Integrated Systems Analysis Deciphers Transcriptome and Glycoproteome Links in Alzheimer's Disease

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Graphical Abstract

Abstract

Glycosylation is increasingly recognized as a potential therapeutic target in Alzheimer's

disease. In recent years, evidence of Alzheimer's disease-specific glycoproteins has been

established. However, the mechanisms underlying their dysregulation, including tissue- and

cell-type specificity, are not fully understood. We aimed to explore the upstream regulators of

aberrant glycosylation by integrating multiple data sources using a glycogenomics approach.

We identified dysregulation of the glycosyltransferase PLOD3 in oligodendrocytes as an

upstream regulator of cerebral vessels and found that it is involved in COL4A5 synthesis,

which is strongly correlated with amyloid fiber formation. Furthermore, COL4A5 has been

suggested to interact with astrocytes via extracellular matrix receptors as a ligand. This

study suggests directions for new therapeutic strategies for Alzheimer's disease targeting

glycosyltransferases.

Keywords:

Glycoproteomics, Transcriptome, Glycosyltransferase, Extracellular Matrix, Alzheimer's

disease

Introduction

Alzheimer's disease (AD) is an age-related neurodegenerative disease[1,2]. The primary causes are neurogenic cell loss, accumulation of misfolded proteins, oxidative stress, and inflammatory responses[3]. Genomic, transcriptomic, and epigenetic mechanisms have been intensively examined[4]. However, our knowledge of the post-translational modifications that regulate cellular functions and interactions between cells is still lacking[5]. In particular, glycosylation is the most diverse and abundant post-translational modification among protein modifications[6].

Protein glycosylation is a complex multistep process involving approximately 200 different glycosyltransferases[6–8]. There are 16 major glycosylation pathways, including lipid glycosylation, N-glycosylation, O-glycosylation, C-mannosylation, lipid glycosylation, and glycosylphosphatidylinositol (GPI)-anchored synthesis. Recently, glycomics / glycoproteomics analysis of the human AD postmortem brain[9,10], serum,[11–17] and cerebrospinal fluid[18–20] for N-glycosylation, the most abundant glycosylation pathway, has revealed dysregulated glycoproteins. In addition, the biological functions of abnormal glycans in AD pathology have been reported in some cases; for example, it is known that inhibition of BACE1 glycosylation reduces the cleavage of the amyloid ß precursor protein (APP) [21–23]. However, most biological functions of glycosylation in the pathogenesis of AD are poorly understood.

Glycan structures are not independent of the DNA template, and glycosylation depends on a combination of approximately 200 glycosyltransferases and 500 related proteins[6–8]. Thus, their dysregulation may act as an upstream regulatory factor that triggers abnormal glycosylation processes[24]. In addition, it is difficult to elucidate biological glycosylation mechanisms at the single-cell resolution using glycomics / glycoproteomics alone because current technology is limited to probing with glycosylation-specific antibodies and glycan-binding proteins, such as lectin [6]. Therefore, a glycogenomics approach that integrates genomics, or functional genomics, and glycoproteomics is critical for a comprehensive

understanding of biological glycosylation pathways[24,25].

Here, we present the factors upstream of aberrant glycosylation in AD. We performed

an integrated analysis of bulk and single-cell/nuclear transcriptomic and glycoproteomics data

from human AD brain tissues. In particular, we showed that the extracellular matrix (ECM)

is a common signature in the glycoproteome and transcriptome, and that ECM gene

expression signatures are enriched for cerebral vascular-related pathways. We identified

Procollagen-Lysine,2-Oxoglutarate   5-Dioxygenase   3   (PLOD3)   as   an   upstream

glycosyltransferase common to ECM pathway. Through an integrated analysis of multiple

single-cell expression data, we showed that PLOD3 is involved in the regulation of collagen

type IV alpha 5 chain (COL4A5), which is strongly correlated with amyloid fiber formation.

Cell–cell interaction and signaling pathway analyses suggested that PLOD3-COL4A5 cascade

is involved in the stress response via the ECM receptor in astrocytes.

Results

Hyperglycosylated proteins are primarily enriched in the ECM

To examine the association between the molecular pathogenesis of AD and

glycosylation, we accessed glycoproteomic data consisting of 2 cohorts of postmortem brain

tissue from AD patients [9,10] (**Figure 1A**). The first dataset consisted of dorsolateral prefrontal

cortex tissue from 8 neuropathologically confirmed AD cases and 8 age-matched controls. The

second dataset comprised a subset of the ROSMAP cohort[14]. Glycoproteomic analysis was

performed on the postmortem brains of 10 patients with asymptomatic AD, 10 patients with

symptomatic AD, and 10 healthy brains in which none of the above were present.

In each cohort, 92 and 10 AD-specific hyperglycosylated proteins (**Supplementary**

Table S1) were identified, respectively, and pathway enrichment analysis was performed

(**Figure 1A**). Among the pathways significantly enriched in the 2 cohorts, we identified the

ECM pathway as the most common pathway among 7 pathways (**Figure 1B, C**). The

relationship between AD and ECM has recently been recognized as a new molecular

pathogenesis, along with other major pathological hypotheses[26,27]. ECM components contain

glycoproteins, including glycosylated proteoglycans and collagen, as major elements[27], and

many glycosylations play important roles in ECM formation and maintenance.

Meta-analysis of the transcriptome reveals that glycogenes are enriched in the ECM

We explored the upstream factors that regulate ECM hyperglycosylation in AD. We

accessed the AD Knowledge Portal (https://adknowledgeportal.synapse.org), which contains

postmortem brain transcriptome data from multiple cohorts of patients with AD, and compiled

gene expression data. The glycogene set consisting of 214 glycosyltransferases was defined

using the gene list in the Glycogene Database (GGDB: https://acgg.asia/ggdb2/)[28] and

literature[6,29,30] (**Figure 2A, Supplementary Table 2**). This gene set was also categorized

according to its glycosylation pathway and synthesis steps (**Figure 2A**).

We derived transcriptional signatures of glycogenes based on a meta-analysis. We

identified 46 differentially expressed genes (DEGs) in the glycogenes (**Figure 2B, Table S3**).

We mapped glycogenes to glycosylation pathways to determine the pathways enriched for the

DEGs (**Figure 2C**). Glycosyltransferases were differentially expressed in all pathways (**Figure

2C**), indicating that the signals triggering aberrant glycosylation had already been observed

at the transcriptional level.

Next, we analyzed the biological functions of these glycogene signatures. The 779

globally enriched biological pathways were estimated based on the effect size from the

differential expression obtained by meta-analysis using all genes (FDR < 5%) (**Figure 2D,**

Supplementary Table S2–S4). Subsequently, a post-hoc enrichment analysis was performed to

infer which glycosylation pathways were associated with these enriched biological pathways

(**Figure 2D, Supplementary Table S5**). Significant glycosylation pathways were extracted with

a hypergeometric test as the final estimation results (**Figure 2D, Table S4–S5; p-value < 5%**).

We found that the ECM is a common biological signature of the transcription and glycosylation

layers in AD (**Figure 3A**). The ECM cluster was strongly associated with the hydroxyl

galactose glycosylation pathway (**Figure 2D**).

PLOD3 is identified as a functional hub glycogene for ECM

Next, we performed an in-depth analysis of the glycogenes that play a central role in

the ECM. Of the 779 globally enriched pathways, we constructed a bipartite graph consisting

of glycogene–pathway relationships based on 48 pathways, including the differentially

expressed glycogenes (**Figure 3B**). We inferred the glycogene importance based on the number

of neighboring pathways, that is, the network degree (**Figure 3C**). As a result, PLOD3 was

identified as a hub glycogene with the highest degree (**Figure 3C**).

PLOD3 is an enzyme that mediates essential glycosylation during the early stages of

collagen formation[31]. In general, collagen is broadly modified by the hydroxylation of proline

and lysine and glycosylation of specific hydroxylysine residues[32]. Hydroxylation of lysine is

catalyzed by PLOD3[33,34]; hydroxylysine undergoes further glycosylation, and COLGALT1

transfers galactose, which are critical steps for maintaining collagen integrity[32].

To further confirm the results at the gene expression level, we examined whether

the changes in PLOD3 expression were consistent among the AD cohorts included in the meta-

analysis. We found that PLOD3 was consistently upregulated in individual cohort studies

(**Figure 3D**), and the expression signatures of ECM organization and collagen formation

showed a consistent overexpression trend (**Figure 3D**). Based on this analysis, we

hypothesized that hyperglycosylation of the ECM in AD brain tissue is mediated by PLOD3.

PLOD3 is expressed in oligodendrocytes and co-expressed with COL4A5

We sought to determine the cellular origin of the PLOD3 and collagen genes. First,

we accessed the scRNA-seq data of normal brain tissue from the Human Protein Atlas

(v22)[35,36]. We found that PLOD3 was co-expressed with COL4A5 in oligodendrocytes (**Figure**

4A). These two genes showed distinct oligodendrocyte-specific expression signatures (**Figure**

4B). We also accessed a human AD cohort of single-nucleus RNA-seq data for the entorhinal

cortex (GSE138852)[37]. The entorhinal cortex is one of the brain regions that shows

neurodegeneration in the early stages of AD[38–40]. The cohort included both non-cognitive

impairment (NCI) and AD brain. Six cell types were identified: microglia, astrocytes, neurons,

oligodendrocyte progenitor cells, oligodendrocytes, and endothelial cells (**Figure 4C**). PLOD3

and COL4A5 were highly expressed in oligodendrocytes (**Figure 4C**). These genes were also

predominantly expressed in the AD group (**Figure 4C**).

COL4A5 consistently correlated with amyloid fiber formation in multiple cohort studies

COL4A5 is partially correlated with amyloid plaque accumulation[41]. However, this

finding has not been validated in large clinical samples. We tested whether COL4A5

expression was significantly correlated with APP expression. We analyzed the bulk RNA-seq

data used in the meta-analysis and examined their relationship with APP gene expression

separately for each brain region. The results showed that COL4A5 was strongly correlated

with the APP gene in all datasets (**Figure 4D**). Furthermore, we defined the gene signatures

of the amyloid plaque formation pathway and analyzed the correlation between their

eigengene expression and COL4A5 in the same way. As expected, a strong correlation was

confirmed (**Figure 4D**). PLOD3 was evaluated similarly, showing a weaker correlation than

COL4A5, but it was significant in several datasets (**Supplementary Figure 1**).

Cerebrovasculature most strongly associated with ECM dysregulation

We explored whether overexpression of the PLOD3–COL4A5 axis is involved in

biological processes in the AD brain. First, we analyzed the biological pathways that best

explained ECM activity. We used AES-PCA[42–44], a principal component analysis (PCA)-based

regression model with ECM activity as the outcome variable and all other biological pathway

activities as predictors, for each AD cohort used in the meta-analysis (**Figure 5A,**

Supplementary Table S6). The estimated p-values were statistically combined using Fisher's

method (**Figure 5A**). Four of the top 10 enriched genes were associated with the vascular

system (**Figure 5A**) and were overexpressed in the AD group at the expression level (**Figure**

5B). We hypothesized that the PLOD3–COL4A5 axis is involved in the cerebrovascular

microenvironment.

PLOD3 and COL4A5 are expressed in oligodendrocytes of the cerebrovasculature

microenvironment

We analyzed recently reported scRNA-seq data from the vascular microenvironment

of the human brain (GSE16357)[45]. These data were used to quantify gene expression by VINE-

seq in the cerebral blood vessels in 8 NCI and 9 AD samples (**Figure 5C**). Gene expression was

quantified in 143,793 cells from 14 cell types, including vascular endothelial cells (arterial,

capillary, and venous), mural smooth muscle cells (SMCs), pericytes, astrocytes, macrophages,

T cells, and perivascular and medullary fibroblasts (**Figure 5C**). We examined cell types

expressing PLOD3 and COL4A5, which were most strongly expressed in oligodendrocytes

(**Figure 5D, E**). In contrast, other type IV collagens were mainly expressed in pericytes and

SMCs, which is consistent with the fact that type IV collagen constitutes the vascular

basement membrane[46].

Oligodendrocytes interact with astrocytes via the COL4A5 ligand

Next, we analyzed the biological functions and pathways mediated by the PLOD3–

COL4A5 axis in the cerebrovascular microenvironment. According to the KEGG pathway

analysis, COL4A5 may contribute to cell-to-cell communication via ECM ligand receptors

(hsa04512). We analyzed how the PLOD3–COL4A5 axis of oligodendrocytes mediates

intercommunication between cell types. CellChat[47] allows for the estimation of cell–cell

interactions for each signaling pathway. We estimated cell–cell interactions based on collagen

signaling pathways in the AD group. Oligodendrocytes interacted with astrocytes via the

COL4A5 ligand and CD44 receptor (**Figure 6A**). This was verified using NicheNet[48], another

intercellular communication estimation algorithm. Among oligodendrocytes, COL4A5 was

identified as one of the most promising candidates (**Figure 6B**). In addition to CD44 identified

by CellChat, SDC4, DDR2, ITGB8, and ITGAV were predicted to be astrocyte receptors

(**Figure 6B**). These receptors were highly expressed in astrocytes (**Figure 6C**).

COL4A5 ligand is involved in the regulatory cascade of the astrocyte stress response

We performed a detailed analysis of signaling pathways to understand the biological

functions of COL4A5-mediated interactions between oligodendrocytes and astrocytes. We

integrated the predicted COL4A5 ligand–receptor pairs (CD44, SDC4, DDR2, ITGB8, and

ITGAV) into the prior knowledge of the signaling network constructed from multiple

perturbation experiments and databases using NicheNet. The results indicated that the

COL4A5 ligand targeted and activated B-cell/CLL lymphoma 6 (BCL6) and serum and

glucocorticoid-regulated kinase 1 (SGK1) via ECM receptors in astrocytes (**Figure 6D**). BCL6

is a transcription factor and master regulator of humoral immunity and B-cell

lymphomagenesis, while SGK 1 encodes a serine/threonine protein kinase that plays an

important role in cellular stress responses[49–51]. Both genes were found to be expressed in

astrocytes (**Figure 6E**).

Based on these results, we inferred the biological functions of the BCL6 and SGK1

gene modules in astrocytes. An astrocyte-specific co-expression network was constructed

based on gene expression using the hdWGCNA algorithm[52] (**Figure 6F**). Next, we applied the

random walk with restart (RWR) algorithm[53], which is a network propagation algorithm

starting from BCL6 and SGK1 on the astrocyte-specific network topology (**Figure 6F**). The

RWR allows for the evaluation of the proximity of the network between BCL6, SGK1, and

other neighboring genes. Based on these results, we prioritized the top 30 neighbors (**Figure**

6G). GO analysis of these neighboring gene groups revealed that they were enriched mainly

for processes involved in stress response (**Figure 6H**). These enriched pathways were also

observed in the GO analysis of BCL6 and SGK1 and were independently identified using the

network propagation method (**Supplementary Figure 3**).

Discussion

Our knowledge of the involvement of glycosylation, a major post-translational

modification, in the pathogenesis of AD is lacking. We systematically explored the

pathogenesis and driving factors based on an integrated analysis of the emerging dimensions

of glycosylation in combination with transcriptomics.

In the brain tissue of patients with AD, hyperglycosylation in the ECM is the main

signature shared by the glycome and transcriptome, and the glycosyltransferase PLOD3 is an

upstream regulator that acts as a functional hub. PLOD3 is predominantly expressed in

oligodendrocytes in AD brain tissue and the cerebrovasculature and is co-expressed with

COL4A5. Importantly, COL4A5 significantly correlated with APP levels and the activity of the

amyloid fiber formation pathway. Single-cell/nuclear analysis revealed that COL4A5 is a

ligand for oligodendrocytes that can mediate cell–cell interactions via ECM receptors on

astrocytes. In addition, signaling pathway network analysis identified BCL6 and SGK1 as its

target genes, and their neighboring genes in the astrocyte-specific network analysis revealed

that these two genes are involved in the regulation of the stress response.

The involvement of the ECM in AD has been supported by a large amount of

literature[27,54–58]. The physiological roles of the ECM are diverse and include developmental

regulation, tissue homeostasis, cell migration, cell proliferation, cell differentiation, neuronal

plasticity, and neurite growth[59]. In particular, the ECM is extensively involved in the

dysregulation of perineuronal networks in AD[58,60–68], which are involved in the maintenance

of spatial structure, neuronal plasticity, scaffolding,[69] and the regulation of aggregation; it is

also involved in amyloid protein dynamics[27,70–75] and brain–blood barrier integrity [41,54,76–79].

As glycoproteins are the major components of the ECM[55,59,80], glycan synthesis is important

for ECM homeostasis in the brain. The enrichment of dysregulated glycoproteins in the ECM

is natural in this sense (**Figure 1A, B**).

We discovered that PLOD3 was enriched in the ECM and upregulated in the AD

meta-analysis (**Figure 2B–D**). PLOD3 is a multifunctional enzyme, and in addition to its role

as a lysyl hydroxylase, it has collagen galactosyltransferase and glucosyltransferase

activity[34,81–83]. Although no direct evidence of PLOD3 in AD has been reported, it is known to

play an essential role in the formation of collagen, a major component of ECM[84]. For instance,

defects in PLOD3 (or lysyl hydroxylase 3; LH3) have been implicated in inherited connective

tissue disorders and have been shown to cause cerebral small vessel injury[85,86], maintenance

of the structural integrity of cerebral blood vessels, and the regulation of inflammatory

processes[87]. This enzyme is also a promising biomarker of AD, as its expression has been

reported to fluctuate in cell-free RNA expression in blood samples from patients with AD[88].

PLOD3 mediates glycosylation during early collagen formation[31]. Type IV collagen is

an essential protein in the cerebral vasculature of patients with AD and is responsible for

network formation in the basement membrane. Indeed, in our analysis of single-cell

expression levels in cerebral vessels, many type IV collagens

(COL4A1/COL4A2/COL4A3/COL4A4) were predominantly expressed in pericytes and SMCs

(**Figure 5E**). In contrast, COL4A5 behaves differently from other type IV collagens and is

predominantly expressed in oligodendrocytes. Oligodendrocytes have been shown to stably

bind to cerebral blood vessels by zonation analysis based on single-cell/nuclear sequencing

analysis[89,90] and electron microscopy[91]. Interestingly, data from multiple studies support that

COL4A5 is strongly correlated with APP and amyloid fiber formation (**Figure 4D**), suggesting

a relationship with amyloid plaque accumulation. This may be relevant because the

overexpression of type IV collagen generally leads to an increase in cortical basement

membrane thickness and has been implicated in the degeneration of cerebral vascular

structures[55]. The functional role of type IV collagen in AD cerebrovasculature should be

examined in detail in future studies.

We also performed an in silico analysis of cell–cell interactions. COL4A5 functioned

as a ligand in oligodendrocyte–astrocyte interactions (**Figure 6A**). Analysis of the signaling

pathway network suggested that this cell–cell interaction may contribute primarily to the

stress response via SGK1 or BCL6 (**Figure 6D–H**). SGK1 is known to be transcriptionally

upregulated under cellular stress[49–51]. On the other hand, both factors have also been reported

to be involved in inflammatory responses in the central nervous system. Recent studies have

shown that inhibition of SGK1 can suppress the NF-κB-mediated inflammatory pathway in

glial cells[92]. There is also evidence that BCL6 plays a central role in regulating astrocytes and

NF-κB in response to inflammatory stimuli and disorders[93]. Indeed, in our glycoprotein

analysis, the immune response pathway was enriched next to the ECM (**Figure 1B, C**), and

inflammatory cytokines were also significantly associated with the ECM organization

pathway at the transcriptome level (**Figure 5A, Supplementary Figure S2A**). Inflammatory

pathways are key signatures in the AD brain; however, their mechanisms of action in the

stress response remain unclear. Further examination of the mechanisms underlying BCL6-

and SGK1-mediated stress responses is required.

This study has several limitations. First, the AD glycomic analysis was limited to N-

type glycans. Therefore, evidence of ECM hyperglycosylation should be verified in future

studies using comprehensive glycoproteomic data. Second, the AD cohort data used in the

meta-analysis were limited to those deposited on the AD knowledge portal. To establish a

higher level of evidence, data from other large cohort studies should be included. Third, single-

cell sequencing data were collected from several different sources; therefore, there is no

guarantee that the results reflect the differential expression results of the bulk sequencing

used in the meta-analysis. It is expected that this limitation can be overcome in the future as

multilayered omics data are collected. However, validation, including experimental

approaches, is required.

Our results suggest that glycosylation is involved in the pathogenesis of AD through

several unknown mechanisms. Our results also indicate that glycogenomics analysis

integrating genetic approaches is a promising method for highlighting the biological functions

of glycans and the molecular pathogenesis of diseases at a single-cell resolution. Data on AD

glycoproteomics in human subjects are limited. However, as glycoproteomic analysis

technology matures, it will be applied to various disease areas, and a vast amount of

glycoproteomic data will be accumulated in the next decade. In the near future, the

glycogenomics approach will play an important role as a bridge between the established AD

genetic pathology and the emerging dimensional omics field of glycoproteomics.

Methods

Glycoproteomics enrichment analysis

The first set of glycoproteomics data[9] was used for enrichment analysis. This dataset

was analyzed for glycoproteins overexpressed in the AD group (BRAAK $\geq$ 5) and the normal

group (BRAAK $\leq$ 2), as defined in the original paper, using the canonical pathway collection

of MSigDB (c2.cp.v2022.1.Hs.symbols.gmt). All genes were analyzed as backgrounds using the

fedup package in R (https://github.com/rosscm/fedup), and the top 30 significantly enriched

pathways were identified. The second set of glycoproteomics data[9] was analyzed in the same

manner. Comparisons were made between the symptomatic group (BRAAK $\geq$ 5 and CERAD 1

or 2), the asymptomatic group (BRAAK $\geq$ 3 and CERAD 1 or 2), and the normal group (BRAAK

$\leq$ 2 and CERAD 4), as defined in the original paper. Glycoproteins specifically identified in the

symptomatic group were extracted. Enrichment analysis was performed to identify the top 30

significantly enriched pathways.

Meta-analysis

Meta-analysis using RNA-seq harmonization of AMP-AD followed the published AD-

CONTROL analysis protocol (https://github.com/th1vairam/ampad-DiffExp/tree/df3efa793f,

379730bae6d4c9e62910fb2c37e525/gene_level_analysis). First, meta-information was used

for data from 3 cohorts (ROSMAP, MSSM, and Mayo), including seven different brain regions,

to define patients with definitive late-onset AD from a clinical and neuropathological

perspective, that is, neurofibrillary changes, neuritic amyloid plaques, and cognitive

dysfunction. The AD control group consisted of patients with AD.

AD controls were defined as patients with few plaques and neurofibrillary changes

and no cognitive impairment; in ROSMAP, LOAD cases were those with a BRAAK of 4 or more,

a CERAD score of 2 or less, and a cognitive diagnosis of probable AD with no other causes

(cogdx = 4); LOAD controls were those with a BRAAK of 3 or less, a CERAD score of 3 or more,

and a cognitive diagnosis of "no cognitive impairment" (cogdx = 1). For the MSBB, LOAD cases

were defined as those with a CDR score of at least 1, a BRAAK score of at least 4, and a

CERAD score of at least 2. LOAD cases were similarly defined as those with a CDR score of

0.5 or less, a BRAAK of 3 or less, and a CERAD of 1 or less as LOAD controls. In Mayo, cases

were defined based on neuropathology, with LOAD cases defined as having a BRAAK score of

4 or higher and LOAD controls as having a BRAAK score of 3 or lower.

A meta-analysis using a mixed-effects model was performed to determine the

differences in the expression levels of each gene in each of the seven brain regions in each

cohort. Effect sizes were estimated using the restricted maximum likelihood method based on

the standard mean difference using Hedge. The Metacont function from the meta package of

R was used for the analysis. The p-values were corrected for multiple testing by "fdr" using

the p.adjust function from the stats package.

Enrichment map

Gene Set Enrichment Analysis (GSEA) was performed on all genes included in the

meta-analysis. The gene set was c2.cp.v2022.1.Hs.symbols from the MsigDB collection, which

was loaded using Enrichment Map in Cytoscape and drawn using default settings. After

drawing the pathways, we manually classified them into several categories and created

several clusters in the network. The list of glycan-related genes manually defined for each

glycosylation pathway was then analyzed by post-hoc analysis using the hypergeometric test

and the Wilcoxon test, and pathways with FDR ≤ 5% and that were significant by two tests

were extracted. Significant pathways in the two tests were extracted.

Functional hub glycogene identification

Among the enriched pathways based on the same GSEA results as the enrichment

map, only pathways containing glycogenes were extracted, and from these, a two-part graph

of the pathway–glycogene was extracted. Based on the two-part graphs obtained, each gene

was ranked according to its degree of expression. The glycogene with the highest degree was

defined as the functional hub glycogene. The results of querying the extracted PLOD3 to the

String database (v11) are shown in **Figure 2D**. Forest plots of PLOD3 are shown with

estimated effect sizes and 95% confidence intervals from the meta-analysis. For pathway

activity, GSEA was performed using the R fgsea package, with gene ranks for effect sizes for

each cohort and c2.cp.v2022.1.Hs.symbols for the gene set. Normalized enrichment scores

were used for the forest plots.

Cell-type specificity of PLOD3

378   For the cell-type specificity of healthy tissues, information was obtained from the

379   Human Proteome Atlas (V22) website by entering the gene name. For data on the entorhinal

380   cortex, information was obtained by entering gene names from http://adsn.ddnetbio.com/.

Pathway-based PCA regression and GSEA

Pathway-based PCA is a PCA-based method for analyzing pathways and phenotypic

associations[43,44,94]. The R Bioconductor PathwayPCA package[42] was used for the analysis.

Using region-specific gene expression data from each AD cohort (Mayo, MSSM, and ROSMAP),

we specified the mean expression levels of the ECM pathway component genes as the ECM

pathway activity for the objective variable and each pathway other than the ECM pathway

for the explanatory variables. The gene set used was c2.cp.v2022.1.Hs.symbols from MSigDB.

The pathway names containing "ECM," "Extracellular," or "Collagen" were defined as ECM

pathways. The genes involved in these pathways were defined as signatures.

The p-values of the list of pathways significantly associated with ECM were combined

using Fisher's method to calculate the integrated p-value. For the calculation, the log-sum

function of the R metapackage[95] was used, and the p-values of the individual datasets were

entered for each pathway. In addition, we cross-checked whether significantly related

pathways were sufficiently enriched at the expression level. Focusing on the top 10 pathways,

we applied GSEA based on the gene set c2.cp.v2022.1.Hs.symbols from MSigDB using the

effect sizes of the 3 cohort meta-analysis as the gene rank. To further validate that the top 10

pathway activities tended to increase by cohort and region, the means of the effect sizes and

confidence intervals were calculated for the signature genes and illustrated as forest plots.

Analysis of brain vasculature with scRNA-seq

Count data were preprocessed using the Seurat package in R. Normalization, feature

selection with VST, scaling, and dimensional reduction using PCA and UMAP were performed.

The cell types were visualized using those previously identified in an original paper[45]. Next,

for each cell type, variation analysis between the AD and cognitively normal groups was

performed using Seurat's FindMarkes function, and enrichment analysis for the identified

groups of DEGs was performed using the R fedup package. The c2.cp.v2022.1.Hs.symbols from

MSigDB was used as the gene set to determine which cell types were enriched in ECM-related

pathways. We selected gene sets with pathway names containing "ECM," "Extracellular,"

"Matrisome," or "Collagen" in the pathway name. The enriched p-values were further

transformed as -Log10(FDR) from the multiple-test-corrected FDR, considered as

differentially expressed activity signals, and visualized using a heatmap. The expression

levels per cell type were obtained by querying https://twc-stanford.shinyapps.io/human_bbb/

for PLOD3.

Cell–cell interaction and signaling network analysis

Cell–cell interactions were analyzed using the R package CellChat[47]

(https://github.com/sqjin/CellChat). Oligodendrocytes and astrocytes identified with CellChat

were further analyzed using another algorithm, NicheNet[48] (https://

github.com/saeyslab/nichenetr). For a detailed analysis, the ligand–receptor prior information

was input by integrating the ligand–receptor pair information used in CellChat with the

ligand–receptor pair information used in NicheNet. This was also used for the signal network

analyses. A pre-built model was downloaded

(https://github.com/saeyslab/nichenetr/blob/master/vignettes/model_construction.md), and

both the ligand–receptor information and expression information were identified in the cell–

cell interactions.

Astrocyte cell-type specific network propagation

For astrocyte-specific network construction using cerebrovascular scRNA-seq, the

Toplogical Overlap Measure (TOM) was estimated using hdWGCNA[52], and edges were further

defined only if they had a TOM above the 90th percentile as a threshold. The network

propagation method was applied using the R package RandomWalkRestartMH[53]. In other

words, we performed an RWR starting from SGK1 and BCL6 in the obtained network topology.

The 30 most relevant neighbors were narrowed down and plotted using the R package igraph.

The R package fedup was used for the enrichment analysis. To estimate the transcriptional

activity of BCL6, curated regulon information was first obtained using the R package

DoRothEA[96], and transcription factor target genes were estimated using the Viper[97] algorithm.

The R package decoupleR[98] was used for the analysis.

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Conflict of interest

The authors declare no competing interests.

Data availability

The glycoproteomics datasets were compiled and used from the supplementary files

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Refences

1.   Guerreiro, R. & Bras, J. The age factor in Alzheimer's disease. *Genome Med.* **7**, 106 (2015).

2.   Xia, X., Jiang, Q., McDermott, J. & Han, J.-D. J. Aging and Alzheimer's disease:

Comparison and associations from molecular to system level. *Aging Cell* **17**, e12802 (2018).

3.   Breijyeh, Z. & Karaman, R. Comprehensive Review on Alzheimer's Disease: Causes and

Treatment. *Molecules* **25**, (2020).

4.   Bennett, D. A. *et al.* Religious Orders Study and Rush Memory and Aging Project. *J.*

Alzheimers. Dis. **64**, S161–S189 (2018).

5.   Gaunitz, S., Tjernberg, L. O. & Schedin-Weiss, S. What Can N-glycomics and N-

glycoproteomics of Cerebrospinal Fluid Tell Us about Alzheimer Disease? *Biomolecules*

11, 858 (2021).

6.   Schjoldager, K. T., Narimatsu, Y., Joshi, H. J. & Clausen, H. Global view of human protein

glycosylation pathways and functions. *Nat. Rev. Mol. Cell Biol.* **21**, 729–749 (2020).

7.   Narimatsu, Y. *et al.* An Atlas of Human Glycosylation Pathways Enables Display of the

Human Glycome by Gene Engineered Cells. *Mol. Cell* **75**, 394-407.e5 (2019).

8.   Joshi, H. J. *et al.* Glycosyltransferase genes that cause monogenic congenital disorders of

glycosylation are distinct from glycosyltransferase genes associated with complex

diseases. *Glycobiology* **28**, 284–294 (2018).

9.   Zhang, Q., Ma, C., Chin, L.-S. & Li, L. Integrative glycoproteomics reveals protein N-

glycosylation aberrations and glycoproteomic network alterations in Alzheimer's disease.

Sci Adv **6**, (2020).

10. Suttapitugsakul, S. *et al.* Glycoproteomics Landscape of Asymptomatic and Symptomatic

Human Alzheimer's Disease Brain. *Mol. Cell. Proteomics* **21**, 100433 (2022).

11. Yu, L. *et al.* Human Brain and Blood N-Glycome Profiling in Alzheimer's Disease and

Alzheimer's Disease-Related Dementias. *Front. Aging Neurosci.* **13**, 765259 (2021).

12. Kerdsaeng, N. *et al.* Serum Glycoproteomics and Identification of Potential Mechanisms

Underlying Alzheimer's Disease. *Behav. Neurol.* **2021**, 1434076 (2021).

13. Gizaw, S. T., Ohashi, T., Tanaka, M., Hinou, H. & Nishimura, S.-I. Glycoblotting method

allows for rapid and efficient glycome profiling of human Alzheimer's disease brain, serum

and cerebrospinal fluid towards potential biomarker discovery. *Biochim. Biophys. Acta*

1860, 1716–1727 (2016).

14. Gaunitz, S., Tjernberg, L. O. & Schedin-Weiss, S. The N-glycan profile in cortex and

hippocampus is altered in Alzheimer disease. *J. Neurochem.* **159**, 292–304 (2020).

15. Reyes, C. D. G. *et al.* LC-MS/MS Isomeric Profiling of N-Glycans Derived from Low-

Abundant Serum Glycoproteins in Mild Cognitive Impairment Patients. *Biomolecules* **12**,

(2022).

16. Frenkel-Pinter, M. *et al.* Interplay between protein glycosylation pathways in Alzheimer's

disease. *Sci Adv* **3**, e1601576 (2017).

17. Chen, C. C. *et al.* Altered serum glycomics in Alzheimer disease: a potential blood

biomarker? *Rejuvenation Res.* **13**, 439–444 (2010).

18. Schedin-Weiss, S. *et al.* Glycan biomarkers for Alzheimer disease correlate with T-tau and

P-tau in cerebrospinal fluid in subjective cognitive impairment. *FEBS J.* **287**, 3221–3234

(2020).

19. Palmigiano, A. *et al.* CSF N-glycoproteomics for early diagnosis in Alzheimer's disease. *J.*

Proteomics **131**, 29–37 (2015).

20. Cho, B. G., Veillon, L. & Mechref, Y. N-Glycan Profile of Cerebrospinal Fluids from

Alzheimer's Disease Patients Using Liquid Chromatography with Mass Spectrometry. *J.*

Proteome Res. **18**, 3770–3779 (2019).

21. Kizuka, Y. *et al.* An aberrant sugar modification of BACE1 blocks its lysosomal targeting

in Alzheimer's disease. *EMBO Mol. Med.* **7**, 175–189 (2015).

22. Kizuka, Y. *et al.* Bisecting GlcNAc modification stabilizes BACE1 protein under oxidative

stress conditions. *Biochem. J* **473**, 21–30 (2015).

23. Kizuka, Y., Kitazume, S., Sato, K. & Taniguchi, N. Clec4g (LSECtin) interacts with

BACE1 and suppresses Aβ generation. *FEBS Lett.* **589**, 1418–1422 (2015).

24. Bennun, S. V. *et al.* Systems Glycobiology: Integrating Glycogenomics, Glycoproteomics,

Glycomics, and Other 'Omics Data Sets to Characterize Cellular Glycosylation Processes.

J. Mol. Biol. **428**, 3337–3352 (2016).

25. West, C. M., Malzl, D., Hykollari, A. & Wilson, I. B. H. Glycomics, Glycoproteomics, and

Glycogenomics: An Inter-Taxa Evolutionary Perspective. *Mol. Cell. Proteomics* **20**, 100024

(2021).

26. Terry, A. V., Jr & Buccafusco, J. J. The cholinergic hypothesis of age and Alzheimer's

disease-related cognitive deficits: recent challenges and their implications for novel drug

development. *J. Pharmacol. Exp. Ther.* **306**, 821–827 (2003).

27. Sun, Y. *et al.* Role of the Extracellular Matrix in Alzheimer's Disease. *Front. Aging*

Neurosci. **13**, 707466 (2021).

28. Narimatsu, H. *et al.* GlycoGene Database (GGDB) on the Semantic Web. in *A Practical*

Guide to Using Glycomics Databases (ed. Aoki-Kinoshita, K. F.) 163–175 (Springer Japan,

2017).

29. Narimatsu, H. Construction of a human glycogene library and comprehensive functional

analysis. *Glycoconj. J.* **21**, 17–24 (2004).

30. *Handbook of Glycosyltransferases and Related Genes*. (Springer Japan).

31. Myllyharju, J. & Kivirikko, K. I. Collagens, modifying enzymes and their mutations in

humans, flies and worms. *Trends Genet.* **20**, 33–43 (2004).

32. Hennet, T. Collagen glycosylation. *Curr. Opin. Struct. Biol.* **56**, 131–138 (2019).

33. Heikkinen, J. *et al.* Lysyl Hydroxylase 3 Is a Multifunctional Protein Possessing Collagen

Glucosyltransferase Activity*. *J. Biol. Chem.* **275**, 36158–36163 (2000).

34. Wang, C. *et al.* The third activity for lysyl hydroxylase 3: galactosylation of hydroxylysyl

556  residues in collagens in vitro. *Matrix Biol.* **21**, 559–566 (2002).

557 35. Sjöstedt, E. *et al.* An atlas of the protein-coding genes in the human, pig, and mouse brain.

558  *Science* **367**, (2020).

559 36. Uhlén, M. *et al.* Proteomics. Tissue-based map of the human proteome. *Science* **347**,

560  1260419 (2015).

561 37. Grubman, A. *et al.* A single-cell atlas of entorhinal cortex from individuals with

562  Alzheimer's disease reveals cell-type-specific gene expression regulation. *Nat. Neurosci.*

563  **22**, 2087–2097 (2019).

564 38. Howett, D. *et al.* Differentiation of mild cognitive impairment using an entorhinal cortex-

565  based test of virtual reality navigation. *Brain* **142**, 1751–1766 (2019).

566 39. Khan, U. A. *et al.* Molecular drivers and cortical spread of lateral entorhinal cortex

567  dysfunction in preclinical Alzheimer's disease. *Nat. Neurosci.* **17**, 304–311 (2014).

568 40. Bottero, V., Powers, D., Yalamanchi, A., Quinn, J. P. & Potashkin, J. A. Key Disease

569  Mechanisms Linked to Alzheimer's Disease in the Entorhinal Cortex. *Int. J. Mol. Sci.* **22**,

570  (2021).

571 41. Lepelletier, F.-X., Mann, D. M. A., Robinson, A. C., Pinteaux, E. & Boutin, H. Early

572  changes in extracellular matrix in Alzheimer's disease. *Neuropathol. Appl. Neurobiol.* **43**,

573  167–182 (2015).

574 42. Odom, G. J. *et al.* PathwayPCA: An R/Bioconductor package for pathway based

integrative analysis of multi-omics data. *Proteomics* **20**, e1900409 (2020).

43. Chen, X., Wang, L., Smith, J. D. & Zhang, B. Supervised principal component analysis for

gene set enrichment of microarray data with continuous or survival outcomes.

Bioinformatics **24**, 2474–2481 (2008).

44. Chen, X. *et al.* Pathway-based analysis for genome-wide association studies using

supervised principal components. *Genet. Epidemiol.* **34**, 716–724 (2010).

45. Yang, A. C. *et al.* A human brain vascular atlas reveals diverse mediators of Alzheimer's

risk. *Nature* **603**, 885–892 (2022).

46. Xu, L., Nirwane, A. & Yao, Y. Basement membrane and blood-brain barrier. *Stroke Vasc*

Neurol **4**, 78–82 (2019).

47. Guerrero-Juarez, C. F. *et al.* Single-cell analysis reveals fibroblast heterogeneity and

myeloid-derived adipocyte progenitors in murine skin wounds. *Nat. Commun.* **10**, 650

(2019).

48. Browaeys, R., Saelens, W. & Saeys, Y. NicheNet: modeling intercellular communication

by linking ligands to target genes. *Nat. Methods* **17**, 159–162 (2020).

49. Lang, F., Stournaras, C., Zacharopoulou, N., Voelkl, J. & Alesutan, I. Serum- and

glucocorticoid-inducible kinase 1 and the response to cell stress. *Cell Stress Chaperones*

3, 1–8 (2018).

50. Leong, M. L. L., Maiyar, A. C., Kim, B., O'Keeffe, B. A. & Firestone, G. L. Expression of

the serum- and glucocorticoid-inducible protein kinase, Sgk, is a cell survival response to

multiple types of environmental stress stimuli in mammary epithelial cells. *J. Biol. Chem.*

278, 5871–5882 (2003).

51. Webster, M. K., Goya, L., Ge, Y., Maiyar, A. C. & Firestone, G. L. Characterization of sgk,

a novel member of the serine/threonine protein kinase gene family which is

transcriptionally induced by glucocorticoids and serum. *Mol. Cell. Biol.* **13**, 2031–2040

(1993).

52. Morabito, S., Reese, F., Rahimzadeh, N., Miyoshi, E. & Swarup, V. hdWGCNA identifies

co-expression networks in high-dimensional transcriptomics data. *Cell Rep Methods* **3**,

100498 (2023).

53. Valdeolivas, A. *et al.* Random walk with restart on multiplex and heterogeneous biological

networks. *Bioinformatics* **35**, 497–505 (2019).

54. Anwar, M. M., Özkan, E. & Gürsoy-Özdemir, Y. The role of extracellular matrix

alterations in mediating astrocyte damage and pericyte dysfunction in Alzheimer's

disease: A comprehensive review. *Eur. J. Neurosci.* **56**, 5453–5475 (2021).

55. Ma, J. *et al.* Extracellular Matrix Proteins Involved in Alzheimer's Disease. *Chemistry* **26**,

12101–12110 (2020).

56. Levy, A. D., Omar, M. H. & Koleske, A. J. Extracellular matrix control of dendritic spine

and synapse structure and plasticity in adulthood. *Front. Neuroanat.* **8**, 116 (2014).

57.   Morawski, M., Filippov, M., Tzinia, A., Tsilibary, E. & Vargova, L. ECM in brain aging and

dementia. *Prog. Brain Res.* **214**, 207–227 (2014).

58.   Soleman, S., Filippov, M. A., Dityatev, A. & Fawcett, J. W. Targeting the neural

extracellular matrix in neurological disorders. *Neuroscience* **253**, 194–213 (2013).

59.   Sethi, M. K. & Zaia, J. Extracellular matrix proteomics in schizophrenia and Alzheimer's

disease. *Anal. Bioanal. Chem.* **409**, 379–394 (2016).

60.   Bosiacki, M. *et al.* Perineuronal Nets and Their Role in Synaptic Homeostasis. *Int. J. Mol.*

Sci. **20**, (2019).

61.   Li, Y., Li, Z.-X., Jin, T., Wang, Z.-Y. & Zhao, P. Tau Pathology Promotes the Reorganization

of the Extracellular Matrix and Inhibits the Formation of Perineuronal Nets by

Regulating the Expression and the Distribution of Hyaluronic Acid Synthases. *J.*

Alzheimers. Dis. **57**, 395–409 (2017).

62.   Duncan, J. A., Foster, R. & Kwok, J. C. F. The potential of memory enhancement through

modulation of perineuronal nets. *Br. J. Pharmacol.* **176**, 3611–3621 (2019).

63.   Wen, T. H., Binder, D. K., Ethell, I. M. & Razak, K. A. The Perineuronal "Safety" Net?

Perineuronal Net Abnormalities in Neurological Disorders. *Front. Mol. Neurosci.* **11**, 270

(2018).

64.   Pantazopoulos, H. & Berretta, S. In Sickness and in Health: Perineuronal Nets and

Synaptic Plasticity in Psychiatric Disorders. *Neural Plast.* **2016**, 9847696 (2015).

65. Logsdon, A. F. *et al.* Decoding perineuronal net glycan sulfation patterns in the

Alzheimer's disease brain. *Alzheimers. Dement.* **18**, 942–954 (2021).

66. Miyata, S. & Kitagawa, H. Chondroitin sulfate and neuronal disorders. *Front. Biosci.* **21**,

1330–1340 (2016).

67. Galtrey, C. M. & Fawcett, J. W. The role of chondroitin sulfate proteoglycans in

regeneration and plasticity in the central nervous system. *Brain Res. Rev.* **54**, 1–18 (2007).

68. Yamada, J. & Jinno, S. Spatio-temporal differences in perineuronal net expression in the

mouse hippocampus, with reference to parvalbumin. *Neuroscience* **253**, 368–379 (2013).

69. Brandan, E. & Inestrosa, N. C. Extracellular matrix components and amyloid in neuritic

plaques of Alzheimer's disease. *Gen. Pharmacol.* **24**, 1063–1068 (1993).

70. Zhang, S. *et al.* The extracellular matrix enriched with membrane metalloendopeptidase

and insulin-degrading enzyme suppresses the deposition of amyloid-beta peptide in

Alzheimer's disease cell models. *J. Tissue Eng. Regen. Med.* **13**, 1759–1769 (2019).

71. Wu, A., Pangalos, M. N., Efthimiopoulos, S., Shioi, J. & Robakis, N. K. Appican expression

induces morphological changes in C6 glioma cells and promotes adhesion of neural cells

to the extracellular matrix. *J. Neurosci.* **17**, 4987–4993 (1997).

72. Small, D. H., Nurcombe, V., Clarris, H., Beyreuther, K. & Masters, C. L. The role of

extracellular matrix in the processing of the amyloid protein precursor of Alzheimer's

disease. *Ann. N. Y. Acad. Sci.* **695**, 169–174 (1993).

73. Stoyanov, S. *et al.* Attenuation of the extracellular matrix restores microglial activity

during the early stage of amyloidosis. *Glia* **69**, 182–200 (2020).

74. Bronfman, F. C., Soto, C., Tapia, L., Tapia, V. & Inestrosa, N. C. Extracellular matrix

regulates the amount of the beta-amyloid precursor protein and its amyloidogenic

fragments. *J. Cell. Physiol.* **166**, 360–369 (1996).

75. Salza, R., Lethias, C. & Ricard-Blum, S. The Multimerization State of the Amyloid-β42

Amyloid Peptide Governs its Interaction Network with the Extracellular Matrix. *J.*

Alzheimers. Dis. **56**, 991–1005 (2017).

76. Potjewyd, G., Kellett, K. A. B. & Hooper, N. M. 3D hydrogel models of the neurovascular

unit to investigate blood-brain barrier dysfunction. *Neuronal Signal* **5**, NS20210027

(2021).

77. Reed, M. J., Damodarasamy, M. & Banks, W. A. The extracellular matrix of the blood-

brain barrier: structural and functional roles in health, aging, and Alzheimer's disease.

Tissue Barriers **7**, 1651157 (2019).

78. Damodarasamy, M. *et al.* The microvascular extracellular matrix in brains with

Alzheimer's disease neuropathologic change (ADNC) and cerebral amyloid angiopathy

(CAA). *Fluids Barriers CNS* **17**, 60 (2020).

79. Brzdak, P., Nowak, D., Wiera, G. & Mozrzymas, J. W. Multifaceted Roles of Metzincins in

CNS Physiology and Pathology: From Synaptic Plasticity and Cognition to

Neurodegenerative Disorders. *Front. Cell. Neurosci.* **11**, 178 (2017).

80. Bres, E. E. & Faissner, A. Low Density Receptor-Related Protein 1 Interactions With the

Extracellular Matrix: More Than Meets the Eye. *Front Cell Dev Biol* **7**, 31 (2019).

81. Wang, C. *et al.* The glycosyltransferase activities of lysyl hydroxylase 3 (LH3) in the

extracellular space are important for cell growth and viability. *J. Cell. Mol. Med.* **13**, 508–

521 (2009).

82. Salo, A. M. *et al.* Lysyl hydroxylase 3 (LH3) modifies proteins in the extracellular space,

a novel mechanism for matrix remodeling. *J. Cell. Physiol.* **207**, 644–653 (2006).

83. Valtavaara, M., Szpirer, C., Szpirer, J. & Myllylä, R. Primary Structure, Tissue

Distribution, and Chromosomal Localization of a Novel Isoform of Lysyl Hydroxylase

(Lysyl Hydroxylase 3)*. *J. Biol. Chem.* **273**, 12881–12886 (1998).

84. De Giorgi, F., Fumagalli, M., Scietti, L. & Forneris, F. Collagen hydroxylysine

glycosylation: non-conventional substrates for atypical glycosyltransferase enzymes.

Biochem. Soc. Trans. **49**, 855–866 (2021).

85. Zhou, J. *et al.* Cerebral small vessel disease caused by PLOD3 mutation: Expanding the

phenotypic spectrum of lysyl hydroxylase-3 deficiency. *Pediatr Investig* **6**, 219–223 (2022).

86. Miyatake, S. *et al.* Biallelic COLGALT1 variants are associated with cerebral small vessel

disease. *Ann. Neurol.* **84**, 843–853 (2018).

87. Li, H. *et al.* Overexpression of LH3 reduces the incidence of hypertensive intracerebral

hemorrhage in mice. *J. Cereb. Blood Flow Metab.* **39**, 547–561 (2019).

88. Toden, S. *et al.* Noninvasive characterization of Alzheimer's disease by circulating, cell-

free messenger RNA next-generation sequencing. *Sci Adv* **6**, (2020).

89. Garcia, F. J. *et al.* Single-cell dissection of the human brain vasculature. *Nature* **603**, 893–

899 (2022).

90. Vanlandewijck, M. *et al.* A molecular atlas of cell types and zonation in the brain

vasculature. *Nature* **554**, 475–480 (2018).

91. Palhol, J. S. C. *et al.* Direct association with the vascular basement membrane is a

frequent feature of myelinating oligodendrocytes in the neocortex. *Fluids Barriers CNS*

20, 24 (2023).

92. Kwon, O.-C. *et al.* SGK1 inhibition in glia ameliorates pathologies and symptoms in

Parkinson disease animal models. *EMBO Mol. Med.* **13**, e13076 (2021).

93. Linnerbauer, M., Wheeler, M. A. & Quintana, F. J. Astrocyte Crosstalk in CNS

Inflammation. *Neuron* **108**, 608–622 (2020).

94. Chen, X. Adaptive elastic-net sparse principal component analysis for pathway

association testing. *Stat. Appl. Genet. Mol. Biol.* **10**, (2011).

95. Dewey, M. Meta-Analysis of Significance Values [R package metap version 1.8]. (2022).

96. Garcia-Alonso, L., Holland, C. H., Ibrahim, M. M., Turei, D. & Saez-Rodriguez, J.

Benchmark and integration of resources for the estimation of human transcription factor

activities. *Genome Res.* **29**, 1363–1375 (2019).

97. Alvarez, M. J. *et al.* Functional characterization of somatic mutations in cancer using

network-based inference of protein activity. *Nat. Genet.* **48**, 838–847 (2016).

98. Badia-I-Mompel, P. *et al.* decoupleR: ensemble of computational methods to infer

biological activities from omics data. *Bioinform Adv* **2**, vbac016 (2022).

Figure 1 - Hyperglycosylated proteins are primarily enriched in the ECM.

A Analysis of glycoprotein data from 2 AD cohorts, using glycoproteins from prefrontal tissues of 2

independent AD cohorts. The first cohort (AD cohort 1) consisted of 8 samples each from healthy subjects

and those with AD, and the second cohort (AD cohort 2) consisted of 10 samples each from healthy subjects,

asymptomatic AD, and symptomatic AD. In each cohort, 92 and 10 AD-specific glycoproteins were identified,

respectively.

B Pathway enrichment of AD-related glycoproteins. Over-representation analysis of AD-specific

glycoproteins was performed.

C Significantly enriched pathways that were common in both cohorts are shown. The horizontal axis is the

p-value representing the enrichment, which is the logarithm of the nominal p-value multiplied by a negative

value.

Figures were created with BioRender.com.

Figure 2 - Meta-analysis of the global transcriptome reveals that glycogenes are enriched in the ECM.

A Number of glycogenes constituting the glycosylation pathway used for transcriptome analysis.

B Meta-analysis of differential gene expression in multiple AD cohorts. Transcriptome data from 3 AD

cohorts: the Mayo cohort (n = 313), the MSSM cohort (n = 315), and the ROSMAP cohort (n = 1168). A meta-

analysis of DEGs based on gene-level expression levels (FDR < 5%) was performed; 46 glycogenes were

identified as DEGs. In the volcano plot, the horizontal axis represents the effect size summarizing the

difference in expression between the non-AD and AD groups across cohorts, and the vertical axis represents

the log of the p-value from the meta-analysis (bottom is 10) multiplied by a negative value.

C Mapped glycosyltransferase DEGs. In total, 46 glycogene DEGs were mapped. Genes overexpressed in the

meta-analysis are shown in red, genes underexpressed are shown in blue, and genes that did not show

significant mutations are shown in gray. Genes are classified into 16 major glycosylation pathways,

including initiation, core elongation, elongation/branching, capping, and sulfation. Glycosyltransferases

with and without pathway specificity are also distinguished.

Figure created by BioRender.com.

Figure 3 - PLOD3 is identified as a hub glycogene for the ECM.

A Comparison of AD trascriptome and glycoprotein signatures. Common pathways are shown.

B Relationship between glycogenes and globally enriched pathways. Orange nodes represent globally

enriched pathways, and green nodes represent glycogen enriched in each pathway.

C Functional hub glycogenes in globally enriched pathways. To identify functional hub glycogenes involved

in multiple pathways, we constructed a pathway-gene bipartite graph, calculated the degree of each

glycogene (number of genes directly connected to the pathway), and ranked the importance of each

glycogene. The vertical axis of the bar graph represents the order of each glycogene.

D Activity changes in PLOD3, ECM, and collagen formation in AD brains in each transcriptome cohort.

Forest plots of Log2 fold changes in PLOD3, ECM organization, and collagen formation activity between

non-AD and AD are plotted by cohort and brain region.

DLPFC: dorsolateral prefrontal cortex; STG: superior temporal gyrus; PHG: parahippocampal gyrus; IFG:

inferior frontal gyrus; FP: frontal pole; TCX: temporal cortex; CBE: cerebellum. Dots indicate estimated

mean effect sizes, bar widths are 95% confidence intervals of the estimates, and vertical lines with red dots

indicate zero (no change).

Figure 4 - PLOD3 is expressed in oligodendrocytes and is co-expressed with COL4A5.

A Cell-type specificity of PLOD3 in healthy brain tissues. Cell clusters obtained from gene expression in

healthy brain tissue by Human Protein Atlas (v22) scRNA-seq, and the Transcripts Per Million (TPM) in

each cluster. PLOD3 and COL4A5 are highly expressed in oligodendrocytes and belong to the same cluster.

B Expression levels of PLOD3 and COL4A5 per cell type.

C Cellular specificity of PLOD3 and collagen in the enthorhinal cortex. Scatter plots show the cluster

structure of cell populations projected by UMAP to 2D coordinates based on gene expression; the first panel

shows cell types, the second non-AD and AD, the third and fourth panels show cell type-specific expression

of PLOD3 and COL4A5 in oligodendrocytes, respectively.

D Correlation of COL4A5 with the expression of APP (upper panel) and the activity of amyloid fiber

formation (lower panel) for each cohort and each region.

DLPFC: dorsolateral prefrontal cortex; STG: superior temporal gyrus; PHG: parahippocampal gyrus; IFG:

inferior frontal gyrus; FP: frontal pole; TCX: temporal cortex; CBE: cerebellum.

Figure 5 - Cerebrovasculature most strongly associated with ECM dysregulation.

A Pathways significantly associated with the activity of the ECM organization were estimated for each

cohort tissue using the AES-PCA model. The p-values estimated for each cohort and for each brain tissue

were estimated as integrated p-values, and the top 10 pathways are shown in the figure. Figures were

generated by BioRender.com.

B Enrichment of pathways involving the cerebrovasculature in AD with gene set enrichment analysis

(GSEA) (FDR < 5%). Forest plots shown below each enrichment plot indicate Log2 fold change for each

pathway in each cohort and each region.

C Analysis using cerebrovascular scRNA-seq data (8 NCI, 9 AD).

D Expression of PLOD3 per cell type.

E Expression of type IV collagen per cell type.

DLPFC: dorsolateral prefrontal cortex; STG: superior temporal gyrus; PHG: parahippocampal gyrus; IFG:

inferior frontal gyrus; FP: frontal pole; TCX: temporal cortex; CBE: cerebellum.

Figure 6 - COL4A5 ligand is involved in the regulatory cascade of the astrocyte stress response.

A Estimated cell-to-cell communication based on ECM ligand–receptor expression.

B Receptor candidates for oligodendrocyte-derived COL4A5 ligands predicted to bind in astrocytes.

C Cell type-specific expression levels of receptors for COL4A5.

D COL4A5-mediated signaling pathways and target genes in astrocytes.

E Expression levels of target genes BCL6 and SGK1 per cell type.

F Analysis flow of the exploration of neighboring genes and functional estimation using network propagation

in astrocyte-specific co-expression networks.

G Top 30 neighboring genes estimated by network propagation based on BCL6 and SGK1.

H Gene set analysis of BCL6 and SGK1 neighbor genes.

Supplementary Figure 1 - Correlation of PLOD3 with APP activity (upper panel) and amyloid fiber formation

(lower panel) for each cohort and each region.

DLPFC: dorsolateral prefrontal cortex; STG: superior temporal gyrus; PHG: parahippocampal gyrus; IFG:

inferior frontal gyrus; FP: frontal pole; TCX: temporal cortex; CBE: cerebellum.

Supplementary Figure 2 - ECM activity is strongly associated with inflammatory cytokines.

A Enrichment of pathways involving the immune system in AD with GSEA (FDR < 5%). Forest plots shown

below each enrichment plot indicate Log2 fold change for each pathway in each cohort and each tissue.

B Pathways significantly associated with ECM activity obtained by applying AES-PCA for each cohort and

region.

DLPFC: dorsolateral prefrontal cortex; STG: superior temporal gyrus; PHG: parahippocampal gyrus; IFG:

inferior frontal gyrus; FP: frontal pole; TCX: temporal cortex; CBE: cerebellum.

Supplementary Figure 3 - COL4A5 ligand is involved in the regulatory cascade of the astrocyte stress

response.

A Top 30 neighboring genes estimated by network propagation based on BCL6.

B Gene set analysis of BCL6 neighbor genes.

C Top 30 neighboring genes estimated by network propagation based on SGK1.

D Gene set analysis of SGK1 neighbor genes.

A

Pathway-based PCA Regression

ECM Organization ⟷ Correlated Pathway

Mayo n= 313
MSSM n=315
ROSMAP n=1168

Combine P-values

REACTOME_RESPONSE_TO_ELEVATED_PLATELET_CYTOSOLIC_CA
REACTOME_CELL_SURFACE_INTERACTIONS_AT_THE_VASCULAR_WALL
REACTOME_CYTOKINE_SIGNALING_IN_IMMUNE_SYSTEM
REACTOME_SMAD2_SMAD3_SMAD4_HETEROTRIMER_REGULATES_TRANSCRIPTION
REACTOME_SIGNALING_BY_TGFB_FAMILY_MEMBERS
REACTOME_PLATELET_AGGREGATION_PLUG_FORMATION
REACTOME_INTERLEUKIN_2_FAMILY_SIGNALING
REACTOME_SIGNALING_BY_TGF_BETA_RECEPTOR_COMPLEX
REACTOME_INTEGRIN_SIGNALING
REACTOME_INTERLEUKIN_3_INTERLEUKIN_5_AND_GM_CSF_SIGNALING

Negative LN (Meta FDR)

B

CELL SURFACE INTERACTIONS AT THE VASCULAR WALL

RESPONSE TO ELEVATED PLATELET CYTOSOLIC CA^{2+}

PLATELET AGGREGATION PLUG FORMATION

INTEGRIN SIGNALING

enrichment score / rank

ROSMAP_DLPFC
MSSM_STG
MSSM_PHG
MSSM_IFG
MSSM_FP
MAYO_TCX
MAYO_CBE

Log fold change (95% CI)

C

NCI n=8
AD n=9

Frontal Cortex
Hippocumpus

Brain Blood Barrier (BBB) scRNA-seq

D

PLOD3

Average Normalized counts

ART CAP VEN aSMC aaSMC T-PC M-PC P.FB M.FB TC EPEN AST-HpcAST-Ctx PM MG OL OPC NEU

Oligodendrocyte

E

Brain Blood Barrier (GSE163577)

Ependymal
Astrocyte
P. Fibro
M. Fibro
Microglia
T cell
Neuron
OPC
SMC
Pericyte
Oligo
Veinous
Arterial
Capillary

UMAP2 / UMAP1

COL4A1   COL4A2   COL4A3
COL4A4   COL4A5   COL4A6