell-type used for all downstream analysis were then identified using Leiden clustering (monocle3). Clusters smaller than 100 cells were removed as outliers. We then used the addReproduciblePeakSet function from the R package ArchR (v1.0.0)⁶⁵ with default parameters to call accessible chromatin peaks using MACS2 (v2.2.7.1) in each cell-type subcluster. For snRNA-seq and snATAC-seq clusters, we performed a bootstrapped cluster composition analysis to robustly assess the composition

of each cluster with respect to AD diagnosis. Over 25 iterations, 20% of cells were sampled from the whole dataset, and the proportion of cells from AD or control samples were computed for each cluster. A two-sided Wilcoxon rank sum test was used to compare the proportion of AD and control samples in each cluster using the `wilcox.test` R (v3.6.1) function with default parameters and Benjamini-Hochberg multiple testing correction.

Annotation of cell subpopulations

snRNA-seq subpopulations for astrocytes, microglia, neurons, and oligodendrocyte progenitors were annotated in a similar way to the major cell-types, using canonical marker gene signals as well as differentially expressed genes. snATAC-seq subpopulations for astrocytes, microglia, neurons, and oligodendrocyte progenitors were annotated using Seurat label transfer prediction scores with the snRNA-seq clusters as a reference annotation. We annotated the snRNA-seq oligodendrocytes by hierarchically clustering oligodendrocyte and oligodendrocyte progenitor clusters based on the gene expression matrix of the top 25 DEGs (by average log fold-change) from each oligodendrocyte subpopulation, grouping oligodendrocytes into major lineage classes such as progenitor, intermediate, and mature. We used the same approach to annotate the snATAC-seq oligodendrocytes, hierarchically clustering the gene activity matrix using the same DEGs. The R package `ComplexHeatmap` (v 2.7.6.1010)⁶⁶ was used for hierarchical clustering and visualization of these gene expression and gene activity matrices.

Single-nucleus Transcription Factor (TF) binding motif analysis

Single-nucleus TF motif enrichment was computed for a set of 452 TFs from the JASPAR 2018 database⁶⁷ using the Signac wrapper for chromVAR (v 1.12.0)²⁵. The motif accessibility matrix was first computed, describing the number of peaks that contain each TF motif for all cells. chromVAR then uses this motif accessibility matrix to compute deviation Z-scores for each motif by comparing the number of peaks containing the motif to the expected number of fragments in a background set that accounts for confounding technical factors such as GC content bias, PCR amplification, and variable Tn5 tagmentation. To further analyze specific TFs of interest, we used the `getFootprints` function in ArchR to perform TF footprinting analysis in pseudo-bulk aggregates of single nuclei in the same cluster or cell-type, splitting nuclei from control or late-stage AD samples where appropriate.

Chromatin Cis Co-Accessibility Network (CCAN) analysis

The correlation structure of chromatin accessibility data was analyzed using the R package `cicero`³⁰ (v1.3.4.7). Briefly, `cicero` quantifies ‘co-accessibility’ between pairs of genomic regions in a population of cells by correlating accessibility signals aggregated from several cells at a time, penalizing for distance between regions using a graphical LASSO with a maximum interaction constraint of 500 kb. Importantly, prior to correlation and regularization, a bootstrap approach was used to generate *metacells* by aggregating 50 cells at a time using k-nearest neighbors, circumventing the sparsity of single-cell chromatin data. Finally, networks of cis co-accessible regions (CCANs) were identified through community detection. We applied this procedure in each major cell-type as well as splitting each cell-type into control and AD cells for CCAN analysis.

Analysis of gene-linked candidate cis-regulatory elements (gl-cCREs)

We sought to further contextualize co-accessible chromatin regions by linking them to likely target genes using an accessibility-expression correlation strategy stratified by major cell-type and disease status of each sample. First, we identified pairs of co-accessible peaks where one of the peaks overlaps a gene's promoter, which serves as a candidate target gene for that particular cCRE. We then computed the Pearson correlation between the expression of the candidate target gene from snRNA-seq with the chromatin accessibility of the linked cCRE from snATAC-seq, where expression and accessibility values have been averaged for all cells within a given cell population. This correlation analysis was performed iteratively across all promoter-cCRE co-accessible links identified separately in each major cell with regard to AD diagnosis status. Retaining links with Pearson correlation coefficient in the 95th percentile and p-value ≤ 0.01 , we defined gene-linked candidate cis-regulatory elements (gl-cCREs) as genomic regions with a significant correlation to at least one target gene, and we defined cCRE-linked genes as genes with a significant correlation to at least one cCRE. We used non-negative matrix factorization (NMF v 0.23.0) as implemented in the R NMF package⁶⁸ using k=30 matrix factors on the gl-cCRE accessibility matrix averaged by each snATAC-seq cluster split by cells from control and AD samples, yielding 30 gl-cCRE modules. The NMF basis matrix (W) was used to assign each gl-cCRE to its top associated module, and the NMF coefficient matrix (H) was used to determine which cell cluster that each module was most associated to. To identify biological process associated with these gl-cCRE modules, we used the enrichR^{69,70} (v 3.0) package to query enriched GO terms for the set of target genes in each gl-cCRE module in the GO Biological Processes 2018, GO Cellular Component 2018, and GO Molecular Function 2018 databases.

TF regulatory network construction

Using snATAC-seq and snRNA-seq data in one cell-type, we identified candidate TF regulatory target genes and used this information to construct cell-type specific TF regulatory networks. We used the same set of TF binding motifs as in our single-cell TF motif enrichment analysis (JASPAR 2018 motifs). For a given TF, we defined candidate target genes as those with an accessible promoter containing the TF binding motif, or an accessible gl-cCRE linked to the target gene's promoter, allowing us to distinguish between TFs that regulate genes through promoter or enhancer binding events. We used this information to construct a directed TF regulatory network using the R package igraph (v 1.2.6), where each vertex represents a TF or target gene, and each edge represents a promoter or linked-cCRE binding event, overlaying additional information onto the network such as DEG or AD GWAS gene status.

Estimating GWAS enrichment using cluster specific accessible chromatin regions

To estimate heritability of a variety of complex traits, we used LDSC (v 1.0.1)⁴³. GWAS summary statistics were input to LDSC, which then computes enrichment of heritability for an annotated set of SNPs conditioned on a baseline model in order to account for genomic features that influence heritability, and jointly modeling multiple annotations together. Sets of cluster specific peaks were constructed by extending peaks up and down stream by 2000 bp, identifying peaks that are accessible in 1% of all cells within each cluster, and removing

all peaks that are accessible in more than one other cell type. Cluster specific peaks were formatted for LDSC using the `make_annotation.py` script, and LD scores were computed for each set using the `ldsc.py` script. Publicly available GWAS summary statistics were collected for AD^{10,11}, Schizophrenia⁴⁶, Frontotemporal Dementia (FTD)⁴⁴, Progressive Supranuclear Palsy (PSP)⁴⁵, Multiple Sclerosis (MS)⁴⁷, Inflammatory Bowel Disease (IBD)⁴⁸, height⁴⁹, and cholesterol⁵⁰. Next, summary statistics were converted to hg38 coordinates using the UCSC liftover tool (`v377`) and formatted for LDSC using the `munge_sumstats` python script. We followed the recommended guidelines for cell-type specific partitioned heritability analysis, using HapMap3 SNPs and their provided hg38 baseline model (v2.2). The `ldsc.py` script was then used to compute cluster specific enrichments of GWAS heritability, with Benjamini-Hochberg multiple testing correction applied to enrichment p-values.

Single-nucleus Consensus Weighted Gene Co-expression Network Analysis (scWGCNA)

We developed a novel co-expression network analysis approach to single-cell data by integrating snRNA-seq and bulk-tissue RNA-seq datasets and called this approach Single-nucleus Consensus Weighted Gene Co-expression Network Analysis (scWGCNA). scWGCNA is based on a co-expression network analysis approach called Weighted Gene Co-expression Network Analysis (WGCNA), implemented using the WGCNA R package (v1.69)^{53,54}. For scWGCNA, we used multiple transcriptomic datasets comprising of our snRNA-seq data, Mathys et al. snRNA-seq data, bulk-tissue RNA-seq data from our UCI cohort and bulk tissue RNA-seq data from ROSMAP cohort⁵⁷. First, we integrated our snRNA-seq and Mathys et al. snRNA-seq datasets using iNMF approach, and then constructed *metacells* in a fashion similar to our CCAN analysis of chromatin accessibility data, in which we apply a bootstrapped aggregation process to single-nucleus transcriptomes. During *metacell* computation, we only pool cells within the same cell-type, and within the same AD diagnosis stage, in order to retain these metadata for scWGCNA. We then employed a signed consensus WGCNA approach⁵⁸ within a given cell-type, by calculating component-wise values for topological overlap for each dataset. First, bi-weighted mid-correlations were calculated for all pairs of genes, and then a signed similarity matrix was created. In the signed network, the similarity between genes reflects the sign of the correlation of their expression profiles. The signed similarity matrix was then raised to power β , varies between cell-types, to emphasize strong correlations and reduce the emphasis of weak correlations on an exponential scale. The resulting adjacency matrix was then transformed into a topological overlap matrix. Modules were defined using specific module cutting parameters which included minimum module size of 100 genes, `deepSplit = 4` and threshold of correlation = 0.2. Modules with correlation greater than 0.8 were merged together. We used first principal component of the module, called the module eigengene, to correlate with diagnosis and other variables. Hub genes were defined using intra-modular connectivity (kME) parameter of the WGCNA package. Gene-set enrichment analysis was done using EnrichR.

Analysis of regulatory targets of SREBP

We downloaded a dataset of ENCODE ChIP-seq validated TF target genes from EnrichR, containing regulatory targets of SREBP. Fisher's enrichment tests were performed with the R function `fisher.test` to test whether oligodendrocyte modules were significantly

over-represented with SREBP target genes, inferring which modules are regulated by SREBP. Module eigengenes were computed for the set of SREBP target genes, and the RNA expression as well as protein expression data from Inweb⁷¹ and Biogrid⁷² was also to analyze SREBP targets throughout the course of AD progression. A protein-protein interaction (PPI) network of SREBP target genes was constructed using SREBF1 ChIP-seq data from ENCODE and visualized using the STRING database⁷³, restricting the edges to known protein-protein interactions. In addition to bulk RNA-seq, we used a proteomics dataset from our group's previous study⁵⁹ of 685 samples representing AD, asymptomatic AD, and controls from the human PFC to interrogate the levels of SREBF1 target genes and target proteins in AD.

Statistics

All statistical methods and tests used in the manuscript were described in the figure legends, Methods, Supplementary Note, or main text as appropriate.

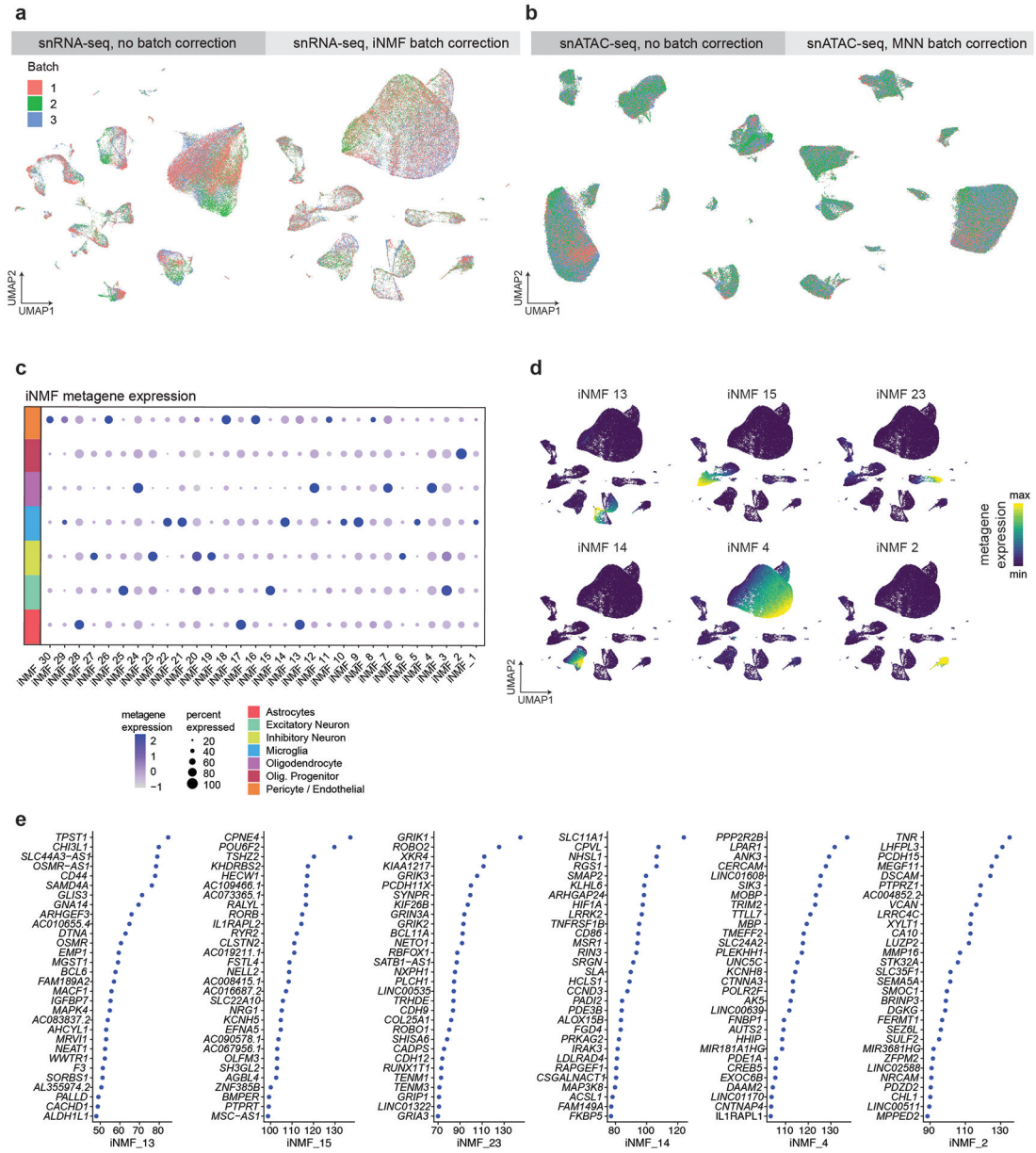
Data availability

All the multi-omics raw and processed data are available here: <https://www.synapse.org/#!Synapse:syn22079621/>. Raw sequencing data have been deposited into the National Center for Biotechnology Information Gene Expression Omnibus with accession numbers GSE174367. Additionally, the data can be accessed through our online web app: <http://swaruplab.bio.uci.edu/singlenucleiAD/>.

Code availability

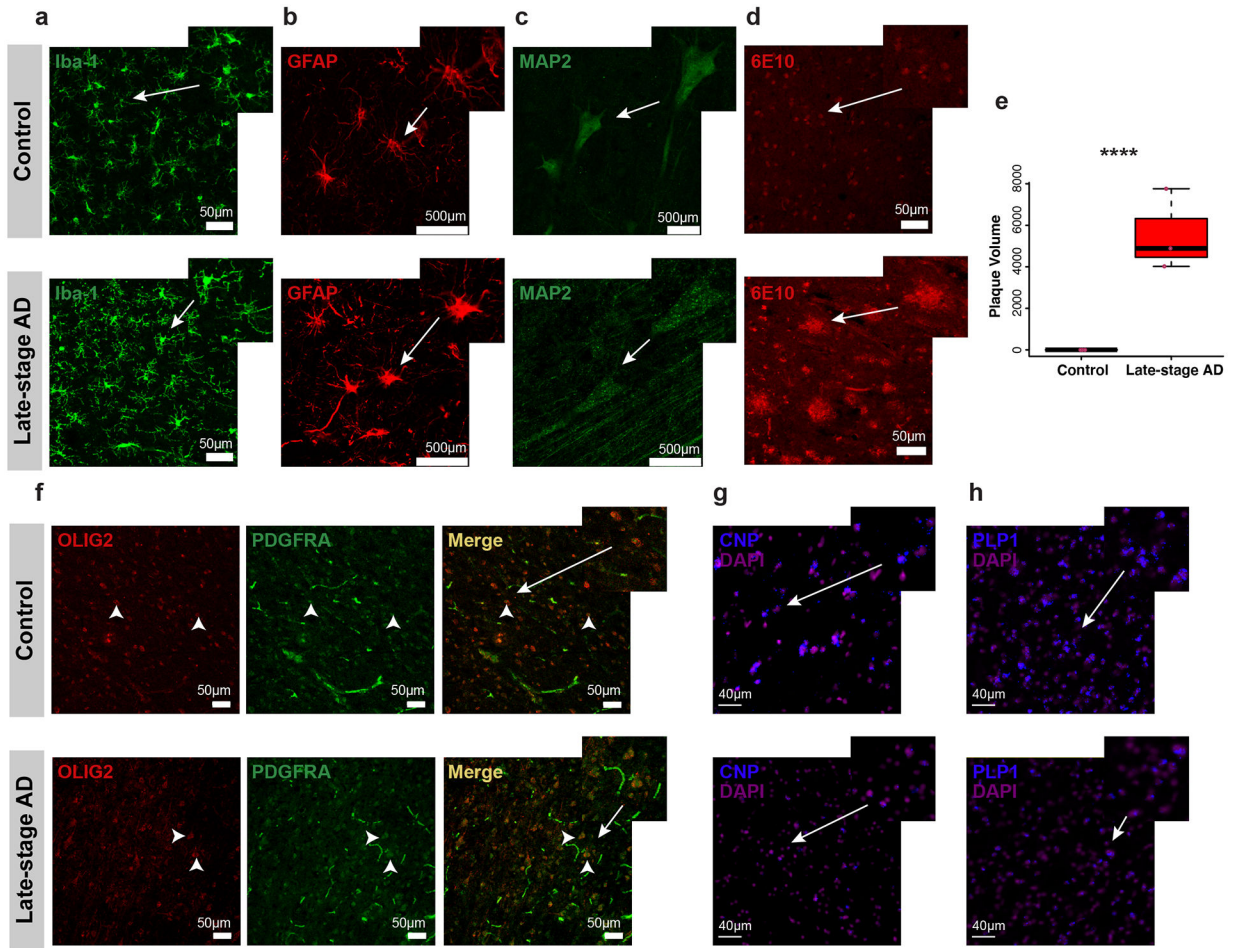
The custom code used for this manuscript is available on GitHub⁷⁴ (doi: 10.5281/zenodo.4681643): <https://github.com/swaruplab/Single-nuclei-epigenomic-and-transcriptomic-landscape-in-Alzheimer-disease>

Extended Data



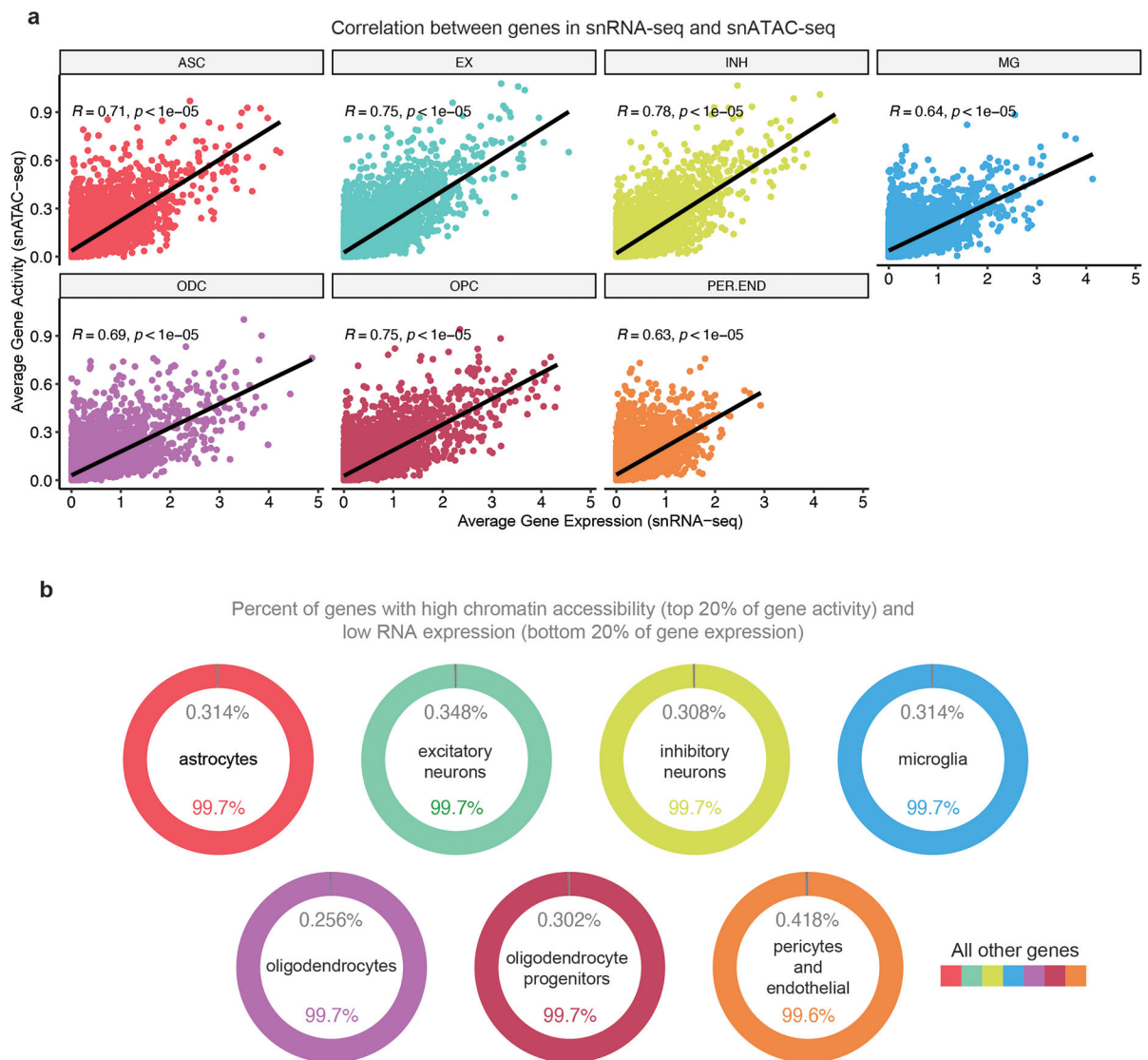
Extended Data Figure 1: Batch correction of snATAC-seq, snRNA-seq, and merged datasets.
a, snRNA-seq UMAPs before (left) and after iNMF batch correction (right), colored by sequencing batch. **b**, snATAC-seq UMAPs before (left) and after MNN batch correction (right), colored by sequencing batch. **c**, Dot plot of iNMF metagene expression in each snRNA-seq cluster. **d**, snRNA-seq UMAPs colored by metagene expression of selected iNMF metagenes. **e**, Dot plots showing the iNMF loading for the top 30 genes for the same metagenes in **d**.

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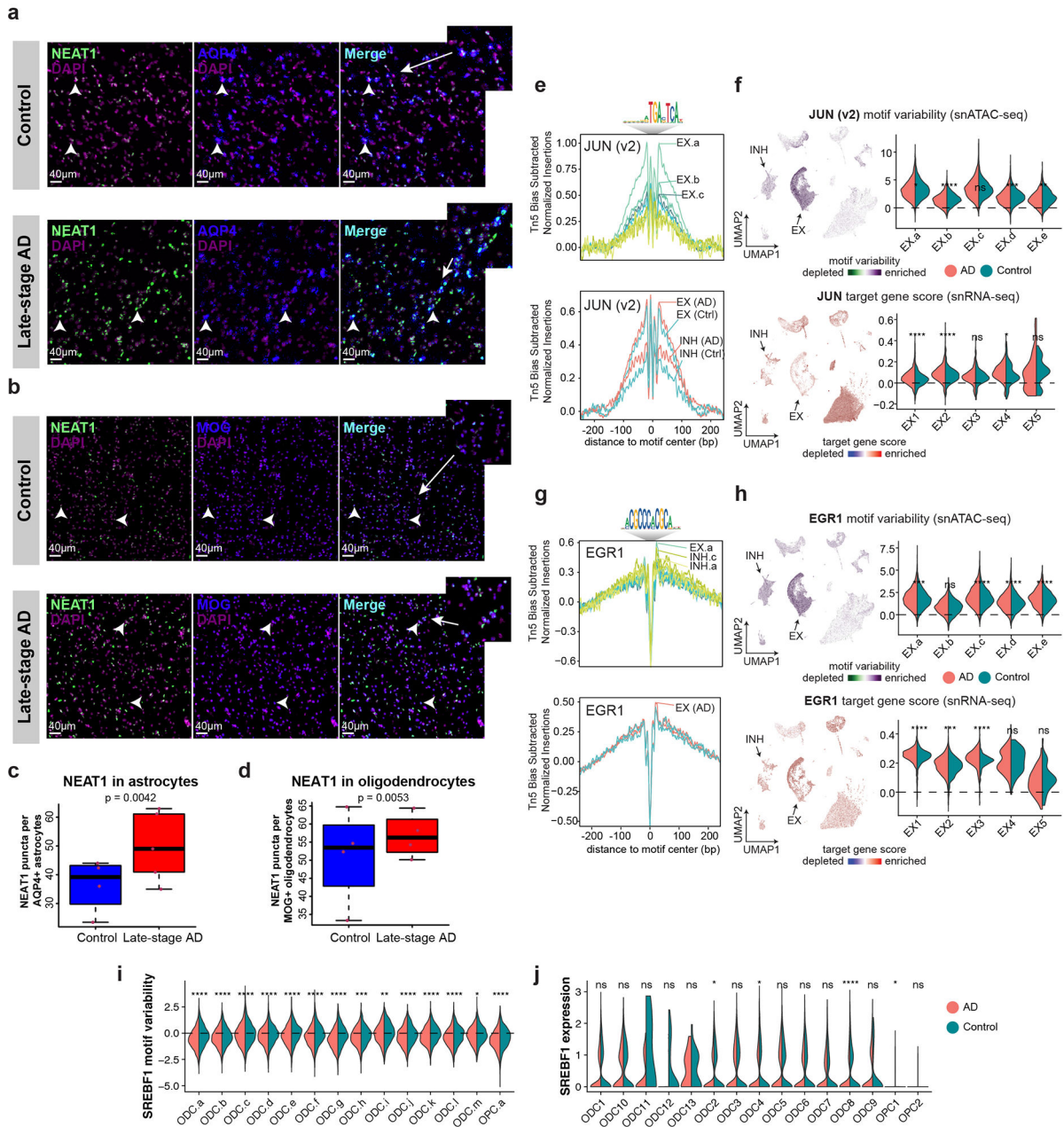
Extended Data Figure 2: Cell-type immunostaining and in situ hybridization.

a-d, Representative immunofluorescence images from postmortem human brain tissue from control and late-stage AD cases for Iba-1 (**a**), GFAP (**b**) MAP2 (**c**), and 6E10 (**d**). **e**, Quantification of 6E10-positive amyloid plaques. n = 3 cognitively healthy controls, 3 late-stage AD. Data is presented as the average of three different sections per sample. Linear mixed-effects model **** p < 0.0001. Box boundaries and line correspond to the interquartile range (IQR) and median respectively. Whiskers extend to the lowest or highest data points that are no further than 1.5 times the IQR from the box boundaries. **f**, Representative immunofluorescence images from postmortem human brain tissue from control and late-stage AD cases for OLIG2 with PDGFRA co-labeling. **g, h**, Representative RNAscope images from postmortem human brain tissue from control and late-stage AD cases for CNP (**g**) and PLP1 (**h**) with DAPI counterstain.



Extended Data Figure 3: Comparison of gene expression and gene activity.

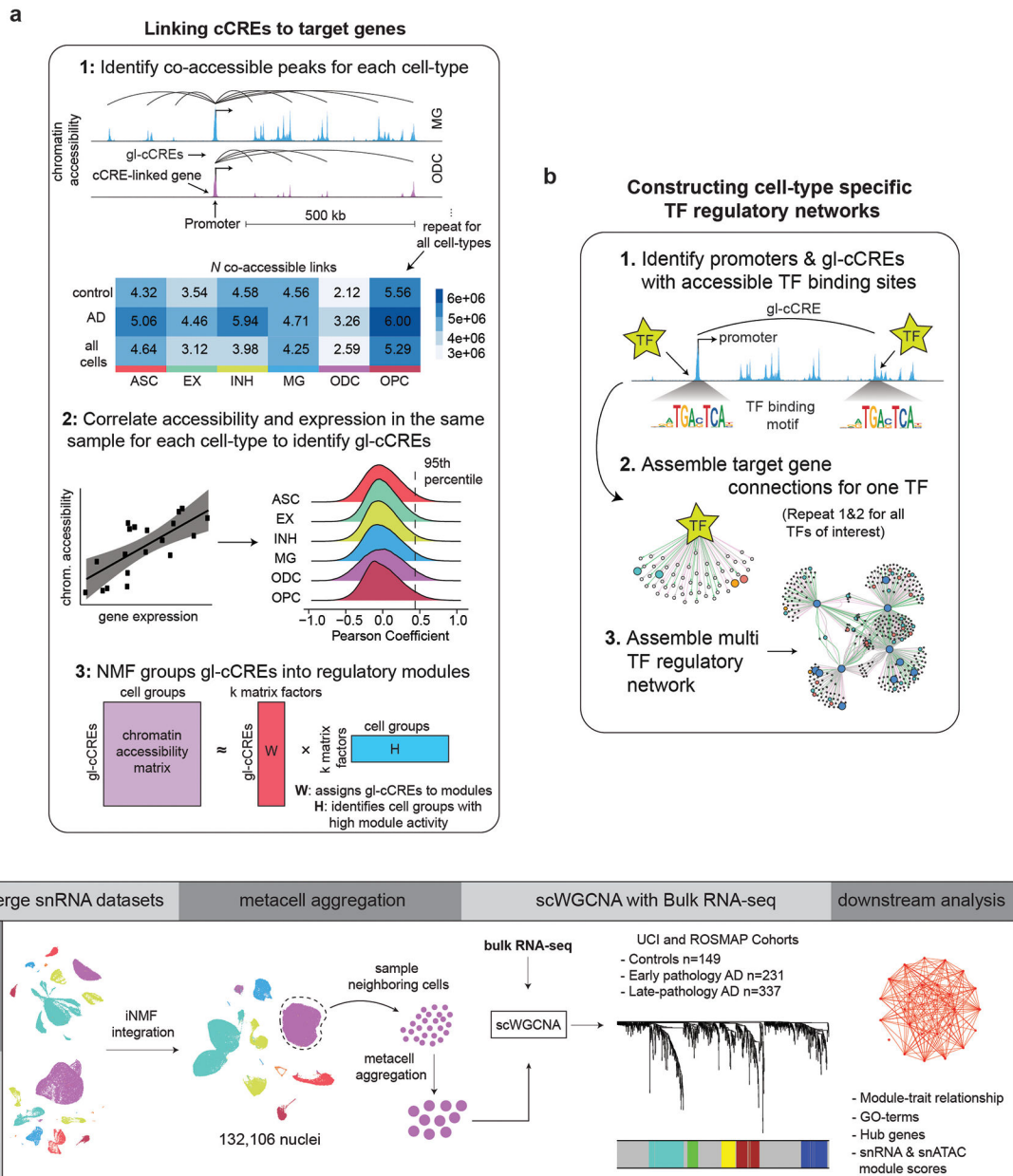
a. Scatter plot comparing average gene activity from snATAC-seq and average gene expression from snRNA-seq by each major cell-type, with accompanying Pearson correlation statistics and linear regression lines. **b.** Donut chart showing the percent of genes with high chromatin accessibility and low gene expression in grey for each major cell-type. High chromatin accessibility was defined as genes in the top 20% of gene activity, while low gene expression was defined as genes in the bottom 20% of gene expression. Percent of all other genes are colored by the cell-type.



Extended Data Figure 4: NEAT1 validation and neuronal TFs.

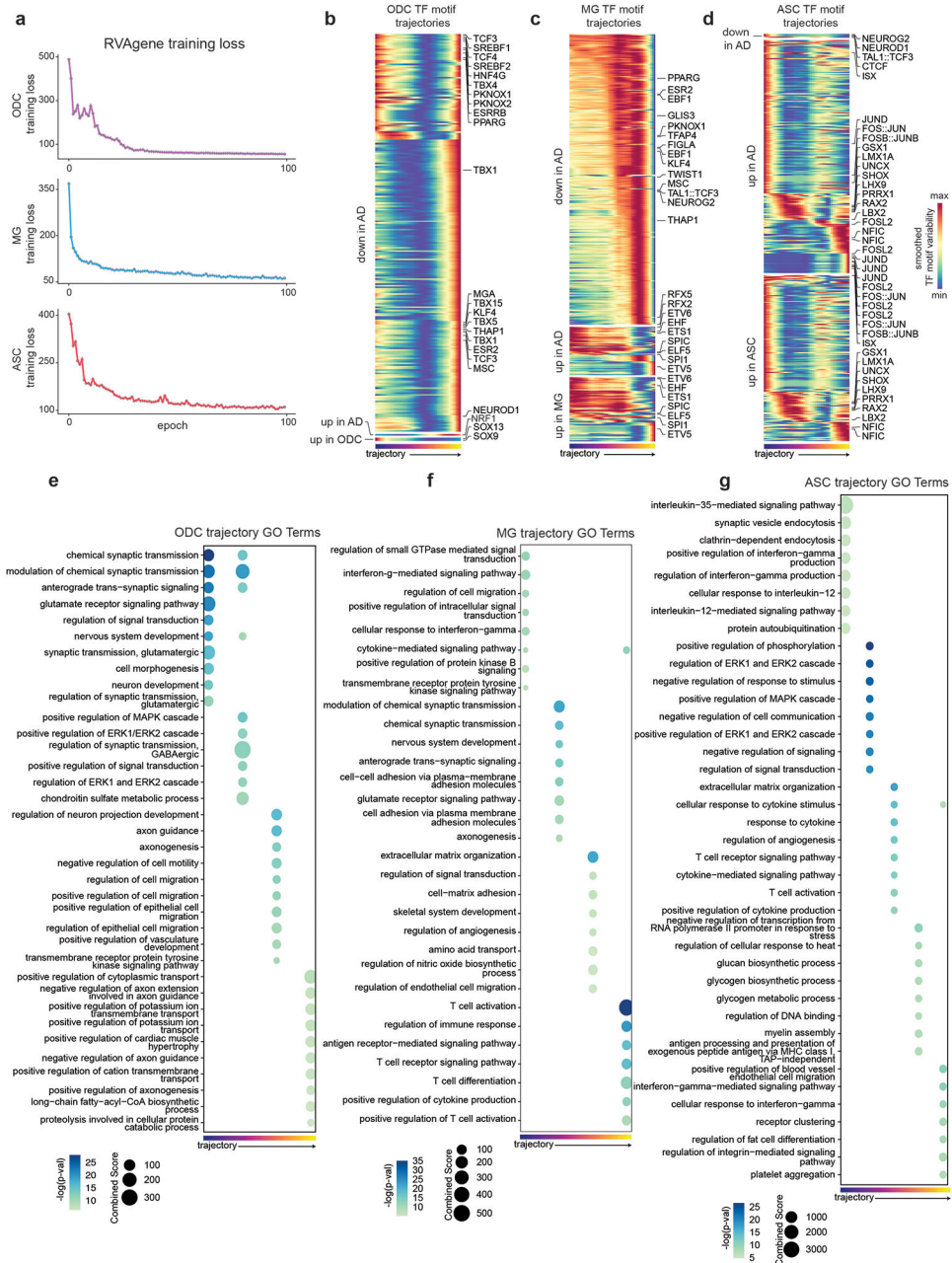
a, b, Representative RNAscope images from postmortem human brain tissue for *NEAT1* and *AQP4* staining (**a**) and *NEAT1* and *MOG* staining (**b**) with DAPI nuclear counterstain. **c**, Boxplots showing quantification of *NEAT1* puncta per *AQP4*⁺ astrocyte as in **a**. n = 4 cognitively healthy controls, 5 late-stage AD. **d**, Boxplots showing quantification of *NEAT1* puncta per *MOG*⁺ oligodendrocyte as in **b**. n = 4 cognitively healthy controls, 4 late-stage AD. Data is represented as the mean of four equally sized regions per sample. Linear mixed-effects model **e**, Tn5 bias subtracted TF footprinting for JUN by snATAC-seq neuron cluster (top) and by AD diagnosis (bottom), with TF binding motif logo above and Tn5 bias insertions below. **f**, Left: Co-embedding UMAP colored by JUN motif variability (top)

and JUN target gene score (bottom). Right: Violin plots of JUN motif variability (top) and JUN target gene score (bottom) in excitatory neuron clusters, split by diagnosis. Wilcoxon test (ns: $p > 0.05$, *: $p \leq 0.05$, **: $p \leq 0.01$, ***: $p \leq 0.001$, ****: $p \leq 0.0001$). **g**, Tn5 bias subtracted TF footprinting for EGR1 by snATAC-seq neuron cluster (top) and by AD diagnosis (bottom), as in **e**. **h**, Left: Co-embedding UMAP colored by EGR1 motif variability (top) and EGR1 target gene score (bottom). Right: Violin plots of EGR1 motif variability (top) and *EGR1* target gene score (bottom) in excitatory neuron clusters, split by diagnosis, as in **f**. **i**, Violin plots of SREBF1 motif variability in oligodendrocyte snATAC-seq clusters, as in **f**. **j**, Violin plots of SREBF1 gene expression in oligodendrocyte snRNA-seq clusters, as in **i**. For boxplots, box boundaries and line correspond to the interquartile range (IQR) and median respectively. Whiskers extend to the lowest or highest data points that are no further than 1.5 times the IQR from the box boundaries.



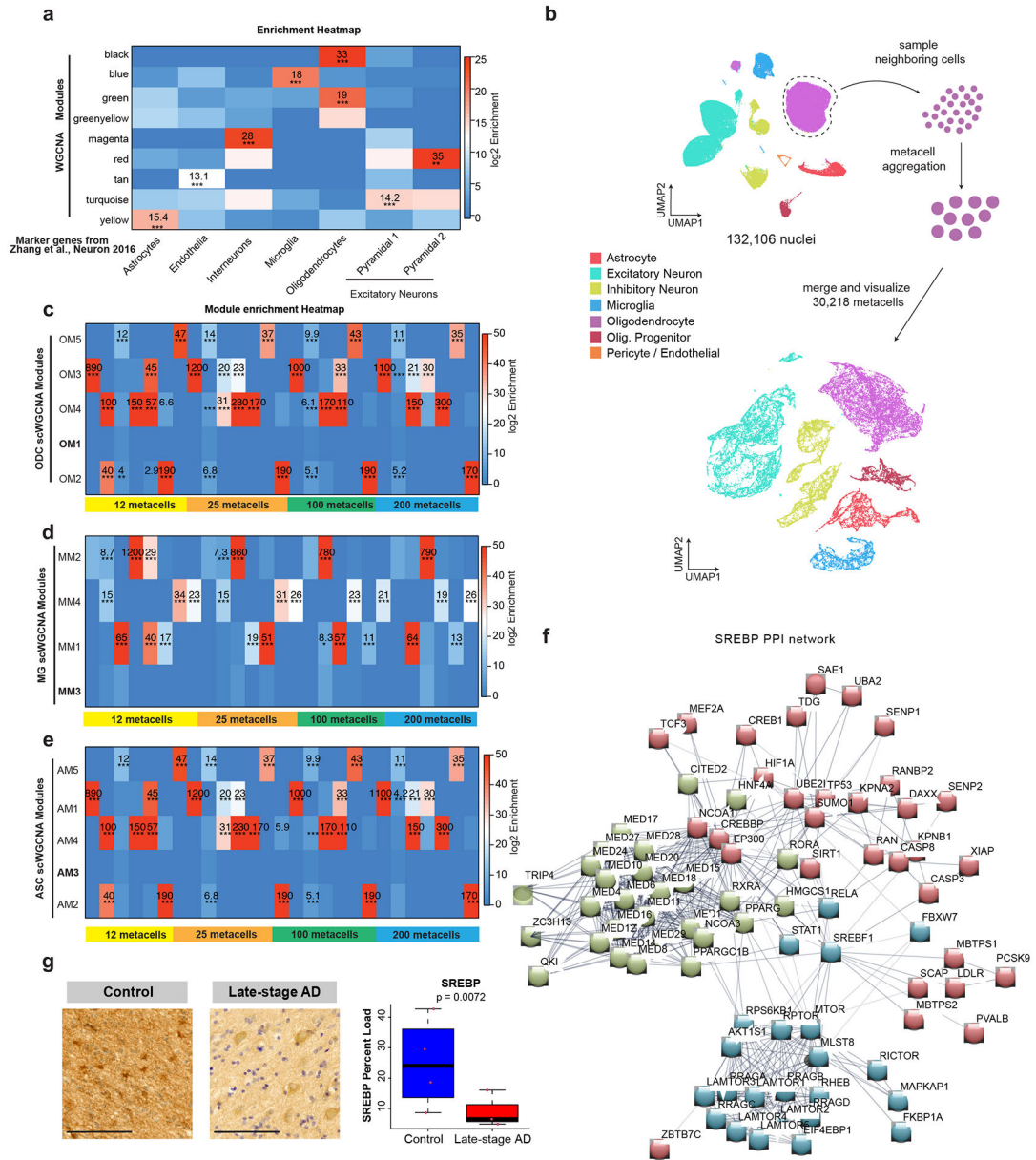
Extended Data Figure 5: Schematics of analyses.

a, Schematic diagram linking cCREs to target genes and downstream analysis. First, we identify co-accessible chromatin peaks in each cell-type for control and late-stage AD. Second, we identify pairs of co-accessible peaks where one peak overlaps a gene promoter and correlate the expression of that gene with the chromatin accessibility of the other peak. Third, NMF is used to group gl-cCREs into functional modules. **b**, Schematic of construction of TF regulatory networks for each cell-type. **c**, Schematic representation of scWGCNA analysis, including iNMF integration with the Mathys *et al.* 2019 dataset, *metacell* aggregation, construction of co-expression networks, and downstream analysis of gene modules.



Extended Data Figure 6: Pseudotime trajectory analysis to identify dysregulated TFs and gene expression in glia.

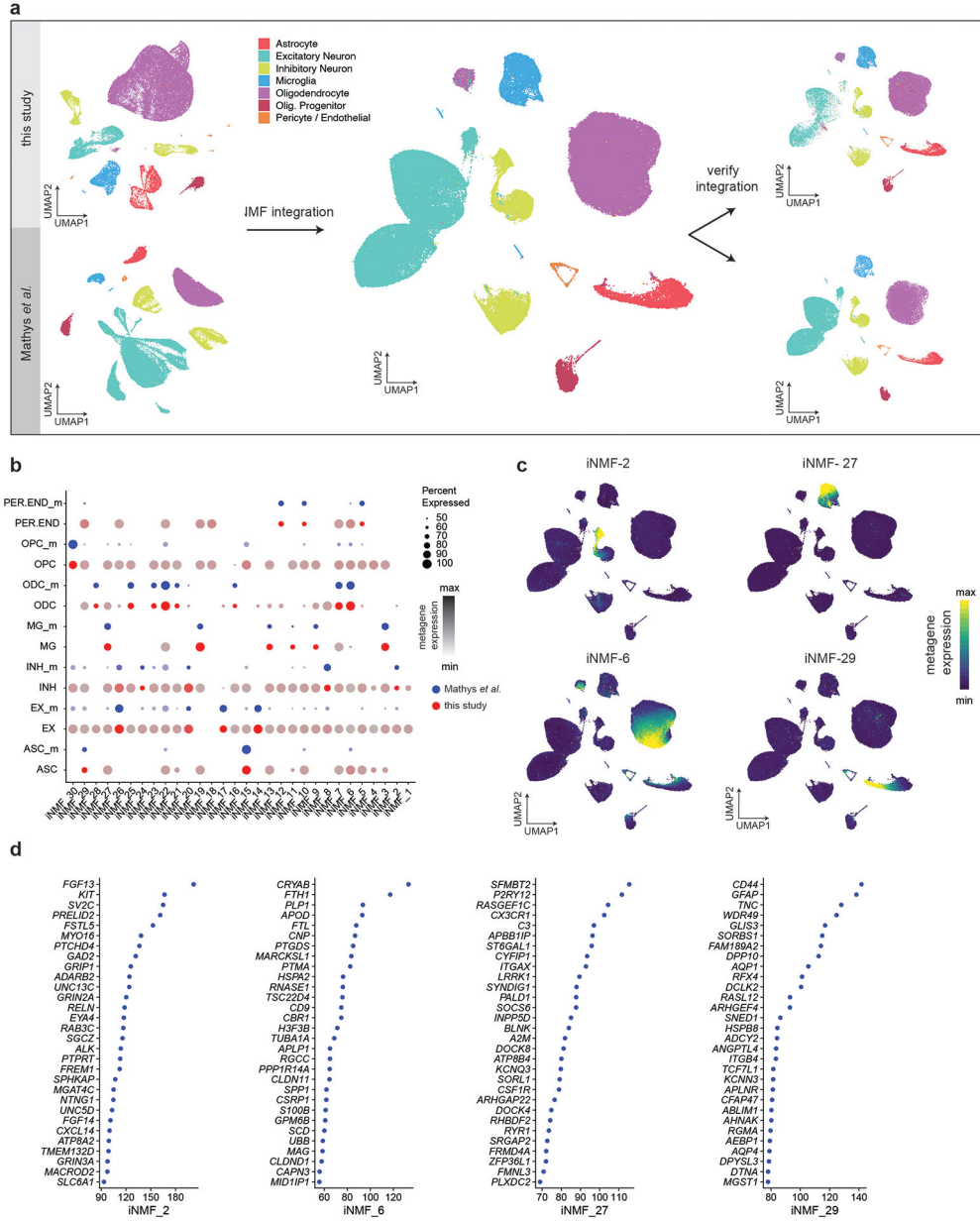
a, Line plot showing the RVAgene training loss at each epoch for oligodendrocyte (ODC), microglia (MG), and astrocyte (ASC) RVAE models. b-d, Heatmaps showing TF motif variability smoothed using loess regression and scaled to minimum and maximum values for TFs up- and down-regulated in AD as well as cell-type marker TFs along the oligodendrocyte trajectory (b), microglia trajectory (c), and astrocyte trajectory (d). TFs are ordered by trajectory rank (point in trajectory where 75% maximum value is reached). e-g, Dot plot showing the enrichR combined score for the top enriched GO terms in oligodendrocyte (e), microglia (f), and astrocyte (g) t-DEGs.



Extended Data Figure 7: Metacell aggregation and SREBP.

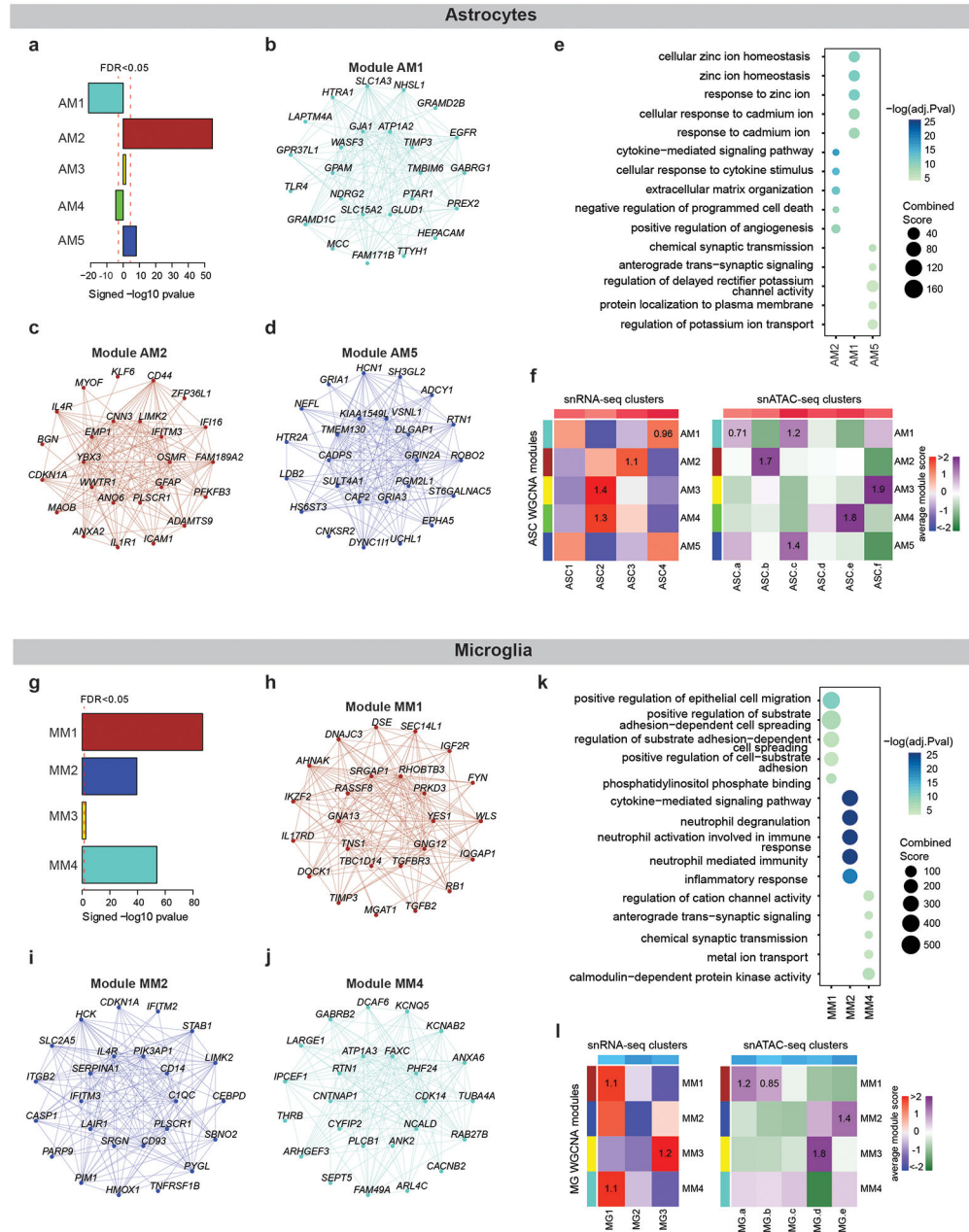
a, Heatmap showing the enrichment of cell-type marker genes in standard WGCNA modules constructed from our snRNA-seq data. **b**, Schematic showing generation of 30,218 *metacells* from the integrated transcriptomic dataset of 132,106 nuclei from our snRNA-seq and Mathys *et al.* **c-e**, Heatmap showing enrichment of oligodendrocyte (**c**), microglia (**d**), and astrocyte (**e**) scWGCNA modules constructed with 12 metacells, 25 metacells, 100 metacells, and 200 metacells in the scWGCNA modules constructed with 50 metacells, as shown in Fig. 7 and Supplementary Fig. 15-16. **f**, SREBP protein-protein interaction (PPI) network. Green circle denotes proteins involved in ribosome processing and transcription pathway, cyan circle for mTOR pathway, and red circle for lipid processing pathway. **g**, Left: Representative immunohistochemistry images from postmortem human brain tissue for SREBP with nuclear counterstain. Right: Quantification of SREBP staining. n = 4

pathological controls, 3 late-stage AD. Data is represented as the mean of four equally sized regions per sample. Scale bar represents 100 μm . Linear mixed-effects model $** p < 0.01$. Box boundaries and line correspond to the interquartile range (IQR) and median respectively. Whiskers extend to the lowest or highest data points that are no further than 1.5 times the IQR from the box boundaries.



Extended Data Figure 8: iNMF integration of snRNA-seq with Mathys et al. snRNA-seq.
a. Schematic representation of iNMF integration of snRNA-seq with Mathys et al. snRNA-seq. UMAP plots are colored by cell-type assignments. **b.** Dot plot of iNMF metagene expression in each cell-type, split by dataset of origin. **c.** UMAP plots of the integrated

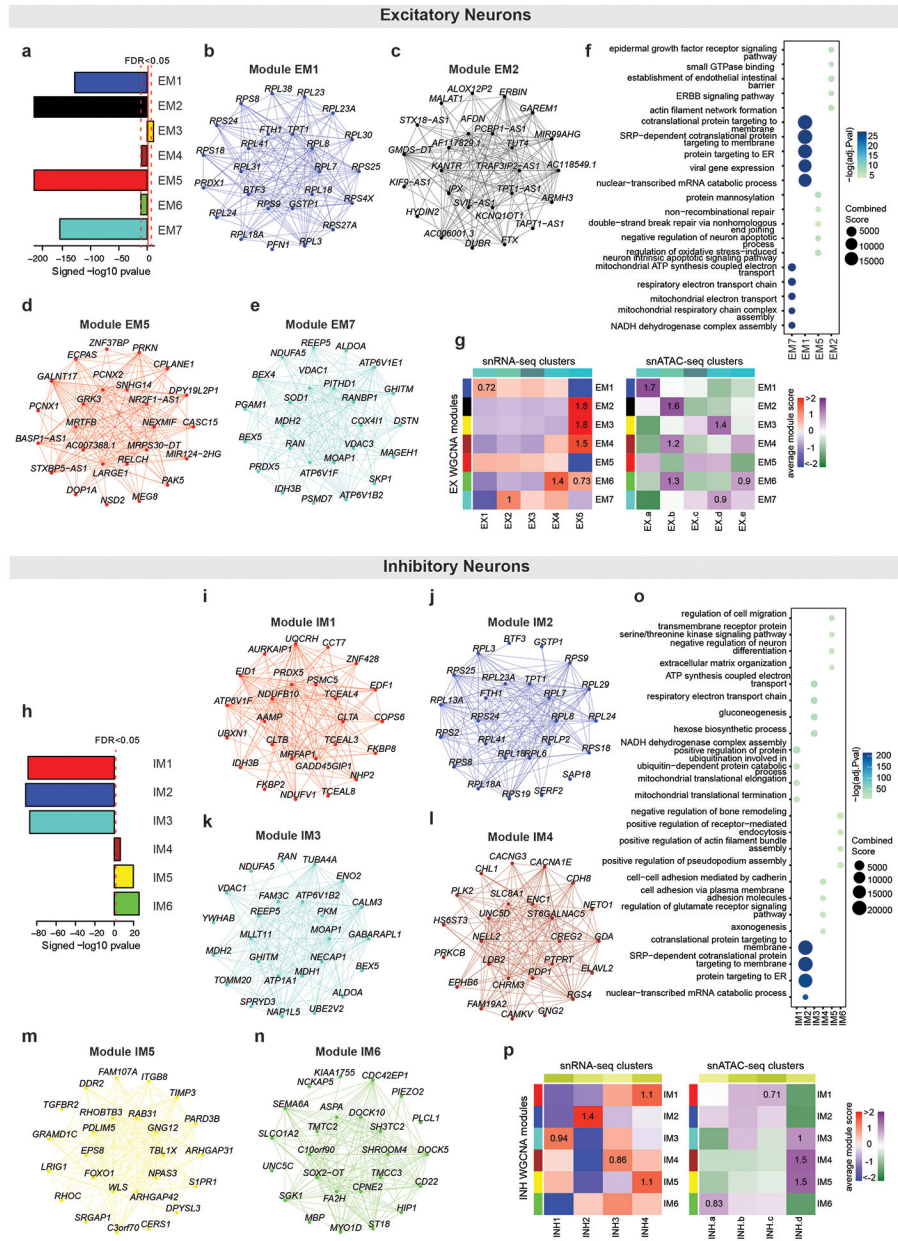
dataset colored by selected iNMF metagenes. **d**, Dot plots showing the iNMF loading for the top 30 genes for the same metagenes in **c**.



Extended Data Figure 9: scWGCNA in microglia and astrocytes.

a, Signed correlation of astrocyte modules to AD diagnosis. **b-d**, Co-expression plots for modules AM1 (**b**), AM2 (**c**), and AM5 (**d**). **e**, GO term enrichment of astrocyte modules. **f**, Heatmaps showing row-normalized Seurat module scores of astrocyte modules in snRNA-seq (left) and snATAC-seq (right) astrocyte clusters. **g**, Signed correlation of microglia co-expression modules with AD diagnosis. **h-j**, Co-expression plots for modules MM1 (**h**), MM2 (**i**), and MM4 (**j**). **k**, GO term enrichment of microglia modules. **l**, Heatmaps

showing row-normalized Seurat module scores of microglia modules in snRNA-seq (left) and snATAC-seq (right) microglia clusters.



Extended Data Figure 10: scWGCNA in neurons.

a, Signed correlation of excitatory neuron modules to AD diagnosis. **b-e**, Co-expression plots for modules EM1 (**b**), EM2 (**c**), EM5 (**d**), and EM7 (**e**). **f**, GO term enrichment of excitatory neuron modules. **g**, Heatmaps showing row-normalized Seurat module scores of excitatory neuron modules in snRNA-seq (left) and snATAC-seq (right) excitatory neuron clusters. **h**, Signed correlation of inhibitory neuron modules to AD diagnosis. **i-n**, Co-expression plots for modules IM1 (**i**), IM2 (**j**), IM3 (**k**), IM4 (**l**), IM5 (**m**), and IM6 (**n**). **o**, GO term enrichment of inhibitory neuron modules. **p**, Heatmaps showing row-normalized

Seurat module scores of inhibitory neuron modules in snRNA-seq (left) and snATAC-seq (right) inhibitory neuron clusters.

Supplementary Material

Refer to Web version on PubMed Central for supplementary material.

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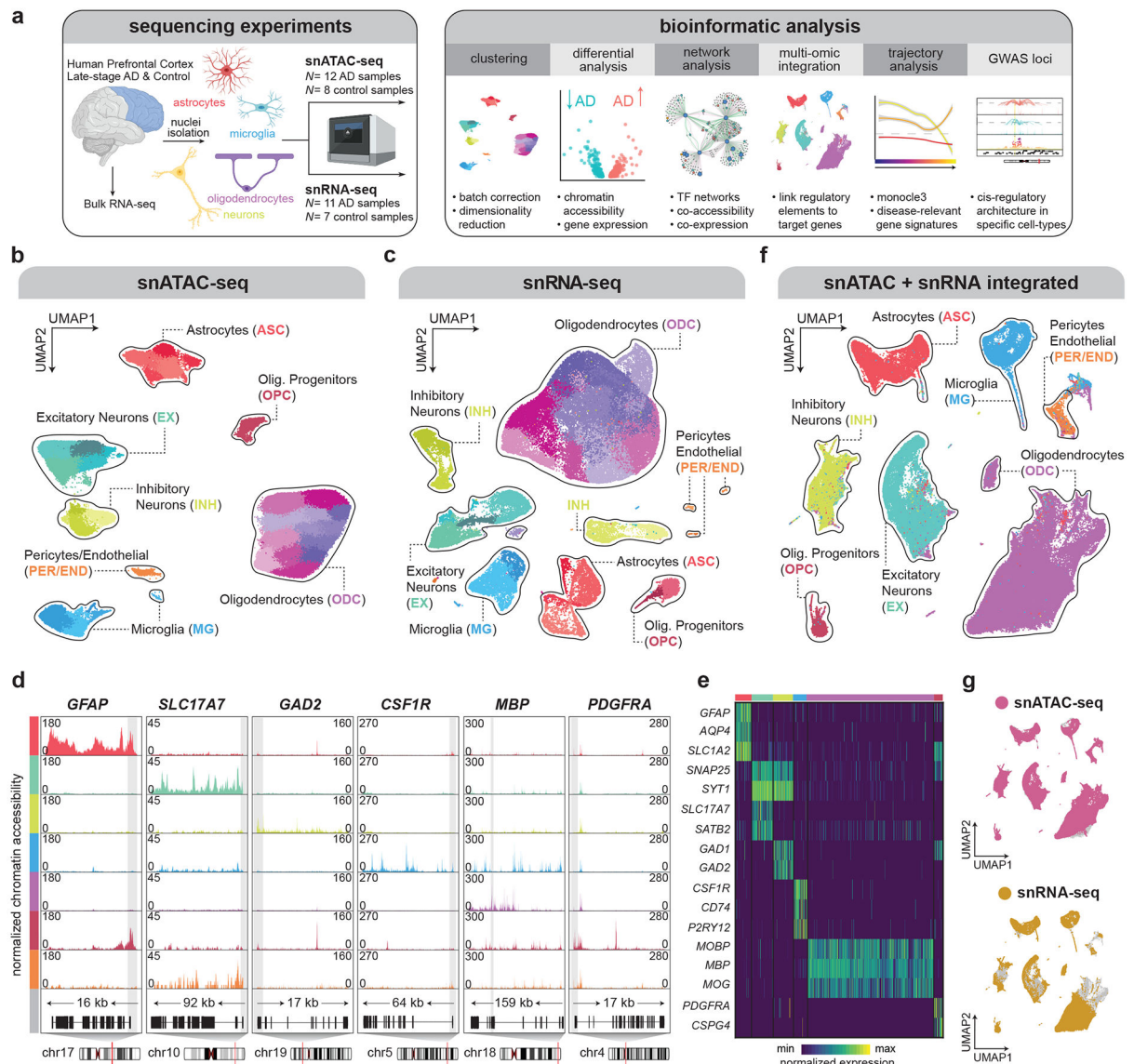


Figure 1: Single-nucleus ATAC-seq and single-nucleus RNA-seq to study cellular diversity in the diseased brain

a, Schematic representation of the samples used in this study, sequencing experiments, and downstream bioinformatic analyses, created with [BioRender.com](https://www.biorender.com/). **b, c**, UMAP visualizations where dots correspond to individual nuclei for 130,418 nuclei profiled with snATAC-seq (**b**) and 61,472 nuclei profiled with snRNA-seq (**c**), colored by Leiden cluster assignment and cell-type (ASC = astrocytes, EX = excitatory neurons, INH = inhibitory neurons, MG = microglia, ODC = oligodendrocytes, OPC = oligodendrocyte progenitor cells, PER/END = pericytes/endothelial cells). **d**, Pseudo-bulk chromatin accessibility profiles for each cell-type at canonical cell-type marker genes. For each gene, 1kb upstream and downstream are shown. Promoter/TSS highlighted in grey with gene model and chromosome position shown below. Chromosome coordinates are the following: *GFAP* chr17:44904008-44919937; *SLC17A7* chr19:49428401-49445360; *GAD2* chr10:26213307-26305558; *CSF1R* chr5:150052291-150116372; *MBP*

chr18:76977827-77136683; *PDGFRA* chr4:54226097-54299247. **e**, Row-normalized single-nucleus gene expression heatmap of cell-type marker genes. **f**, UMAP plot of 186,167 nuclei from a jointly learned subspace of snATAC-seq and snRNA-seq, colored by cell-type assignment. **g**, Integrated UMAP as in **f**, colored by originating dataset. Smaller gray dots represent nuclei from the other data modality. A consistent coloring scheme for each cell-type and cluster is used throughout the manuscript.

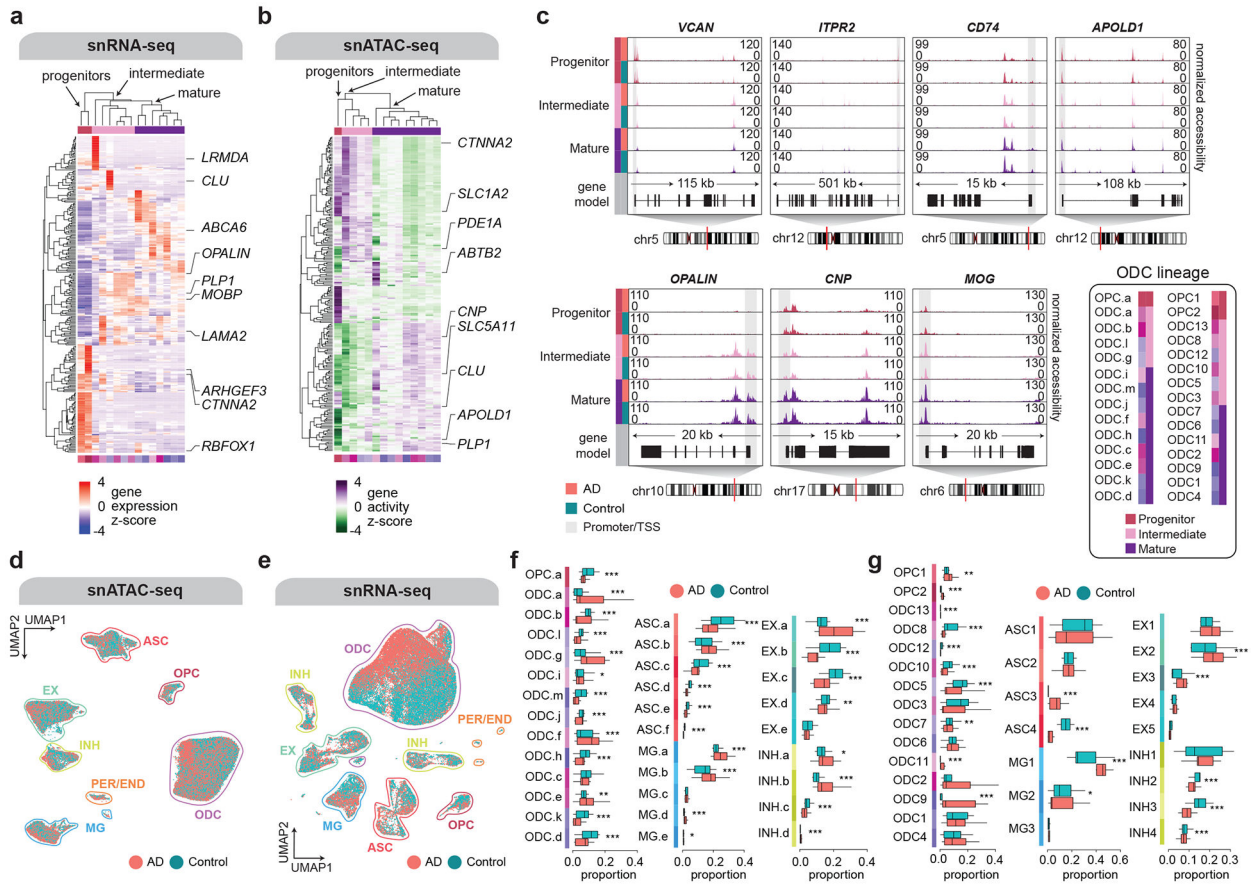


Figure 2: Epigenetically and transcriptionally distinct cell subpopulations in human AD prefrontal cortex
a,b, Hierarchically clustered heatmaps of row-normalized gene expression in snRNA-seq OPC and oligodendrocyte clusters (**a**) and gene activity in snATAC-seq OPC and oligodendrocyte clusters (**b**) for the top 25 upregulated DEGs (sorted by average log fold change) identified in each oligodendrocyte subpopulation. **c**, Pseudo-bulk chromatin accessibility coverage profiles for OPC (progenitor), intermediate oligodendrocyte and mature oligodendrocyte snATAC-seq clusters, assignments as in **b**. Promoter/TSS highlighted in grey with gene model and chromosome position shown below. Chromosome coordinates are the following: *VCAN* chr5: 83468465-83583303; *ITPR2* chr12: 26335515-26836198; *CD74* chr5: 150400637-150415929; *APOLD1* chr12: 12722917-12830975; *OPALIN* chr10: 96342216-96362365; *CNP* chr17: 41963741-41978731; *MOG* chr6: 29653981-29673372. **d,e**, snATAC-seq (**d**) and snRNA-seq (**e**) UMAPs as in Fig. 1, where nuclei are colored by AD diagnosis. Clusters annotated by cell type. **f,g**, Box and whisker plots showing the proportion of nuclei mapping to each cluster for each sample, split by control and late-stage AD samples for snATAC-seq (**f**) and snRNA-seq (**g**) clusters, with measures of significance from bootstrapped cluster composition analysis (Wilcoxon test, see Methods, *** FDR <= 0.001, ** FDR <= 0.01, * 0.01 < FDR <= 0.05) and n as in Supplementary Tables 7-9. For box and whisker plots, box boundaries and line correspond to the interquartile range (IQR) and median respectively.

Whiskers extend to the lowest or highest data points that are no further than 1.5 times the IQR from the box boundaries.

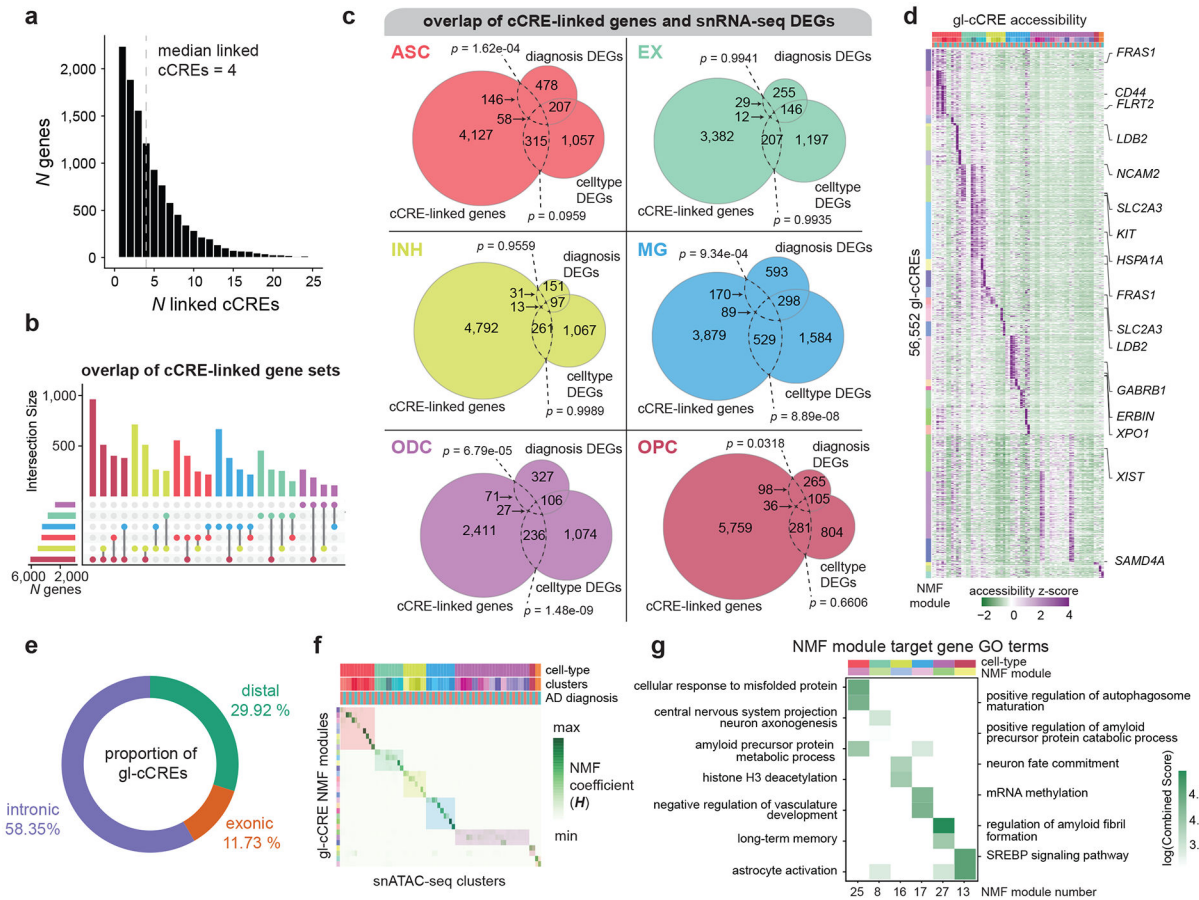


Figure 3: Linking cis-regulatory elements to downstream target genes in specific cell-types
a, Histogram showing the number of genes that have 1 through 25 linked cCREs. **b**, Upset plot showing the size of overlaps between the sets of cCRE-linked genes identified in each cell-type. The barplot on the left shows the set size of cCRE-linked genes for each cell-type, and the barplot on the top shows the number of overlapping genes between two sets, or the number of unique genes in one set. **c**, Venn diagrams for each major cell-type showing the overlaps between the set of cCRE-linked genes and genes upregulated in that cell-type (celltype DEGs) and genes upregulated in AD within this cell-type (diagnosis DEGs). A one-sided Fisher's exact test was used for gene set overlap significance (***) $p \leq 0.001$, ** $p \leq 0.01$, * $p < 0.05$). **d**, Heatmap showing row-normalized pseudo-bulk chromatin accessibility in each snATAC-seq cluster split by nuclei from control and late-stage AD samples. Rows (cCREs) are organized based on NMF module assignment. Annotations correspond to genes from DGE analysis that are upregulated in AD in at least one cell-type. **e**, Donut chart showing the percentage of gl-cCREs that map to intronic, exonic, or distal regions. **f**, Heatmap showing NMF coefficients in each snATAC-seq cluster split by nuclei from control and late-stage AD samples. **g**, Heatmap showing log transformed enrichR combined scores for GO terms for gene sets of selected NMF modules.

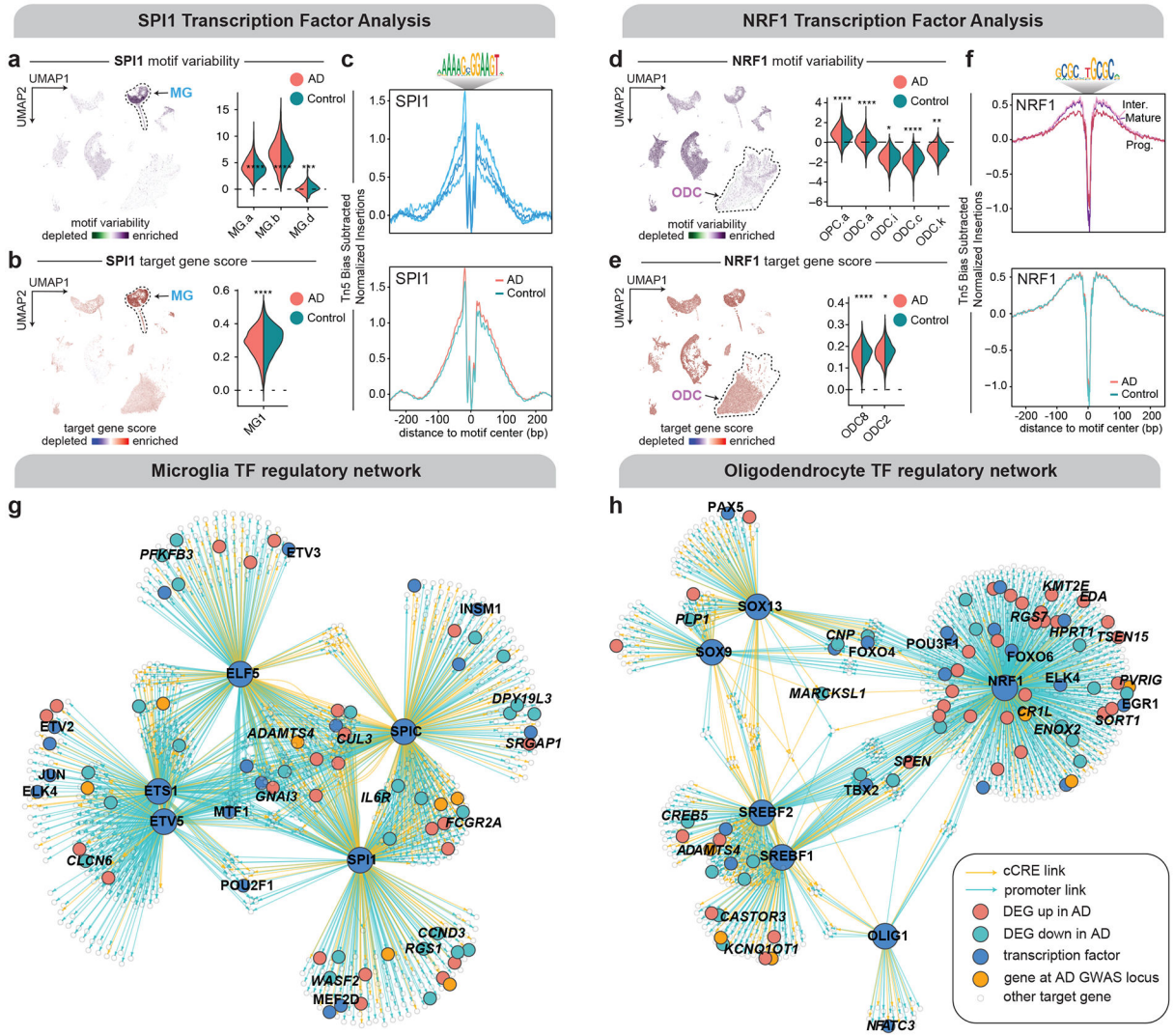


Figure 4: Cell subpopulation-specific transcription factor regulation in late-stage AD
a, Left: snATAC-seq and snRNA-seq integrated UMAP colored by SPI1 motif variability with microglia circled. Right: Violin plots of SPI1 motif variability in significant snATAC-seq microglia clusters, split by diagnosis. **b**, Left: Integrated UMAP colored by SPI1 target gene score with microglia circled. Right: Violin plots of SPI1 target gene score in significant snRNA-seq microglia clusters, split by diagnosis as in **a**. **c**, Tn5 bias subtracted TF footprinting for SPI1 by snATAC-seq microglia cluster (top) and by AD diagnosis (bottom). TF binding motif shown as motif logo above. **d**, Left: Integrated UMAP colored by NRF1 motif variability with oligodendrocytes circled. Right: Violin plots of NRF1 motif variability in significant snATAC-seq oligodendrocyte clusters, split by diagnosis as in **a**. **e**, Left: Integrated UMAP colored by NRF1 target gene score with oligodendrocyte circled. Right: Violin plots of NRF1 target gene score in significant snRNA-seq oligodendrocyte clusters, split by diagnosis as in **a**. **f**, Tn5 bias subtracted TF footprinting for NRF1 by snATAC-seq oligodendrocyte cluster (top) and by AD diagnosis (bottom) as in **b**. **g, h**, TF regulatory networks showing the predicted candidate target genes for the following TFs:

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ELF5, ETS1, ETV5, SPIC, and SPI1 in microglia (**g**); SOX9, SOX13, SREBF1, SREBF2, OLIG1, and NRF1 in oligodendrocytes (**h**). For violin plots, two-sided Wilcoxon test was used to compare control versus AD, ns: $p > 0.05$, *: $p \leq 0.05$, **: $p \leq 0.01$, ***: $p \leq 0.001$, ****: $p \leq 0.0001$.

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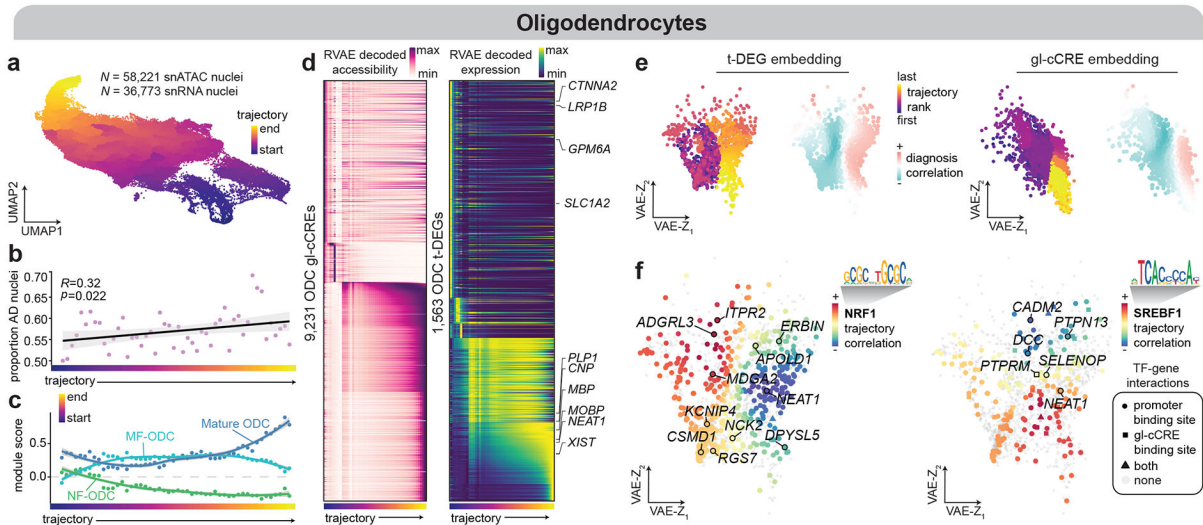


Figure 5: Multi-omic oligodendrocyte trajectory analysis

a, UMAP dimensionality reduction of oligodendrocytes from the integrated snATAC-seq (n=58,221 nuclei) and snRNA-seq (n=36,773 nuclei) analysis. Each cell is colored by its pseudotime trajectory assignment. **b**, Scatter plot showing the proportion of oligodendrocyte nuclei from AD samples at 50 evenly sized bins across the trajectory. The black line shows a linear regression, and the gray outline represents the 95% confidence interval. Pearson correlation coefficient and p-value from two-sided test are shown. **c**, Scatter plot of module scores for newly formed oligodendrocyte (NF-ODC), myelin forming oligodendrocyte (MF-ODC) and mature oligodendrocyte gene signatures^{36,37} (see Supplementary Note for full gene lists) averaged for nuclei in each of the 50 trajectory bins. Solid colored lines represent loess regressions for each signature, and the gray outlines represent 95% confidence intervals. **d**, Left: heatmap of chromatin accessibility at 9,231 oligodendrocyte gl-cCREs reconstructed using RVAE. Right: heatmap of gene expression for 1,563 oligodendrocyte trajectory DEGs (t-DEGs) reconstructed using RVAE. Annotated genes are DEGs in oligodendrocytes, in respect to other cell-types, or AD upregulated genes in oligodendrocytes. **e**, 2D latent space learned by RVAE modeling of oligodendrocyte t-DEGs (left) and gl-cCREs (right), where each dot represents one gene. Left: genes colored by trajectory rank, the point in the trajectory where the gene reaches 75% of max expression. Right: genes colored by correlation of RVAE reconstructed expression with AD diagnosis proportion as in **b**. **f**, Oligodendrocyte t-DEG latent space colored by correlation of reconstructed gene expression to NRF1 (left) and SREBF1 (right) motif variability. The shape of each point represents the regulatory relationship between the TF and each gene, while genes without regulatory evidence are shown as small gray dots. Annotated genes are AD upregulated genes in oligodendrocytes (AD DEGs). TF binding motifs are shown as motif logos.

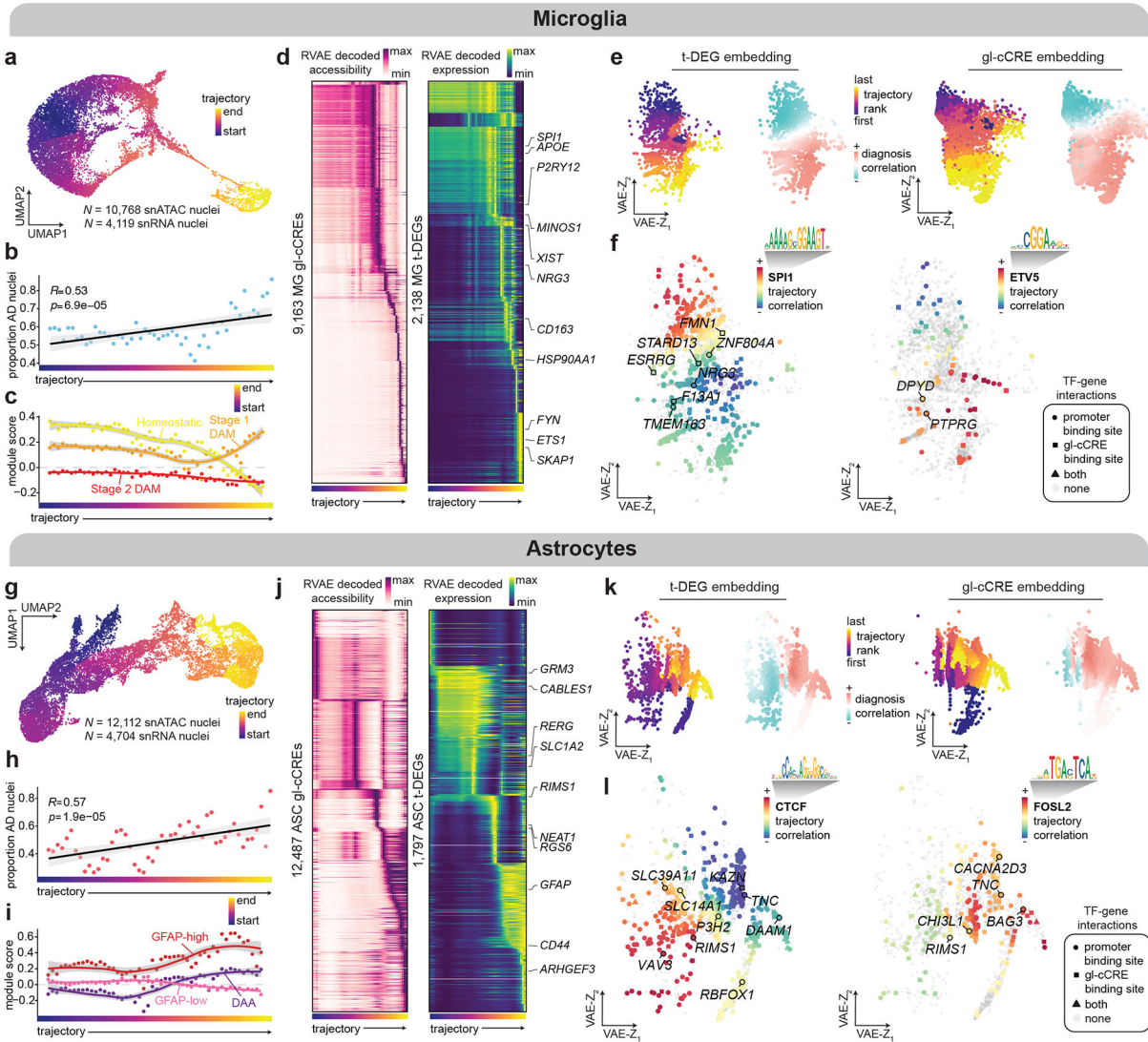


Figure 6: Multi-omic microglia and astrocyte trajectory analyses
a, UMAP dimensionality reduction of microglia from the integrated snATAC-seq (n=10,768 nuclei) and snRNA-seq (n=4,119 nuclei) analysis. **b**, Scatter plot of the proportion of AD microglia nuclei as in Fig. 5b. **c**, Scatter plot of module scores as in Fig. 5c for gene signatures from Keren-Shaul *et al*⁴⁰: homeostatic microglia, Stage 1 disease-associated microglia (DAM), and Stage 2 DAM (see Supplementary Note for full gene lists). **d**, Heatmaps of RVAE reconstructed chromatin accessibility and gene expression as in Fig. 5d, for 9,163 microglia gl-cCREs (left) and 2,138 microglia t-DEGs (right). **e**, 2D latent space learned by RVAE modeling of microglia t-DEGs (left) and gl-cCREs (right), as in Fig. 5e. **f**, Microglia t-DEG latent space colored by correlation of gene expression to SPI1 (left) and ETV5 (right) motif variability, as in Fig. 5f. **g**, UMAP dimensionality reduction of astrocytes from the integrated snATAC-seq (n=12,112 nuclei) and snRNA-seq (n=4,704 nuclei) analysis. **h**, Scatter plot of the proportion of AD astrocyte nuclei as in **b**. **i**, Scatter plot of module scores as in **c** for gene signatures from Habib *et al.* 2020²⁹: GFAP-low, GFAP-high, and Disease Associated Astrocytes (DAA, see Supplementary Note for full

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gene lists). **j**, Heatmaps of RVAE reconstructed chromatin accessibility and gene expression as in **d** for 12,487 astrocyte gl-cCREs (left) and 1,797 astrocyte t-DEGs (right). **k**, 2D latent space learned by RVAE modeling of astrocyte t-DEGs (left) and gl-cCREs (right), as in **e**. **l**, Astrocyte t-DEG latent space colored by correlation of gene expression to CTCF (left) and ETV5 (right) motif variability, as in **f**.

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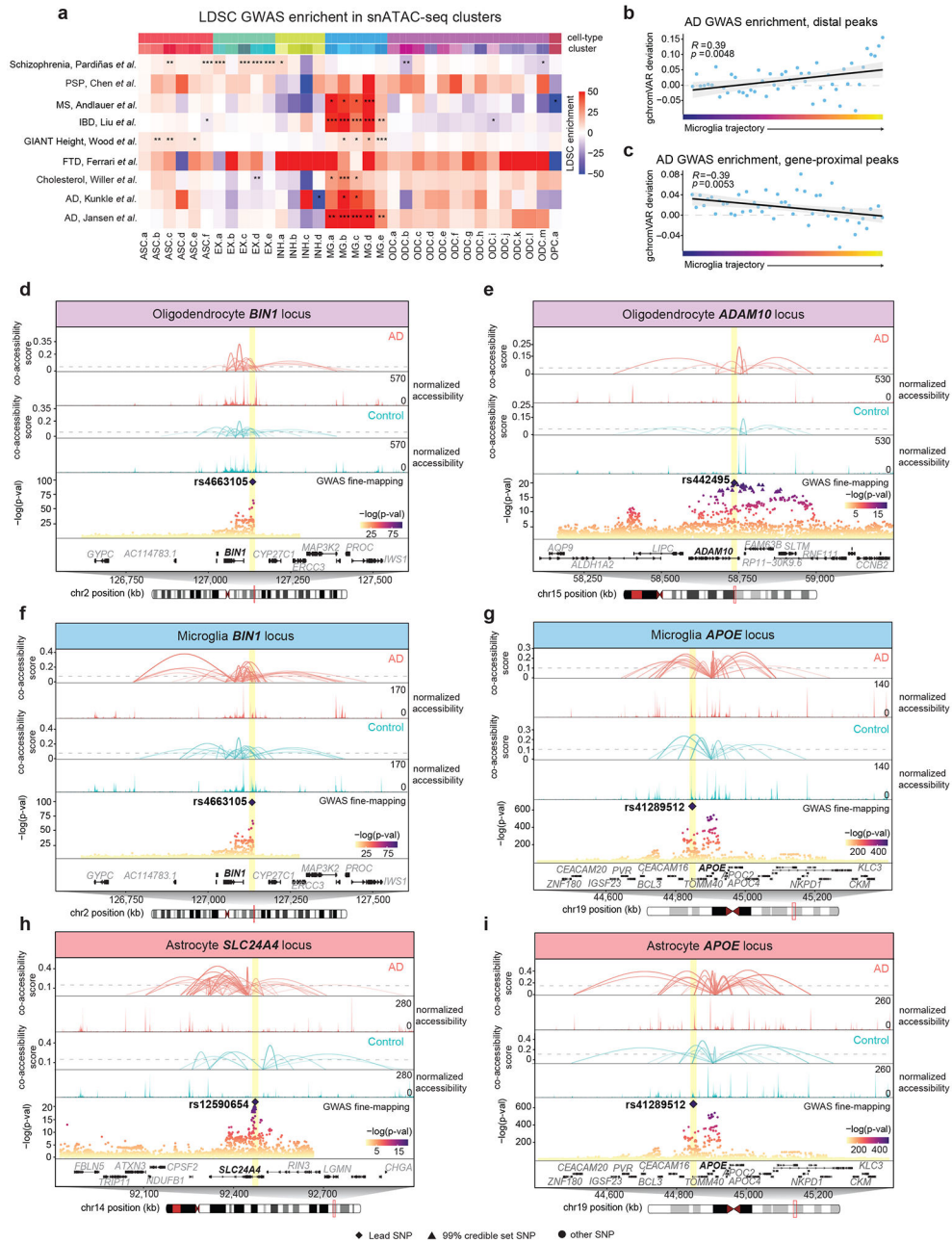


Figure 7: Cell-type specific regulatory landscapes of GWAS loci in the AD brain
a, Heatmap showing LDSC enrichment of GWAS traits and disorders in snATAC-seq clusters. P-values are derived from LDSC enrichment tests, and FDR corrected p-values are overlaid on the heatmap (*: FDR < 0.05, **: FDR < 0.005, ***: FDR < 0.0005). **b**, **c**, Scatter plots showing gchromVAR enrichments along the microglia pseudotime trajectory in distal peaks (**b**) and gene-proximal peaks (**c**) averaged for nuclei in each of the 50 trajectory bins. The black line shows a linear regression, and the gray outline represents the 95% confidence interval. Pearson correlation coefficient and p-value are shown. **d-i**, Cis-regulatory architecture at the following GWAS loci and cell-types: *BIN1* (**d**) and *ADAM10* (**e**) in oligodendrocytes; *BIN1* (**f**) and *APOE* (**g**) in microglia; *SLC24A4* (**h**) and *APOE*

(i) in astrocytes. Co-accessible links for late-stage AD and control are shown separately, with the line height and opacity corresponding to the co-accessibility score; links with a score below the gray dotted line are removed for visualization purposes. Genomic coverage plots for AD and control are shown separately. Jansen *et al.* AD GWAS statistics for SNPs at each locus are shown. Lead SNPs are shown as diamonds, and SNPs in 99% credible set are shown as triangles. Chromosome ideogram indicates genomic coordinates in a 500 kilobase radius centered at each GWAS gene. Chromosome coordinates are the following: *BIN1* chr2:127047027-127110355; *ADAM10* chr15:58587807-58752978; *APOE* chr19:44902754-44910393; *SLC24A4* chr14:92319581-92502483.

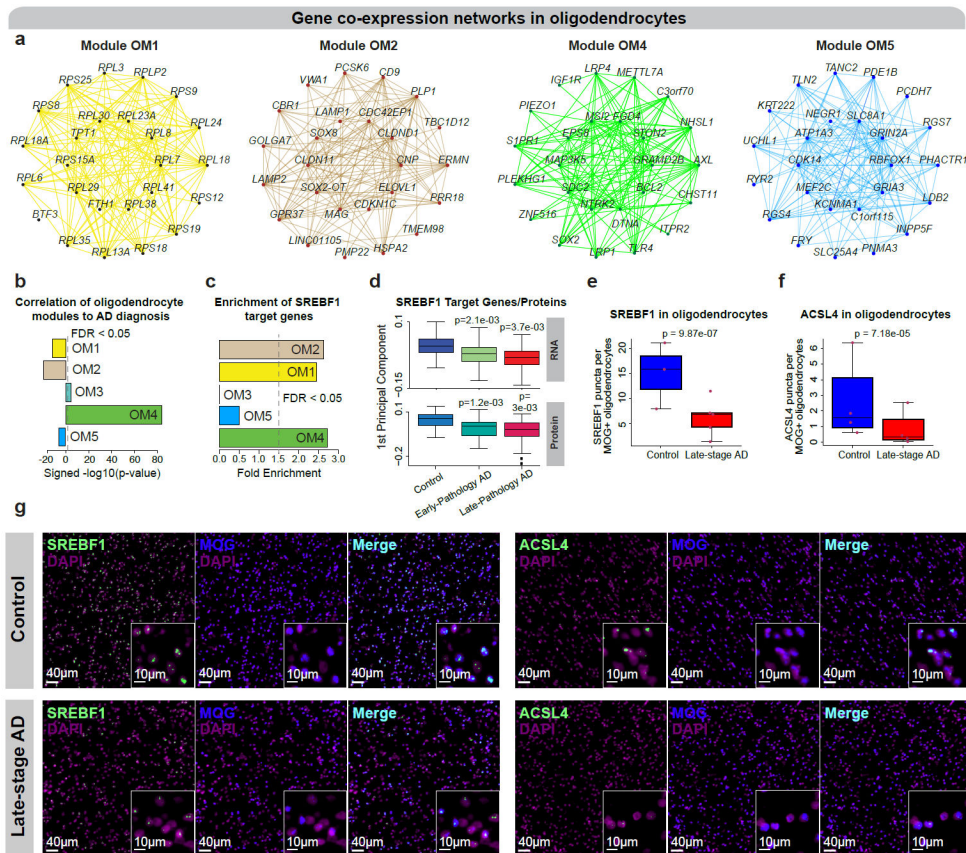


Figure 8: Robust co-expression modules revealed using integrated bulk and single cell co-expression network analysis

a, Co-expression plots for modules OM1, OM2, OM4, and OM5. **b**, Signed correlation oligodendrocyte co-expression modules with AD diagnosis. **c**, Enrichment of SREBF1 target genes in oligodendrocyte co-expression modules. **d**, Boxplots showing RNA (top) and protein expression⁵⁹ (bottom; $n = 98$ controls, 76 early-pathology, 101 late-pathology) of SREBF1's targets with AD pathological staging. Two-sided Wilcoxon test. **e**, Boxplots showing quantification of *SREBF1* puncta per *MOG*⁺ oligodendrocyte. $n = 3$ cognitively healthy controls, 5 late-stage AD. Data is represented as the mean of four equally sized regions per sample. Linear mixed-effects model. **f**, Boxplots showing quantification of *ACSL4* puncta per *MOG*⁺ oligodendrocyte. $n = 4$ cognitively healthy controls, 4 late-stage AD. Data is represented as the mean of four equally sized regions per sample. Linear mixed-effects model. **g**, Representative RNA fluorescence *in situ* hybridization (RNAscope) images from postmortem human brain tissue for combined *SREBF1* and *MOG* staining as in **e** (left) and *ACSL4* and *MOG* staining as in **f** (right) with DAPI nuclear counterstain. For box and whisker plots, box boundaries and line correspond to the interquartile range (IQR) and median respectively. Whiskers extend to the lowest or highest data points that are no further than 1.5 times the IQR from the box boundaries.