Identification of the Gene Signature that Constitutes Pathologic Pathways by Comprehensive Gene Expression Analyses

January 2024

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A Dissertation Submitted to the Graduate School of Science and Technology, University of Tsukuba in Partial Fulfillment of Requirements for the Degree of Doctor of Philosophy in Science

Doctoral Program in Biology, Degree Programs in Life and Earth Sciences

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Abstract

In recent times, the significant advancement of comprehensive gene expression technologies has led to a shift in the validation of disease-causing genes and the elucidation of disease mechanisms. Disease-causing genes were identified and validated by measuring the expression of specific genes. More recently, comprehensive gene expression analyses at the level of gene signatures, which represent a collection of multiple gene groups, became applicable for identifying and validating disease-causing genes. In these situations, I successfully combined RNA-sequencing (RNA-seq) and single-cell RNA-sequencing (scRNA-seq) with in vitro experiments to clarify gene signatures controlled by specific genes that could cause and associate diseases. The results allowed me to identify key gene signatures that constitute disease-causing pathways and explore their potential as drug targets. In the first study, I elucidated how the TREM2 gene, a risk factor for Alzheimer's disease (AD), contributes to the disease. By comparing the gene signatures of activated TREM2 in iPS-microglia treated with an anti-TREM2 agonist antibody and the gene signatures extracted from microglia of AD patients using single-nucleus RNA-sequencing (snRNA-seq), I revealed that TREM2 activation is reduced in AD microglia compared to healthy individuals and further declines with disease progression. These results suggested that controlling AD progression is achievable through an anti-TREM2 agonist antibody due to the decreased TREM2 activation in AD patients' microglia. In the second study, I comprehensively elucidated

the signaling mechanism of the TNFR2 gene, which is involved in the proliferation of regulatory T cells (Treg). Through RNA-seq and scRNA-seq analyses, the comparison between the gene signatures of TNFR2-activated Treg and that of Treg in cancer demonstrates that TNFR2 signaling induces Treg proliferation by coordinating multiple pathways simultaneously. Indeed, high expression of TNFR2 gene and upregulation of the aforementioned pathways were observed in cancer Treg, possibly aiding in the evasion of immune surveillance on cancer cells. Thus, I propose TNFR2 signaling as a potential target for suppressing cancer Treg. I regard comprehensive gene expression analyses as a powerful research method that allows identifying gene signatures constituting disease-causing pathways and increasing the success rate of drug development. I also discuss a few points to consider when one carries out the research method proposed here.

Abbreviations

B-cells inhibitor α

General Introduction

Molecular biology began with the elucidation of the structure of DNA by J. Watson and F. Crick in 1953 and has made remarkable progress since the completion of the Human Genome Project in 2003 [1]. The expression levels of individual genes were measured using real-time PCR technology from the 1990s and early 2000s. Then, semicomprehensive gene expression using Microarray emerged in the late 2000s [2]. In the 2010s, RNA-seq technology using next-generation sequencers emerged and overcame the weaknesses of Microarray in comprehensiveness and quantitation, and by the 2020s, comprehensive gene expression analysis by RNA-seq became mainstream [3]. In addition, single-cell RNA-seq (scRNA-seq) and single-nucleus RNA-seq (snRNA-seq) technologies, which enable comprehensive gene expression analysis at the single-cell level, have gained popularity [4].

With the advance in sequence technology in recent years, two academic fields have been formed: omics, which systematically collects vast amounts of biological data, and bioinformatics, which handles and analyzes omics data efficiently by applying data processing techniques/technologies established in informatics [5]. Before the current high-speed and cost-efficient sequence technology developed, the gene expression of a single or a set of genes was often measured to examine the molecular background of a biological phenomenon of interest. Nevertheless, the current sequence technology enables us to measure the expression of all the genes in a genome. By comparing two

genome-wide expression data generated under different biological conditions, we capture changes in the expression of a large number of genes and define a gene signature as a set of multiple genes that have a specific function among the set of altered genes, and a gene signatures as a set of gene signature that refer to all altered genes. The detailed examination of the content of the gene signatures identified is anticipated to provide keys to understanding the biological phenomenon of interest [6-8]. For instance, disease research, such as searching for disease-causing genes and elucidating disease mechanisms, has shifted from the investigation focusing on specific disease-causing genes to identifying and interpreting gene signatures derived from comparative analyses of genome-wide gene expression data [9-13]. Furthermore, the pathways comprising the gene signatures related to disease may include the ones that tightly associate with the pathogenesis.

In this study, I conducted genome-wide gene expression analyses to clarify the gene signatures regulated by disease-causing genes. Further, I explored the correlation between a disease and the gene signature identified. First, I focused on TREM2, a prominent etiologic gene in Alzheimer's disease (AD). In Chapter 1, I identified the gene signatures from the microglia cells in which TREM2 was up-regulated and compared it with the gene signatures retrieved from the comparison between the brain samples from healthy controls and AD patients. Second, I investigated TNFR2 involved in the proliferation of cancer-enhancing cells, Tregs. In Chapter 2, the gene signatures were obtained by analyzing the Treg cells with enhanced TNFR2 expression and were then compared with the gene signatures from the Treg cells isolated from cancer and other tissues in the same patients. The two works successfully provided clues to the candidate genes for future drug targets.

Chapter 1: Reduced TREM2 activation in microglia of patients with Alzheimer's disease

Abstract

Loss-of-function variants of triggering receptor expressed on myeloid cells 2 (TREM2) increase the risk of developing Alzheimer's disease (AD). The mechanism through which TREM2 contributes to the disease (TREM2 activation vs inactivation) is largely unknown. Here, I analyzed changes in a gene set downstream of TREM2 to determine whether TREM2 signaling is modified by AD progression. I generated an anti-human TREM2 agonistic antibody and defined TREM2 activation in terms of the downstream expression changes induced by this antibody in microglia developed from human induced pluripotent stem cells (iPSC). Differentially expressed genes (DEGs) following TREM2 activation were compared with the gene set extracted from microglial single nuclear RNA sequencing data of patients with AD, using gene set enrichment analysis. I isolated an anti-TREM2-specific agonistic antibody, Hyb87, from anti-human TREM2 antibodies generated using binding and agonism assays, which helped me identify 300 upregulated and 251 downregulated DEGs. Pathway enrichment analysis suggested that TREM2 activation may be associated with Th2-related pathways. TREM2 activation was lower in AD microglia than in microglia from healthy subjects or patients with mild cognitive impairment. TREM2 activation also showed a significant negative correlation with disease progression. Pathway enrichment analysis of DEGs controlled by TREM2 activity indicated that TREM2 activation in AD may lead to anti-apoptotic signaling,

immune response, and cytoskeletal changes in the microglia. I showed that TREM2 activation decreases with AD progression, in support of a protective role of TREM2 activation in AD. In addition, the agonistic anti-TREM2 antibody can be used to identify TREM2 activation state in AD microglia.

Introduction

Alzheimer's disease, the most common cause of dementia, is characterized by cognitive decline and memory deficits. According to the World Health Organization, more than 30 million people suffer from AD worldwide. Despite the high prevalence of the disease, disease-modifying agents that can slow or stop neurodegeneration are not known, and the unmet therapeutic requirements for AD are immense. Currently, the available therapies for AD, such as acetylcholinesterase inhibitors and/or a non-competitive N-methyl-Daspartate (NMDA) receptor antagonist, provide only symptomatic relief and do not restrict or halt disease progression [14].

Human genetic studies have indicated that loss-of-function of the triggering receptor expressed on myeloid cells 2 (TREM2) correlates with an increased risk of AD [15,16]. Furthermore, as the ε4 allele of apolipoprotein E—a TREM2 ligand—is the dominant genetic risk factor for late-onset AD (LOAD) [17], and TYROBP—a TREM2 adaptor protein—has been identified as the key regulator of LOAD using an integrative networkbased approach [18], TREM2 has emerged as an important signaling molecule in AD. TREM2 risk variants are associated with neuropathology [16]. The R47H mutation—a rare TREM2 loss-of-function variant—impairs TREM2 ligand recognition [19–22] and

alters its glycosylation pattern, leading to its instability on the cell surface and degradation in the lysosomes [23,24], and attenuation of downstream signaling [19,22]. In AD and mild cognitive impairment (MCI), TREM2 R47H carriers exhibit substantial gray matter loss in the orbitofrontal cortex and the anterior cingulate cortex, with relative sparing of the parietal lobes [25]. Furthermore, R47H carriers with LOAD have increased neuritic plaque and neurofibrillary tangle densities [26]. Even cognitively normal elderly people with R47H are known to have poorer cognitive function than non-carriers 2. A brainimaging volumetric study of individuals with a risk allele near R47H revealed that the mutation carriers lose brain volume at a significantly faster rate than the non-carriers [27]. These findings prompted the scientific community to verify whether TREM2 activation could be a therapeutic option for AD [28], and ameliorate AD disease pathology in several mice models. TREM2 activation of microglia reduces extracellular amyloid plaques and increases the number of microglia surrounding the plaques in multiple mouse AD models, including the APP/PS1 model with lentiviral TREM2 over-expression [29] and the 5xFAD model with microglial TREM2 over-expression [30]. Furthermore, TREM2 overexpression attenuates neuronal loss and promotes behavioral improvement in 5xFAD and APP/PS1 models [29,30]. Similar findings have been reported in studies based on mutant tau mice models. TREM2 over-expression reduces tau phosphorylation and inflammatory cytokine production, and improves neuronal survival and spatial memory function in the tau P301S mouse model [31]. Recent studies have reported the protective functions of TREM2 in AD preclinical models using anti-TREM2 antibodies (Abs) [32,33]. These studies have highlighted the importance of TREM2 in AD onset and progression and

indicated that TREM2 activation may provide a therapeutic option for patients with AD. TREM2 expression in AD brain tissues has been examined in several reports. However, findings are divided on whether TREM2 expression is altered in the AD tissues. One study found that TREM2 mRNA expression increased in the hippocampus of patients with AD [34]. However, other studies have shown downregulation or no significant changes in TREM2 expression in the hippocampus samples from AD patients at protein and/or mRNA levels [35–37]. TREM2 expression was higher in the temporal cortex of patients with AD than in the corresponding tissues of non-AD donors at mRNA and/or protein levels [38,39]. In the frontal cortex, TREM2 expression was significantly elevated at the protein level in AD patients but not at the mRNA level. A recent report indicated that TREM2 is upregulated in the microglia of the dorsolateral prefrontal cortexes of patients with AD [40]. Considering the supporting genetic evidence that TREM2 loss-offunction mutation increases the risk of AD, it is highly important to decipher if TREM2 upregulation is associated with enhanced TREM2 signaling, thereby retarding the disease progression. Another notable feature of TREM2 is the presence of a soluble form (sTREM2). The membrane protein TREM2 is cleaved by the proteases ADAM10 and ADAM17 to release sTREM2 in response to various stimuli [41,42]. sTREM2 has been used as a microglial activation marker, and its levels were found to be high in the cerebrospinal fluid (CSF) of patients with AD; moreover, it correlates positively with total and phosphorylated tau levels [43–45]. Although reports have shown that sTREM2 is produced following TREM2 over-expression and that sTREM2 levels depend on TYROBP [41,46], whether sTREM2 levels reflect TREM2 activation in the disease

remains unclear. sTREM2 levels in AD may indicate TREM2 upregulation, change in activity, or expression of the responsible proteases. However, considering that the rarely occurring R47H loss-of-function mutant produces sTREM2 more efficiently than the common variant of TREM2 [47], sTREM2 levels may not necessarily reflect the activation status of TREM2. Therefore, further studies are necessary to understand TREM2 activation status in the AD brain and elucidate the mechanism through which changes in TREM2 signaling contribute to AD.

In this study, I used a gene set acting downstream of TREM2 and aimed to investigate whether the TREM2 signal is modulated with AD progression. I further analyzed the potential of using TREM2 activation as a therapeutic option for AD.

Materials and Methods

Generation of anti-TREM2 monoclonal antibody (mAb)

All animal-related research protocols used in this study were approved by the Takeda Institutional Animal Care and Use Committee. Five CD2F1 mice (6 weeks old, female; The Jackson Laboratory, Bar Harbor, ME, USA) and five Trianni IgH kappa mice (6 weeks old, female; Trianni, Inc., San Francisco, CA, USA) were housed in the animal facilities of Takeda California and maintained under regular specific pathogen-free conditions. Following 1 week of acclimatization, the mice were immunized subcutaneously into the hock with 5 µg human TREM2-Fc (R&D Systems, Minneapolis, MN, USA) emulsified with TiterMax Gold adjuvant (TiterMax, Norcross, GA, USA) as part of the first immunization. For the second through the ninth immunizations, the mice were injected subcutaneously into the hock twice weekly with 3 μg human TREM2-Fc

using ODN-1826 (InvivoGen, San Diego, CA, USA) and alum adjuvant. On the day of the third immunization, the mice were intraperitoneally injected with 100 μg anti-mCD40 Ab (BioXcell, West Lebanon, NH, USA). Three days after the final boost, the popliteal and inguinal lymph nodes were isolated from each mouse, and the lymphocytes were fused with P3U1 mouse myeloma cells (ATCC, Manassas, VA, USA) in a 2:1 ratio and subjected to electrofusion using a Legacy ECM 2001 electrocell fusion and electroporation system (BTX, Holliston, MA, USA) to generate hybridomas. The fused cells were seeded in a semi-solid selective culture media containing hypoxanthineaminopterin-thymidine, and the grown hybridoma clones were manually transferred to 96-well plates. Hybridomas secreting anti-TREM2 mAbs were screened using enzymelinked immunosorbent assay (ELISA). First, the human TREM2-Fc protein was coated on a 96-well ELISA plate and then incubated with hybridoma culture supernatant and goat anti-mouse IgG (H+L) conjugated with horseradish peroxidase (HRP) (Jackson ImmunoResearch Laboratories, Inc., West Grove, PA, USA). The plates were washed with phosphate-buffered saline (PBS) containing 0.05% Tween-20 after each incubation step. The TMB HRP substrate (Bio-Rad, Hercules, CA, USA) was added to each well and incubated for 5 min. The reaction was stopped using $1 \text{ M H}_2\text{SO}_4$ and the absorbance at 450 nm was measured using an EnVision plate reader (PerkinElmer, Waltham, MA, USA). The Hyb87 hybridomas were expanded in Ab expression medium, which was a mixture of Iscove's modified Eagle medium and Ham's F-12 nutrient medium (FujiFilm Wako Pure Chemical, Osaka, Japan) supplemented with MEM non-essential amino acid solution, sodium pyruvate, L-alanyl-L-glutamine, 100 U/mL of penicillin and streptomycin (FujiFilm Wako Pure Chemical), and 10% ultra-low IgG fetal bovine serum (Thermo Fisher Scientific, Waltham, MA, USA). Hyb87 was purified from the culture supernatant using Ab-Capcher ExTra (ProteNova, Higashikagawa, Japan).

Determination of Ab binding to TREM2 on cells

Expi293 cells

We tested the specificity of Hyb87 binding to TREM2 using flow cytometry (FCM). Briefly, a vector expressing human TREM2 and the NeoFection reagent (Astec Co. Ltd., Kasuya, Japan) were mixed at 1:1 ratio in OptiMEM I (Thermo Fisher Scientific). After 15 min, the mixture was added to Expi293 cells (Thermo Fisher Scientific) at a density of 1×10^6 cells/mL. One day after transfection, the cells were reacted with Hyb87 or control IgG (R&D Systems), followed by incubation with anti-mouse IgG-Alexa Fluor 488 (Thermo Fisher Scientific). Cell surface fluorescence was detected using BD Accuri C6 Plus (BD Biosciences, San Jose, CA, USA) and analyzed using the FlowJo software (Becton Dickinson, Ashland, OR, USA).

THP-1 cells

Similarly, I tested the specificity of Hyb87 using the human monocytic THP-1 cells (ATCC) and *TREM2* knockout (KO) THP-1 cells following the Expi293 procedures. *TREM2* KO THP-1 cells were established as mentioned below. The Fc receptor blocking reagent (BD Biosciences) was used during Ab incubation with THP-1 cells or *TREM2* KO THP-1 cells. In brief, duplex RNA was prepared by annealing equimolar amounts of crRNA (5'-ACCCAGGGTATCGTCTGTGATGG-3'or 5'- CACAGTGTTCCAGGGCGTGGCGG-3') and tracrRNA at $95\Box$ C for 5 min and cooling to room temperature. To form the ribonucleoprotein (RNP) complex, Cas9 was added to

the duplex RNA and incubated for 15 min at room temperature. The THP-1 cells were simultaneously transfected with both complexes using the Neon transfection system (Thermo Fisher Scientific) and seeded at a density of 2×10^5 cells/well in THP-1 culture medium supplemented with 1 μM RS-1 and 0.1 μM SCR7 (Xcess Biosciences, Chicago, IL, USA) in a 24-well plate. Seven days following the transfection, the cells were subcloned using limiting dilution method at 0.3 or 1 cell/well. Genomic DNA was extracted from the outgrown cells using the SimplePrep reagent for DNA (Takara Bio, Kusatsu, Japan) and sequenced using the BigDye Terminator v3.1 cycle sequencing kit (Thermo Fisher Scientific). I selected clone17 with a frameshift mutation in the *TREM2* exon as *TREM2* KO THP-1 and used it for FCM.

Determination of Ab affinity

The kinetic analysis of the affinity of Ab to TREM2 was performed using bio-layer interferometry with an Octet Red96e system (Molecular Devices, Sunnyvale, CA, USA). First, Hyb87 was captured on anti-mouse Fc Octet biosensors (Molecular Devices) for 120 s. The biosensors were reacted with serially diluted recombinant human TREM2-His (R&D Systems) for 120 s, followed by dissociation in PBS for 180 s. The kinetics of the Ab was analyzed with a sensorgram aligned at the beginning of the association step after background subtraction. The sensorgram was analyzed using a 1:1 Langmuir fitting model.

Nuclear factor of activated T cells (NFAT) assay

TREM2 activation was detected as described below. Hyb87 or control IgG (10 μg/mL) was immobilized on a 96-well plate (Corning, New York, NY, USA, #3912) overnight at 4°C. One million THP-1 or *TREM2* KO THP-1 cells were transfected with 5 μg of the luciferase reporter plasmid driven by the NFAT response element using the Neon transfection system (Thermo Fisher Scientific) according to the manufacturer's instructions. In total, 30,000 transfected cells were seeded on the Ab-immobilized plate. After 3 h, luciferase activity was detected with NanoGlo reagent (Promega, Madison, WI, USA) using an EnVision plate reader (PerkinElmer).

Treatment of induced pluripotent stem cell (iPS-)-derived microglia-like cells (iMGs) with Hyb₈₇

Culture of human iPSCs

All human cell protocols used in this study were approved by the Takeda Institutional Ethical Committee and followed the guidelines of the Declaration of Helsinki. Human iPSCs (Clone XCL-1, XCell Science, Novato, CA, USA) were cultured on laminincoated plates in StemFit (Ajinomoto Healthy Supply Co., Inc, Tokyo, Japan) containing penicillin and streptomycin. The cells were passaged every 6 to 7 days using 0.5 mM EDTA, seeded at a density of 2.0×10^4 cells/well on a 6-well plate and maintained in the presence of 10 μM Y-27632 (FujiFilm Wako Pure Chemical). The culture medium was replaced with StemFit containing penicillin and streptomycin in the absence of Y-27632, 24 h after passaging.

Differentiation of iPSCs to hematopoietic progenitor cells (HPCs)

iPSC-derived hematopoietic progenitors (iHPCs) were generated using defined conditions with several modifications to previously published protocols [48,49]. Briefly, 0.5 -1.0 \times 10⁵ cells were plated per well in a tissue culture-treated 6-well plate (day 0). The cells were cultured in 2 mL StemFit containing Y-27632 for 24 h under normoxic conditions.

Day 1: The medium was changed to basal medium [50] supplemented with 50 ng/mL FGF2, 50 ng/mL BMP4, 12.5 ng/mL activin-A, 10 μM Y-27632, and 2 mM LiCl. The cells were then placed under hypoxic cell culture conditions of 5% O_2 and 5% CO_2 for 2 days.

Day 3: The cells were further maintained in basal medium supplemented with 50 ng/mL each of FGF2 and VEGF under hypoxic conditions.

Day 5: The medium was changed to basal medium containing 50 ng/mL FGF2, 50 ng/mL VEGF, 50 ng/mL TPO, 10 ng/mL SCF, 50 ng/mL IL-6, and 10 ng/mL IL-3. The cells were placed under normoxic conditions.

Day 7 and day 9: The medium was changed to the one used on day 5.

Differentiation of iHPCs to iMGs

iMGs were differentiated from iPSCs via embryoid bodies and HPCs using defined conditions with several modifications to a previously published protocol [50].

Day 11: iHPCs were washed using iMG basal differentiation medium [50]. After

centrifugation, the iHPCs were gently suspended in iMG complete differentiation medium containing 25 ng/mL M-CSF, 100 ng/mL IL-34, and 50 ng/mL TGF-β and seeded at a density of 2×10^5 cells per well on 6-well plates. One milliliter iMG complete differentiation medium was added every 2 days.

Day 23 and day 37: The cells were collected as iMGs and seeded in a 1:1 mixture of conditioned medium and iMG complete differentiation medium [50]. The cells were supplemented with 1 mL iMG complete differentiation medium every two days.

The reagents used in this experiment were purchased from Thermo Fisher Scientific (BMP4, activin-A, VEGF, TPO, IL-6, SCF, and IL-3) or PeproTech (FGF2, M-CSF, and TGF-β).

Treatment of iMGs with Hyb87

iMGs were collected on day 39 and seeded on a 24-well non-tissue culture-treated plate (Corning) coated with 10 μg/mL Hyb87 or control mouse IgG. After 6 h, the cells were harvested for RNA isolation.

AmpliSeq analysis

AmpliSeq libraries were constructed for iMGs and sequenced in biological triplicates using the Ion Proton platform (Thermo Fisher Scientific) according to the manufacturer's instructions. Briefly, 10 ng of total RNA was reverse transcribed using the SuperScript VILO cDNA synthesis kit (Thermo Fisher Scientific), followed by library generation using the Ion AmpliSeq transcriptome human gene expression kit. The libraries were

diluted to 45 pM and pooled equally with $9 \square 10$ individual samples per pool. The pooled libraries were multiplexed and clonally amplified using the Ion Chef System, and subsequently, sequenced on Ion PI chips using an Ion Proton sequencing system. Data were first analyzed using the Torrent Suite and the ampliSeqRNA analysis plugin was used to generate count data. Principal component analysis (PCA) was performed using the "prcomp" function of stats package in R [51]. Tukey's honest significant difference test was conducted to compare the first principal component (PC1) in each group using "Tukey HSD" of stats package in R. Visualization of the scatter plot and boxplot was performed using the ggplot2 package in R. All the AmpliSeq data were deposited in the Gene Expression Omnibus (GEO) repository at http://www.ncbi.nlm.nih.gov/geo (accession number: GSE159333).

Identification of differentially expressed genes (DEGs) induced by TREM2 activation The DEGs representing TREM2 activation (TREM2 DEGs) were identified based on the gene-wise negative binomial generalized linear model with the quasi-likelihood method using the edgeR package in R [52,53]. The criteria for the significance of DEGs were set at false discovery rate-adjusted (FDR-adjusted) P value < 0.05 and absolute fold change > 1.5. Volcano plots of the DEG analysis were drawn using EnhancedVolcano package in R. TREM2 DEGs were defined as genes common between DEGs from Hyb87 vs. PBS and Hyb87 vs. control IgG, and those with the same direction of expression change in the DEGs.

Pathway enrichment analysis

Pathway enrichment analyses of TREM2 DEGs were conducted using the Cortellis MetaCore software (Clarivate, Philadelphia, PA, USA) using "Enrichment Analysis" workflow (default setting).

GSEA

The Religious Order Study and Rush Memory and Aging Project (ROSMAP) data (syn18485175), the single-cell expression profile of human dorsolateral prefrontal cortex derived from 75,060 cells of 48 individuals [54], was downloaded from AD Knowledge Portal (https://adknowledgeportal.synapse.org/Explore/Studies?Study=syn18485175). The data included quality-filtered single-nucleus RNA-sequenced read counts of 17,926 genes of the human reference genome 38 (GRCh38) and the clustering results of the reads to each cell type. The reads from microglial cells were extracted and genes with less than three aligned reads were removed, resulting in a total of 13,039 genes. PCA was performed on log-normalized read counts, and three individuals whose PC1 or second principal component (PC2) were outside of more than three standard deviations from that of the other samples were removed. Healthy controls (HC) and patients with AD in the original report [41] were re-classified into HC, MCI, and AD using Mini-Mental State Examination (MMSE) (HC, \geq 29; MCI, 24 to 28; AD, \leq 23) [55] or clinical consensus diagnosis of cognitive status (cogdx: HC, 1; MCI, 2 or 3; AD, 4 or 5) [54].

I compared the expression of genes across HC, MCI, and AD using DESeq2 [56] in Seurat [57]. Finally, I multiplied the $-log_{10} P$ value with the sign of the log-scale fold change (signed P value) for GSEA. I also quantile-normalized the read counts on each gene and conducted linear regression on cognitive, MMSE, Consortium to Establish a Registry for Alzheimer's Disease (CERAD), and Braak scores with covariates of sex, years of education, and age. The CERAD score decreased with the progress of the neuritic plaques, whereas Braak or MMSE scores increased with the deterioration of neurofibrillary tangles or cognitive decline, respectively. To interpret the CERAD GSEA result in the same correlation direction as the MMSE and Braak GSEA results, I calculated the correlations between each gene and CERAD score and converted them to the signed P values by reversing the positive and negative direction.

Another single-nucleus RNA-seq (snRNA-seq) dataset generated using ROSMAP data (syn21125841) [50] was analyzed for a replication study. Data included the number of aligned reads per gene in each cell, which were quantified using Cell Ranger Single-Cell Software Suite (10x Genomics, Pleasanton, CA, USA). Data of 19 individuals which did not overlap with that of ROSMAP syn18485175 data [54] and had the common variant, TREM2, were downloaded from AD Knowledge Portal (https://adknowledgeportal.synapse.org/Explore/Studies?Study=syn21670836). The 19 individual datasets comprised ten patients with AD and nine HCs. The clustering of the cells was conducted using the R package, Seurat [57]. The cells with a high ratio of mitochondrial reads $(> 5\%)$, abnormally high or low number of unique molecular identifiers $(< 400$ or $> 40,000$, respectively), or an abnormally high or low number of detected genes (> 9,000 or < 200, respectively) were filtered out—resulting in a remainder of 42,087 cells. Next, the read counts for each gene were divided by the total counts in

the cell and log-normalized following multiplication of 10,000. Then, 20,000 features (genes) that were highly variable among the cells were selected using FindVariableFeature in Seurat package [57].

The cells were clustered using shared nearest neighbor modularity optimization using 1 to 20 PCs after the dimension reduction analysis. Then, the clusters were identified as one of the following cell types via the mean expression level of the marker genes selected by the Allen Institute for Brain Science [58]: *GAD1* (interneuron), *SLC17A7* (excitatory neuron), *TYROBP* (microglia), *AQP4* (astrocyte), *PDGFRA* (oligodendrocyte precursor), *OPALIN* (oligodendrocyte), and *NOSTRIN* (endothelial cell). As a result, 2,200 cells were identified as microglia. The reads in the microglia were summed per individual, and genes with less than three reads in total were removed. The gene expression was then compared between AD and HC groups using DESeq2 [56]. The results of each gene were used for GSEA.

GSEA was conducted between TREM2 DEGs and genes extracted from the abovementioned data sets using the GSEA_R package in R. The criterion for the significance of GSEA was set at FDR-adjusted q-value < 0.05. The datasets generated and analyzed during the current study are available in the GEO repository, https://www.ncbi.nlm.nih.gov/geo/query/acc.cgi?acc=GSE159333

Results

Generation and characterization of agonistic anti-TREM2 mAb, Hyb87

I attempted to obtain an anti-TREM2 agonistic Ab. I used hybridoma techniques

following the immunization of mice with TREM2-Fc protein. The culture supernatant of the hybridomas was screened using ELISA to identify the clone secreting suitable mAbs, and my results showed that the anti-TREM2 Ab clone, Hyb87, bound to human TREM2. I further characterized Hyb87 using multiple assays. First, I tested the binding of Hyb87 to TREM2, both exogenously and endogenously expressed in cells. I prepared Expi293 cells transfected with the human TREM2 expression plasmid. Although the fluorescence intensity of the control IgG did not increase in parental or human TREM2-overexpressing Expi293 cells in FCM, that of Hyb87 did when human TREM2 was expressed (Fig. 1A). I further confirmed the binding of Hyb87 to endogenous TREM2. I used human monocytic THP-1 cells for TREM2 expression [59]. As shown in Fig. 1B, fluorescence intensity was detected in THP-1 cells after adding Hyb87. To further verify the specific binding of Hyb87, I established *TREM2* KO THP-1 cells and observed that Hyb87 binding was lost in these cells (Fig. 1B). These results indicated that Hyb87 bound specifically to human TREM2 on the cell surface. The affinity of Hyb87 to TREM2 was then determined using bio-layer interferometry (BLI). The Ab was immobilized onto the sensor chip as a ligand, and TREM2-His was applied as an analyte. According to an analysis using a Langmuir fitting model, the K_D value of Hyb87 to human TREM2 was 1.07×10^{-9} M. The K_a of the Ab was determined to be 2.32×10^{5} (1/M/s) and the K_d was 2.48×10^{-4} (1/s) (Fig. 1C).

I investigated whether Hyb87 activated TREM2. A previous study reported that TREM2 activation increases intracellular Ca^{2+} concentration and can be detected using the NFAT reporter [60,61]. Hence, I used the NFAT reporter system in this study. THP-1 cells were transiently transfected with the reporter plasmid and then allowed to react with Hyb87. Compared to the PBS-treated group, Hyb87 increased NFAT activity by 10.4-fold, whereas the increase by control IgG was 1.8-fold (Fig. 1D). This indicated that Hyb87 activated TREM2. Furthermore, I observed a slight increase in NFAT reporter activity by control IgG. I believe that the increment in NFAT activity by the control IgG was a consequence of the binding of the control IgG to the Fc receptor [62]. Meanwhile, NFAT reporter activity by Hyb87 was not significantly different than that by control IgG in *TREM2* KO THP-1 cells (Fig. 1D), suggesting that NFAT activity by Hyb87 in the THP-1 cells was mediated through TREM2.

Isolation of TREM2 DEGs from iMG

I investigated how TREM2 activation changed in the microglia of patients with AD. I assessed the changes in the expression of genes downstream of TREM2 to understand TREM2 activation in AD. I consistently used human data, as significant differences in the transcriptional signatures of human AD and the 5xFAD mouse model have been reported [40]. To determine gene expression changes downstream of TREM2, iMG cells were treated with Hyb87, PBS, or the control IgG, and subjected to transcriptome analysis using the AmpliSeq approach. In PCA of the iMG AmpliSeq data, the variance of PC1 and PC2 was found to be 29.7% and 15.9 %, respectively (Fig. 2A). In the PC1 that explained the maximum variabilities, Hyb87 differed significantly from the PBS control and IgG, indicating that Hyb87-induced changes in the expression of specific genes could be detected. Next, I isolated DEGs in response to Hyb87 treatment (vs. PBS or vs. control

IgG; Table 1). I observed significant changes in gene expression after Hyb87 treatment as per the following criteria: FDR-adjusted P value ≤ 0.05 and absolute fold change ≥ 1.5 , which involved 1,274 genes in Hyb87 vs. PBS and 710 genes in Hyb87 vs. control IgG (Fig. 2B, C, and Table 1). In contrast, the DEGs from the control IgG (vs. PBS) comprised as few as 81 genes (Table 1). To exclude gene expression changes due to IgG via Fc receptors, I attempted to define TREM2 DEGs that overlapped in the direction of altered expression between Hyb87 vs. PBS and Hyb87 vs. the control IgG. This allowed me to define TREM2 activation for 551 genes (Fig. 2C and Table 2) consisting of 300 upregulated (TREM2 up) and 251 downregulated (TREM2 down) DEGs (Fig. 2B and Table 1). The TREM2 DEGs were applied to pathway enrichment analysis using MetaCore. TREM2 up showed enrichment in "Immune response TSLP signaling" ($P =$ 3.0E-7), "Th2 cytokine-induced alternative activation of alveolar macrophages in asthma" $(P = 1.1E-06)$, and "Immune response IL-4-induced regulators of cell growth, survival, differentiation, and metabolism" ($P = 1.2E-06$). TREM2 down was associated with "Development NOTCH-induced EMT" ($P = 1.3E-06$), "Eosinophil granule protein release in asthma" ($P = 2.0E-05$), and "Signal transduction Cyclic AMP signaling" ($P =$ 4.6E-05) (Fig. 2D, E, and Table 3).

Reduction in TREM2 activation with disease progression in patients with AD

Next, I investigated how TREM2 is activated in patients with AD by comparing the TREM2 DEGs with the transcriptome data of microglia from these patients. I used GSEA to determine statistically significant and consistent differences between gene sets from

two biological states [63, 64]. I separately used TREM2 up (300 upregulated genes) and TREM2 down (251 downregulated genes) to clarify the direction of gene expression regulated by TREM2 activation. I selected snRNA-seq data of patients with AD for comparison, for the following reasons: The microglial population that expresses TREM2 exclusively consisted of only 5-10% brain cells; TREM2 DEGs were from iMG, but not limited to microglia. Therefore, single-cell-derived RNA-seq data was ideal for my study, as gene expression changes in microglia may not be detected in the bulk RNA-seq data of tissues consisting of a mixed cell population. I performed GSEA using TREM2 DEGs in two ways: (1) Statistical analysis using DEGs among divided populations; (2) Correlation analysis using AD disease scores obtained from CERAD, Braak, and MMSE. First, I excluded three out of the 48 individuals using PCA, which suggested low data quality, and then I classified 45 individuals into three populations of HC, MCI, or AD using two clinical scores; MMSE of HC (\geq 29), MCI (24-28), and AD (\leq 23), or cogdx of HC (value 1), MCI (value 2, 3), and AD (value 4, 5), leading to six HC, 17 MCI, and 22 AD individuals determined using MMSE, or 13 HC, 10 MCI, and 21 AD individuals determined using cogdx (Table 4), after assessing the quality using PCA and excluding one individual from cogdx classification due to the possibility of other diseases. Next, I calculated the statistical values and signed P value in each population by comparing HC with MCI, HC with AD, or MCI with AD. GSEA was then conducted using these signed P values as the score on the side of the molecular profile data and TREM2 up or down as the data on the dataset side. Intriguingly, I observed that TREM2 up was significantly lower in AD microglia than in HC or MCI microglia when each population was defined

using both MMSE and cogdx (Fig. 3A–D and Table 5). Furthermore, no significant enrichment was observed when I compared HC and MCI microglia. These findings clearly showed that TREM2 activation was lost in AD. However, TREM2 down was significantly associated only with cogdx AD vs. MCI, which meant that TREM2 down was significantly lower in AD microglia than in MCI microglia.

I speculated that the fluctuation range of the fold change was significantly lower in TREM2 down than in TREM2 up, as absolute values of mean fold change were 1.09 in TREM2 up and 0.98 in TREM2 down, with $P = 0.03$. Second, the relationship between CERAD-, Braak-, or MMSE-correlated microglia genes and TREM2 DEGs (TREM2 up or TREM2 down) was investigated using GSEA to determine whether TREM2 activation changed with the progression of AD. Toward this, I used GSEA to compare TREM2 DEGs with genes that correlated with CERAD, Braak, or MMSE scores, which represented the semi-quantitative measure of neuritic plaques, neurofibrillary tangles, and cognitive function, respectively. TREM2 up showed a significant correlation with CERAD (FDR q-value = 0.009) and Braak-correlated genes (FDR q-value = 0), but not with MMSE-correlated genes (FDR q-value = 0.562) (Fig. 3E–F and Table 6). Furthermore, TREM2 down was not significantly associated with any of the scores tested. Collectively, these results suggested that TREM2 activation decreased with the progression of AD pathology.

Based on these findings, genes enriched in GSEA between TREM2 up and the core enrichment genes in AD (vs. HC) that regulated TREM2 activation in AD were applied to pathway enrichment using MetaCore. Interestingly, the following were selected as the

common pathways: "Apoptosis and survival anti-apoptotic TNFs/NF-kB/IAP pathway" $(P = 1.0E-6$ on cogdx; P = 2.9E-7 on MMSE), "Immune response IFN- α/β signaling via JAK/STAT" ($P = 3.4E-5$ on cogdx; $P = 1.0E-5$ on MMSE), and "Immune response BAFF-induced non-canonical NF-kB signaling" (P = 1.1E-4 on cogdx; P = 4.3E-5 on MMSE). In contrast, pathway enrichment analysis with genes from GSEA and Braak or CERAD indicated "Development regulation of cytoskeleton proteins in oligodendrocyte differentiation and myelination" ($P = 1.8E-6$ on Braak; $P = 5.6E-5$ on CERAD), "Inhibition of remyelination in multiple sclerosis: regulation of cytoskeleton proteins" ($P = 1.6E-5$ on Braak; $P = 1.7E-5$ on CERAD), and "Cell adhesion gap junctions" ($P = 3.3E-6$ on Braak; $P = 3.6E-6$ on CERAD) as the common pathways (Fig. 3G, H, and Table 7).

I investigated whether TREM2 expression differed between AD, MCI, and HC, or whether TREM2 expression correlated with CERAD or Braak scores. My results showed that TREM2 expression did not differ significantly between AD, MCI, and HC, and did not show any correlation with the scores (FDR-adjusted P value > 0.85 ; Tables 8 and 9). I analyzed another snRNA-seq dataset, ROSMAP data (syn21125841) [40], to replicate my observations. Nineteen individuals were classified into three populations of HC, MCI, or AD using two clinical scores; MMSE or cogdx. Three HC, five MCI, and 11 AD individuals were determined using MMSE, or nine HC, and ten AD individuals were determined using cogdx. (Table 10). I calculated the signed P value from the snRNA-seq data between HC and AD microglia and performed GSEA using TREM2 up for
replication. My results showed that TREM2 up was significantly lower in AD microglia than that in HC microglia (Fig. 4a and b).

Discussion

In this study, I generated an agonistic anti-TREM2 mAb, Hyb87, and utilized it as a tool for activating TREM2. Further, I defined TREM2 activation by assessing changes in the expression of downstream genes. Previous studies used anti-TREM2 Ab as a TREM2 activation tool in various types of cells, including the microglia, dendritic cells, macrophages, osteoclasts, and astrocytes [32,33,50,65–71]. However, in these studies, the Abs were used to visualize signals and/or assess the cellular functions of activated TREM2 in terms of intracellular Ca^{2+} mobilization, ERK phosphorylation, SYK phosphorylation, apoptotic cell death, the formation of TRACP⁺ osteoclasts, migration of osteoclasts, pro- and anti-inflammatory responses, phagocytosis, cell survival, migration, and amyloidogenesis, but not for defining TREM2 activation, as performed in this study. I used Hyb87 to activate TREM2 in iMG cells and identified TREM2 DEGs after comparison with control IgG stimulation (Fig. 2A–C). I observed a slight increase in the NFAT signal by the control IgG (Fig. 1D). The control IgG-mediated responses were possibly due to Fc receptor engagement. A previous report showed that NFAT, as well as other transcription factors, transmit signals downstream of the Fc receptor [62]. Fc receptor engagement and TREM2 increase the expression levels of some of the cell surface molecules, including CD86, CD40, or CCR7 [60]. TREM2 induces signaling downstream of the Fc receptor, suggesting that the DEGs shared between TREM2 and control IgG treatment, which were not included in my TREM2 DEGs, may primarily be a part of TREM2 DEGs. Wang et al. demonstrated that mutations abolishing IgG binding to the Fc receptor in the agonistic anti-TREM2 mAb, marginally affect its pro-survival effect on macrophages, suggesting that the Ab-mediated TREM2 activation is largely independent of the IgG-mediated cross-linking of Fc receptors [32]. This finding strongly supports my definition of TREM2 DEGs.

The pathway enrichment analysis of TREM2 up showed type2 immune response as represented by the Th2 type cytokine pathways, including TSLP and IL-4 (Fig. 2D and Table 3). My findings agree with those of the previous studies, wherein TREM2 was reported to enhance Th2 cytokine production [46,67,72]. Th2 cytokines also inhibit $Aβ_1$. 42-induced pro-inflammatory cytokines, including IL-6 and IL-1β, in microglia and THP-1 cells [73]. IL-4 induces the uptake and degradation of $\mathbb{A}\beta_{1-42}$ [74]. Intracerebral microinjection of IL-4 and IL-13 reduces Aβ accumulation in APP23 mice via microglial activation [75]. Thus, the TREM2 signal may modulate Th2 type cytokine pathways in Aβ clearance.

I successfully showed low TREM2 activation in microglia of patients with AD and that TREM2 activation decreased with the progression of neuritic plaques and neurofibrillary tangles, represented by CERAD and Braak scores, respectively. My findings indicated TREM2-mediated regulation of AD pathology via controlling microglial functions and corroborated a previous finding that the TREM2 loss-of-function variant R47H is associated with increased density of neuritic plaques and neurofibrillary tangles in multiple brain regions [26]. R47H is associated with amyloid compaction and increased

tau hyperphosphorylation around amyloid deposits [76]. In my analysis, TREM2 activation was not associated with the cognition score, MMSE my . A report examining the association of MMSE and R47H variant revealed no significant difference in the annual rate of MMSE decline between patients with AD carrying a TREM2 common variant and an R47H variant, although the number of participants was small [77]. Further, the R47H risk variant did not significantly affect cognitive performance in a longitudinal study [78]. Out of the 45 donors in the dataset that I used in the evaluation study (Fig. 3), 29 were registered as harboring a TREM2 common variant. On the other hand, the TREM2 sequences of the remaining 16 donors were not available. Therefore, I cannot rule out the possibility that the 16 donors possessed the R47H variant that affected my analysis in elucidating TREM2 activation. However, my replication study recapitulated the results of the evaluation study (Fig. S1), and the dataset used in the replication study comprised TREM2 common variant carriers alone. This indicates that TREM2 signal is low in the microglia of patients with AD regardless of the R47H variant.

I speculated that lower TREM2 activation in the microglia of patients with AD could be caused by proteases. Several proteases, including ADAM10, ADAM17, or meprin β, are known to reduce the levels of membrane-bound TREM2 [41,42,79]. The ADAM17 mediated shedding of the membrane-bound TREM2 is triggered by pro-inflammatory stimulation, such as lipopolysaccharide, TNF α or IFN γ [80]. The reduction of the membrane-bound TREM2 levels by ADAM10 or meprin β has been shown to inhibit TREM2-mediated phagocytosis [79]. Another study reported that γ-secretase degrades the C-terminal fragment of TREM2 and that impaired γ-secretase activity leads to an accumulation of the C-terminal fragment of TREM2, thereby trapping its adaptor protein—TYROBP to reduce TREM2 signaling [81,82].

My GSEA data showed that TREM2 activation was not significantly different in MCI (vs. HC), suggesting that TREM2 activation could be maintained in the microglia of patients with MCI. As discussed earlier, the function of TREM2 could be affected by proteases that behave differently in MCI and AD microenvironments. Interestingly, a previous report showed that the levels of active form of γ-secretase activating protein reduced in the frontal cortex of severe AD subjects, but not in that of MCI subjects [83]. This difference in protease regulation could contribute to the varying amounts of membranebound TREM2 capable of transmitting TREM2 signal in the microglia of patients with MCI and AD. Previously, Jiang et al. reported that TREM2 failed to improve Aβ pathology when the lentiviral over-expression of TREM2 was tried in 18-month-old APP/PS1 mice [84], whereas its over-expression improved Aβ pathology in 7-month-old APP/PS1 mice [29]. This suggests that the TREM2 signal is no longer viable once AD has been established. However, further studies are required to understand how TREM2 activation changes with disease progression.

In the present study, the TREM2 expression levels alone showed no correlation with the clinical scores from the snRNA-seq data used. Although some previous studies reported TREM2 expression changes in AD brains due to aging [34–40], the direction of alteration of TREM2 expression levels is not unilateral. For example, in the hippocampus of patients with AD, TREM2 mRNA has been reported to be higher than that of controls [34], but different groups exhibit either downregulation of TREM2 or no alteration at protein and/or mRNA levels [35–37]. Although extensive efforts are required to address this discrepancy, some reasons for it may be as follows. TREM2 is mainly expressed in microglia in the brain. Differences in the population size of microglia could lead to changes in the relative expression of TREM2. Additionally, the use of different internal controls for normalization may lead to difficulty in the interpretation of TREM2 expression. The expression level of a molecule is typically normalized with an internal control, such as *GAPDH*, *ACTB*, or *HPRT*. In practice, TREM2 mRNA has been differently normalized in previous studies: with *GAPDH* [35,37], a combination of *ACTB* and *HPRT* [34], or a combination of *GAPDH* and *HPRT* [38]. Moreover, patient demographics may have been different in those studies or sample storage conditions could have affected sample quality. However, none of those studies reported an association of TREM2 expression with its activation.

In previous reports, the sTREM2 level was investigated in CSF to determine its association with AD. Interestingly, a few studies revealed that sTREM2 level in the CSF of patients with AD is associated with hallmarks of AD, such as $A\beta_{1-42}$ [85], total tau, and phosphorylated tau in CSF [30–32]. However, whether sTREM2 levels reflect TREM2 activation remains unknown. The levels of TREM2 proteases, ADAM10 and ADAM17, are altered in AD CSF or brain [86–89]. Hence, the usability of sTREM2 for TREM2 activation warrants further investigation.

The brain snRNA-seq data of 5xFAD mice and human patients with AD elucidated distinct AD gene signatures between human and mouse microglia [40]. Notably, the human brain shows more qualitative changes in the number of microglia than that of mice,

and the signature of human microglia in AD is different from that of disease-associated microglia in the 5xFAD model. This finding prompted me to use human cell and tissue data instead of mouse data. The study reported higher expression of the transcription factor IRF8 in AD, indicating that IRF8 may be a major driver of human microglia signature in AD. In my study, *IRF8* was significantly downregulated in response to Hyb87 vs. PBS (FDR-adjusted P = 2.6E-5 and log₂ fold change = -0.54 for IRF8), indicating that Hyb87 could reverse the IRF8-signature in human AD microglia. Pathway enrichment data with genes enriched in GSEA between TREM2 up and core enrichment genes in AD (vs. HC) yielded the anti-apoptotic pathway as the top hit. This corroborated anti-apoptotic function of TREM2 in microglia from 5xFAD mice crossed with *TREM2* KO mice⁶ or in microglial BV-2 cells [90]. In addition to the pathway enrichment data, some of the genes were enriched in GSEA function in microglia and could control microglial fate downstream of TREM2.

Genes such as heparin-binding epidermal growth factor-like growth factor (*HBEGF*), baculoviral IAP repeat-containing 3 (*BIRC3*), BTG anti-proliferation factor 1 (*BTG1*), CD300 molecule-like family member B (*CD300LB*), IL3 receptor subunit α (*IL3RA*), and platelet-derived growth factor-α (*PDGFA*) were upregulated in response to Hyb87 treatment. Thus, TREM2 activation might efficiently combat AD by orchestrating the expression of the microglial genes involved in microglial fate. HBEGF is a potent stimulator of cell proliferation and migration and plays diverse physiological roles, including wound healing and cardiac development [91]. Previous reports suggest the involvement of HBEGF in microglia and AD. HBEGF signaling stimulates cell

proliferation and phagocytosis of microglia [92]. Furthermore, a trans-ethnic metaanalysis of a genome-wide association study identified an intergenic single nucleotide polymorphism between *HBEGF* and *PFDN1* as an AD susceptibility locus [93]. Study of *Hbgef* KO also showed that HBEGF regulates Aβ1-42 and phosphorylated tau levels [94], as well as neurogenesis and cognitive function [95]. BIRC3, also known as cIAP2, is an IAP family protein that regulates apoptosis by blocking caspase activation and inflammation via innate immune receptors [96]. In microglia, BIRC3 acts as a switch between pro-inflammatory activation and cell death by regulating caspase-3 processing [97]. BIRC3 confers resistance to cell death in microglia subjected to chronic inflammatory stress [98]. BTG1 plays an important role in cell growth and differentiation [99]. In microglia, it regulates microglial apoptosis by functioning as a sensitizer in activation-induced cell death [100]. CD300LB is an activator of the CD300 family of myeloid immunoglobulin receptors. Interestingly, CD300LB shares similarity with TREM2, as it associates with DAP12 and recognizes phosphatidylserine as a ligand on the outer plasma membrane of apoptotic cells, thereby regulating the efferocytosis and phagocytosis of apoptotic cells [101,102]. Induction of CD300LB by TREM2 activation indicated that TREM2 may mobilize functionally similar molecules to enhance its effects. IL3RA transduces the IL3 signal. Different groups have demonstrated IL3 induced microglial proliferation using a neutralizing anti-IL3 Ab [103] and its dependence on JAK2 [104]. PDGFA plays physiological roles via PDGFR-α during gastrulation and in the development of multiple tissues, including the lungs, intestine, and central nervous system [105]. A recent report revealed that PDGFA also exerts proliferative effects on the

microglial cells [106]. To validate my speculation, further research is needed for elucidation of the role of TREM2 in AD microglia.

In this study, I focused on microglial data. Interestingly, although peripheral monocytes do not generally express TREM2, its expression was upregulated in monocytes from patients with AD [60,107], thereby potentially corroborating the upregulated TREM2 expression in the microglia of patients with AD [39,40]. Monocyte population and functions have also been reported to change in peripheral blood of patients with AD. Previous studies on peripheral immune cells of patients with AD demonstrated an increase in the population of activated monocytes [108,109], suggesting its pro-inflammatory nature [109,110]. If such monocytic changes correlate with TREM2 activation status in the microglia, they may act as a potential biomarker for microglial TREM2 activation in AD, which can be determined in a less invasive approach. However, further investigations are required to validate these speculations.

Conclusions

My results show that low TREM2 activation in patients with AD and the agonistic anti-TREM2 mAb may render microglia resistant to AD progression. Furthermore, my study outcomes provide evidence that agonistic anti-TREM2 mAb is a powerful tool to identify TREM2 activation in the microglia of patients with AD.

Figure 1 Binding and agonist activities of Hyb87 toward TREM2. **A, B** Binding of Hyb87 to TREM2 in cells was determined using FCM. Cells were incubated with Hyb87, followed by incubation with Alexa488-labeled anti-mouse IgG Ab. **A** Parental and human TREM2-transfected Expi293 cells. **B** THP-1 cells and *TREM2* KO THP-1 cells. Control IgG, dashed line; Hyb87, gray histogram. **C** Analysis of Hyb87 affinity to TREM2. BLI was used to determine the affinity of Hyb87 to TREM2. The vertical axis indicates the BLI signal response (nm), and the horizontal line indicates the time after analyte (TREM2 protein) loading. Kinetic parameters were analyzed using a 1:1 Langmuir fitting model. Association (K_a) and dissociation (K_d) constants were calculated and used to determine the K_D value (K_d/K_a). **D** NFAT response of Hyb87. THP-1 cells and *TREM2* KO THP-1 cells transiently transfected with a NFAT-luc plasmid were incubated on a Hyb87-coated plate. Data points represent the mean + SD of values acquired in triplicate. ** for P value < 0.005 vs. control IgG-treated group by Student's *t*-test. All data are representative of at least two independent experiments. TREM2, triggering receptor expressed on myeloid cells 2; FCM, flow cytometry; Ab, antibody; BLI, biolayer interferometry; NFAT, nuclear factor of activated T cells.

Figure 2 Identification of TREM2 DEGs from iMG. **A** PCA and boxplot analysis of the PC1 distribution of the iMG transcriptome data from PBS, control IgG, and Hyb87 treatment groups. Each group had three replicates. Percentages with each axis represent the variance of the data captured by each PC. * or ** for boxplot indicates P value calculated using Tukey's honest significant difference test between groups. * for P value < 0.05 and ** for P value < 0.01. **B** Volcano plots depicting the results of differential gene expression analysis between Hyb87 and PBS treatment or between Hyb87 and control IgG treatment. The criteria for significance were set at FDR-adjusted P value < 0.05 and absolute fold change > 1.5. DEGs that satisfy the criteria are shown in red. **C** Venn diagram showing TREM2 DEGs. Genes that overlapped between those from Hyb87 treatment vs. PBS and from Hyb87 treatment vs. control IgG treatment were defined as TREM2 DEGs. Considering the direction of expression alteration, the TREM2 DEGs comprised genes, the expression of which changed in the same direction in Hyb87 treatment (vs. PBS and vs. control IgG). **D, E** Top five significant pathways in pathway enrichment analysis using TREM2 up (**D**) and TREM2 down (**E**). TREM2, triggering receptor expressed on myeloid cells 2; DEG, differentially expressed genes; iMG, induced pluripotent stem cell-derived microglia-like cells; PCA, principal component analysis; PBS, phosphate-buffered saline; FDR, false discovery rate.

Figure 3 Reduction in TREM2 activation in AD microglia. **A-F** GSEA enrichment plots* of ROSMAP syn18485175 data (samples from 45 individuals were used: six HC, 17 MCI, and 22 AD individuals classified by MMSE or 13 HC, 10 MCI, and 21 AD individuals classified by cogdx) that were significantly enriched. The vertical axis shows all genes arranged in the order of signed P value. The horizontal axis indicates the enrichment score of each gene. **G, H** Top five significant pathways in pathway enrichment analysis using genes enriched in GSEA between TREM2 up and DEGs in AD (vs. HC) (**G**) and between TREM2 up and Braak or CERAD (**H**). TREM2, triggering receptor expressed on myeloid cells 2; AD, Alzheimer's disease; GSEA, gene set enrichment analysis; DEG, differentially expressed genes; CERAD, Consortium to Establish a Registry for Alzheimer's Disease; ROSMAP, Religious order Study and the Memory and Aging Project.

*GSEA enrichment plots indicate that: The lower part of the plot shows the fold change of the referenced gene set (in this case, the AD gene set) and is ordered by fold change score; the middle part of the plot (like a barcode) shows where the gene set (in this case, the TREM2 activated microglia gene set) is enriched where in the reference gene set; the upper part of the plot shows the enrichment score (ES) of the gene set under analysis, and the score at the peak of the plot (the score farthest from 0) is the ES of the gene set. The positive ES peak (ES peak greater than 0) indicates the positive correlation, while the negative ES peak (ES peak less than 0) indicates the negative correlation.

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A GSEA normalized enrichment scores (NES) and FDR q-value. **B** GSEA enrichment plots of the replication data set (ROSMAP syn21125841 data: samples from 19 individuals were classified into three HC, five MCI, and 11 AD by MMSE, or nine HC and 10 AD by cogdx) that was significantly enriched. The vertical axis shows all genes arranged in the order of signed P value. The horizontal axis indicates the enrichment score of each gene.

Table 1. DEGs of Hyb87 (vs. PBS or control IgG)

Gene Hyb87 vs. PBS Hyb87 vs. control IgG log₂FC P value FDRadjusted P value log₂FC P value FDRadjusted P value AARS2 0.678936 0.000515 0.007997 0.626018 0.001052 0.022418 ABCB1 1.594127 8.71E-05 0.001969 1.097794 0.002668 0.044055 ABHD11 -0.69441 0.005487 0.047904 -0.77782 0.001432 0.028316 ABHD2 0.913806 1.07E-11 1.59E-09 0.709984 6.33E-08 9.34E-06 ABHD6 0.993414 8.71E-11 1.12E-08 0.594339 4.56E-05 0.002015 ABTB2 2.958083 7.77E-11 1.00E-08 1.11308 0.000836 0.018889 ACAD11 0.770594 3.06E-05 0.000814 0.733622 5.25E-05 0.002246 ACBD4 -1.03825 3.38E-05 0.000884 -1.02027 3.46E-05 0.001662 ACCS $\begin{array}{|l}\n -0.84124 \\
0.001049 \\
0.01379\n \end{array}$ -0.7519 0.002858 0.046388 ACO1 0.734748 6.83E-07 3.04E-05 0.714499 1.12E-06 9.97E-05 ACOT9 0.620892 1.65E-05 0.00048 0.604775 2.41E-05 0.00124 ACP6 -0.75401 0.001039 0.013689 -0.82589 0.000275 0.007977 ACPP -0.64516 0.000291 0.005134 -0.66721 0.000152 0.00503 ADAM19 0.837569 8.84E-09 7.00E-07 0.67671 2.15E-06 0.000171 ADAMTS10 -1.04985 1.49E-07 8.29E-06 -0.64909 0.000944 0.020781 ADCK2 -0.75855 4.83E-06 0.000167 -0.66869 4.54E-05 0.002009 ADD2 1.220102 1.65E-07 9.08E-06 0.699303 0.001156 0.023942 AGRN 0.764304 4.12E-05 0.001043 0.719482 8.04E-05 0.003134 AHNAK 0.968346 1.16E-08 8.92E-07 0.811596 8.65E-07 7.96E-05 AK4 1.297972 1.37E-05 0.000411 0.890674 0.001188 0.024409 AKNA -0.86173 1.89E-07 1.01E-05 -0.79375 1.27E-06 0.000113 AKT1S1 0.905996 8.45E-07 3.67E-05 0.900484 6.92E-07 6.69E-05 ALCAM 1.485524 7.55E-23 4.58E-20 0.962777 7.29E-12 3.05E-09 ALOX5 -0.95268 9.76E-12 1.47E-09 -0.80567 4.76E-09 9.74E-07 ANKRD23 -0.87196 0.000712 0.010256 -0.85483 0.000704 0.016735 ANKRD28 0.794594 1.74E-05 0.000507 0.683873 0.000142 0.004792 ANKRD33B 1.172116 2.43E-06 9.22E-05 1.152835 1.92E-06 0.000156 ANTXR2 1.165132 5.19E-11 6.76E-09 0.70393 2.19E-05 0.001155 AP1S3 1.383863 1.28E-08 9.78E-07 1.189905 2.41E-07 2.87E-05 APAF1 -0.99631 1.28E-09 1.28E-07 -0.7177 7.69E-06 0.000499 APBB1IP -0.73164 8.62E-07 3.71E-05 -0.6562 8.19E-06 0.000524 APEX1 -1.07532 3.57E-10 4.02E-08 -0.89106 1.23E-07 1.61E-05 AQP9 0.843237 0.002069 0.023365 1.436268 4.87E-07 4.89E-05 ARAP2 1.161799 1.30E-11 1.90E-09 1.128087 2.43E-11 9.09E-09 ARHGAP10 0.868109 1.17E-09 1.19E-07 0.655973 2.34E-06 0.000182 ARHGAP15 -1.26624 2.98E-10 3.38E-08 -1.23172 5.32E-10 1.44E-07 ARHGAP22 1.536658 0.000107 0.002347 2.082124 3.66E-07 3.88E-05 ARHGAP9 -1.05222 2.30E-10 2.68E-08 -0.88616 5.81E-08 8.81E-06 ARID4B 0.662711 2.49E-05 0.000688 0.588286 0.000145 0.00489 ARID5B 1.564844 3.62E-19 1.48E-16 0.777914 6.30E-07 6.15E-05 ARNTL2 1.610864 1.56E-12 2.67E-10 1.078001 2.56E-07 3.00E-05 ARV1 -0.97702 9.35E-06 0.0003 -0.94821 1.31E-05 0.00077 ATF3 2.287533 4.46E-35 7.83E-32 1.419953 1.00E-18 1.17E-15 ATM -0.94666 4.80E-06 0.000167 -0.86848 2.09E-05 0.001116 ATP10A -0.74842 0.000941 0.012735 -0.73456 0.000942 0.020761 ATP1B3 0.813066 7.30E-10 7.69E-08 0.641395 7.06E-07 6.75E-05 ATP2A3 -1.46407 1.95E-12 3.21E-10 -1.20524 3.31E-09 7.37E-07 ATP6V1B2 0.620607 1.43E-06 5.73E-05 0.636685 7.78E-07 7.31E-05 AVPI1 1.953837 1.14E-20 5.72E-18 0.854045 1.57E-06 0.000134 AXIN2 1.866793 2.40E-07 1.24E-05 1.103108 0.000469 0.012137 B3GALNT1 -1.14051 7.51E-06 0.000245 -1.14645 4.74E-06 0.000332 B3GNTL1 -0.83504 0.000462 0.007366 -0.82434 0.000438 0.011489 BASP1 1.142756 6.17E-09 5.18E-07 0.717432 9.50E-05 0.003522 BAZ1B -0.7453 6.98E-05 0.001653 -0.6007 0.001179 0.024328 BCAP31 0.654293 0.002414 0.026084 0.671756 0.001459 0.028667 BCAR3 1.815312 5.81E-13 1.10E-10 1.090348 9.54E-07 8.69E-05

Table 2. TREM2 DEGs (1/10)

Gene Hyb87 vs. PBS Hyb87 vs. control IgG log2FC P value FDRadjusted P value log2FC P value FDRadjusted P value BCL2L11 | 1.751835 6.79E-18 2.59E-15 | 0.648249 0.000203 0.006311 BIRC3 2.134204 5.38E-30 5.56E-27 1.333807 1.57E-15 1.32E-12 BMP6 2.719963 1.97E-19 8.46E-17 0.949333 2.38E-05 0.001226 BRCA1 -1.40577 4.89E-08 3.06E-06 -0.76575 0.002716 0.044715 BTG1 1.812673 1.68E-29 1.56E-26 1.111127 1.49E-14 1.01E-11 C11orf84 -0.97229 4.46E-06 0.000157 -0.80883 0.00011 0.003897 C11orf96 5.491615 0.001084 0.014133 5.491615 0.000428 0.011275 C12orf75 -1.13963 1.26E-06 5.14E-05 -1.00997 1.30E-05 0.000766 C15orf38 -0.77905 1.92E-05 0.000546 -0.71711 6.93E-05 0.002795 C15orf48 0.762135 8.28E-08 5.02E-06 0.749469 1.26E-07 1.64E-05 C16orf45 0.772412 3.18E-05 0.000841 0.612166 0.000693 0.016526 C17orf96 1.415739 1.02E-09 1.04E-07 1.036952 1.77E-06 0.000147 C19orf35 -0.69703 0.002154 0.024142 -1.01799 4.78E-06 0.000332 C19orf60 -1.33229 2.20E-08 1.53E-06 -0.98824 2.48E-05 0.001262 C1orf162 -0.87909 0.002258 0.024841 -0.8931 0.00135 0.026971 C1RL -0.64021 0.000914 0.012481 -0.66593 0.000497 0.012672 C6orf223 2.405711 9.83E-14 2.11E-11 1.021039 7.59E-05 0.003018 CABLES1 -1.02485 1.30E-06 5.28E-05 -0.93315 7.45E-06 0.000487 CACNB3 1.477825 1.39E-05 0.000416 1.299457 4.39E-05 0.001953 CALCRL 1.184105 5.51E-07 2.53E-05 0.739947 0.000677 0.016257 CARD9 -0.67148 2.46E-05 0.000682 -0.63321 6.12E-05 0.002527 CBFA2T3 -0.64657 0.000269 0.004857 -0.64381 0.000242 0.007298 CBLB 1.552928 8.00E-16 2.38E-13 1.150538 1.48E-10 4.40E-08 CBX5 -0.72117 2.41E-06 9.17E-05 -0.5901 9.56E-05 0.00353 CCDC68 1.713803 1.22E-08 9.38E-07 1.398949 4.44E-07 4.58E-05 CCDC85B -1.09124 3.84E-07 1.87E-05 -1.06017 5.96E-07 5.85E-05 CCL1 1.553035 3.78E-08 2.43E-06 1.842772 1.06E-10 3.37E-08 CCL22 2.328392 1.73E-42 6.09E-39 1.182616 1.18E-16 1.09E-13 CCL24 2.964714 1.36E-31 1.70E-28 1.777302 1.03E-17 1.06E-14 CCL7 4.182746 2.58E-22 1.51E-19 3.530185 1.33E-21 2.13E-18 CCNA1 1.79587 0.002173 0.024293 1.68881 0.002043 0.036613 CCND3 -0.74944 3.17E-07 1.59E-05 -0.73562 4.54E-07 4.61E-05 CCNJL 1.479306 2.99E-08 2.01E-06 0.950669 0.000112 0.003985 CCR1 -0.74484 4.52E-06 0.000159 -0.74617 3.81E-06 0.000276 CCR7 3.45875 3.38E-47 1.98E-43 1.386783 5.47E-15 4.18E-12 CD101 -0.69991 1.89E-06 7.39E-05 -0.63879 1.17E-05 0.000699 CD109 0.790779 8.61E-09 6.88E-07 0.711663 1.61E-07 2.06E-05 CD1A -0.84499 3.57E-09 3.17E-07 -0.75239 1.08E-07 1.47E-05 CD1B 1.505634 7.06E-09 5.80E-07 0.983886 3.52E-05 0.001664 CD244 -0.60316 0.002728 0.028511 -0.71334 0.000303 0.008584 CD28 -0.9393 3.53E-07 1.74E-05 -0.70833 9.51E-05 0.003522 CD300A -0.80704 1.48E-08 1.09E-06 -0.68929 9.63E-07 8.73E-05 CD300LB 1.039153 2.18E-09 2.10E-07 0.715138 1.56E-05 0.000875 CD38 -2.66341 0.000107 0.002348 -2.34767 0.000667 0.016038 CD3EAP -1.10285 3.60E-06 0.00013 -0.89918 0.000127 0.004386 CD47 -0.80879 1.23E-06 5.03E-05 -0.67085 4.72E-05 0.002064 CD83 0.753089 5.25E-08 3.26E-06 0.740821 8.12E-08 1.15E-05 CD93 -1.25124 1.06E-06 4.41E-05 -1.63763 1.10E-10 3.39E-08 CDH1 -1.64122 7.62E-14 1.75E-11 -1.25445 4.49E-09 9.39E-07 CDH20 -2.1501 2.61E-07 1.34E-05 -1.79664 1.53E-05 0.000858 CDK14 1.034444 3.98E-10 4.43E-08 0.6437 4.11E-05 0.001863 CHST11 0.847015 2.15E-10 2.56E-08 0.653469 5.38E-07 5.31E-05 CHST7 1.194629 1.18E-12 2.12E-10 0.809275 3.62E-07 3.88E-05 CISH 1.516252 1.32E-08 1.00E-06 1.076896 1.01E-05 0.000625 CLCF1 5.120227 7.62E-10 7.97E-08 1.878247 8.77E-05 0.003336 CLN8 0.802398 1.85E-08 1.31E-06 0.671084 1.75E-06 0.000146 CMPK2 -1.10012 0.003083 0.031369 -1.37892 8.47E-05 0.003265

Table 2. TREM2 DEGs (2/10)

Table 2. TREM2 DEGs (3/10)

Table 2. TREM2 DEGs (4/10)

Table 2. TREM2 DEGs (5/10)

Table 2. TREM2 DEGs (6/10)

Table 2. TREM2 DEGs (7/10)

Table 2. TREM2 DEGs (8/10)

Table 2. TREM2 DEGs (9/10)

Table 2. TREM2 DEGs (10/10)

Table 3. Pathway enrichment analysis of TREM2 DEGs (2/3)

Donor ID	Age at death	MMSE	Braak	CERAD	Cogdx	Classification by MMSE	Classification by cogdx
10101291	83.4	22.0	3	$\overline{4}$	\overline{c}	AD	MCI
10101327	89.7	12.0	5	$\mathbf{1}$	$\overline{4}$	AD	AD
10222853	85.8	1.0	5	$\mathbf{1}$	$\overline{4}$	AD	AD
10248033	88.5	12.0	3	$\mathbf{2}$	$\overline{4}$	AD	AD
10260309	88.4	29.0	3	$\overline{4}$	1	HC	HC
10261026	80.9	29.0	3	$\overline{4}$	$\mathbf{1}$	HC	HC
10288185	76.9	24.0	\overline{c}	$\overline{4}$	$\overline{2}$	MCI	MCI
10514454	79.5	28.0	$\mathbf{2}$	$\overline{4}$	$\mathbf{1}$	MCI	HC
10536568	85.0	28.0	$\mathbf{1}$	3	$\mathbf{1}$	MCI	HC
11072071	88.0	27.0	$\overline{2}$	$\overline{4}$	1	MCI	HC
11159965	86.9	0.0	5	$\mathbf{1}$	$\overline{4}$	AD	AD
11200645	83.7	29.0	$\overline{4}$	$\mathbf{2}$	$\mathbf{1}$	HC	HC
11302830	85.8	27.0	3	$\mathbf{2}$	$\overline{4}$	MCI	AD
11310718	80.5	27.0	5	$\mathbf{2}$	$\mathbf{2}$	MCI	MCI
11336574	89.0	0.0	6	$\mathbf{1}$	$\overline{4}$	AD	AD
11342432	$90+$	29.0	$\overline{2}$	$\overline{4}$	1	HC	HC
11345331	87.2	2.0	$\overline{4}$	$\mathbf{1}$	$\overline{4}$	AD	AD
11399321	86.9	25.0	$\mathbf{1}$	$\overline{4}$	3	MCI	MCI
11399871	86.1	12.0	3	$\overline{4}$	$\overline{4}$	AD	AD
11409232	80.1	30.0	3	$\overline{4}$	\overline{c}	HC	MCI
11609672	86.3	27.0	$\overline{4}$	$\mathbf{2}$	$\mathbf{1}$	MCI	HC
11630705	83.5	17.0	6	$\mathbf{1}$	$\overline{4}$	AD	AD
20104101	$90+$	0.0	$\overline{2}$	3	$\overline{4}$	AD	AD
20112377	74.8	8.0	5	$\mathbf{1}$	$\overline{4}$	AD	AD
20149910	$90+$	27.0	$\overline{4}$	$\overline{4}$	$\mathbf{1}$	MCI	HC
20170043	$90+$	0.0	5	$\mathbf{1}$	$\overline{4}$	AD	AD
20173942	$90+$	13.0	$\overline{4}$	$\mathbf{1}$	$\overline{4}$	AD	AD
20179164	83.7	8.0	3	$\overline{4}$	6	AD	
20207013	$90+$	27.0	1	$\overline{4}$	$\mathbf{1}$	MCI	HC
20249897	87.3	25.0	3	$\overline{4}$	$\overline{2}$	MCI	MCI
20261901	$90+$	17.0	5	$\mathbf{2}$	$\overline{4}$	AD	AD
20275399	87.5	25.0	\mathfrak{Z}	$\overline{4}$	$\sqrt{5}$	MCI	AD
20282398	87.4	28.0	3	$\mathbf{1}$	$\overline{2}$	MCI	MCI
20956867	79.1	30.0	3	$\overline{4}$	1	HC	HC
20963866	83.6	$0.0\,$	6	1	$\overline{4}$	AD	AD
20977678	$90+$	1.0	3	$\overline{4}$	$\mathbf{2}$	AD	MCI
20978133	87.7	21.0	5	1	$\overline{4}$	AD	AD
21126823	$90+$	27.0	1	4	\overline{c}	MCI	MCI
21135554	$90+$	10.0	5	$\mathbf{2}$	$\overline{4}$	AD	AD
21142003	88.9	28.0	$\overline{4}$	4	$\mathbf{1}$	MCI	HC
21159840	82.7	16.0	5	1	$\overline{4}$	AD	AD
21172121	76.1	27.0	5	$\mathbf{1}$	3	MCI	MCI
21189544	$90+$	3.0	5	1	$\overline{4}$	AD	AD
21412626	$90+$	24.0	3	4	1	MCI	HC.
76647134	81.5	$0.0\,$	5	1	$\overline{4}$	AD	AD

Table 4. Clinical profiles of donors from ROSMAP syn18485175 data

Dataset	TREM2 DEG	NES	FDR q-value*
Cogdx AD vs. HC	TREM2 Up	-1.638	Ω
Cogdx AD vs. MCI	TREM2 Up	-1.565	θ
MMSE AD vs. HC	TREM2 Up	-1.350	0.001
MMSE AD vs. MCI	TREM2 Up	-1.557	0.002
Cogdx AD vs. MCI	TREM2 Down	1.342	0.019
MMSE AD vs. MCI	TREM2 Down	1.191	0.085
Cogdx MCI vs. HC	TREM2 Down	-1.117	0.265
Cogdx AD vs. HC	TREM2 Down	1.099	0.477
MMSE AD vs. HC	TREM2 Down	1.087	0.514
MMSE MCI vs. HC	TREM2 Up	1.111	0.663
Cogdx MCI vs. HC	TREM2 Up	0.797	0.811
MMSE MCI vs. HC	TREM2 Down	0.823	0.903

Table 5. Correlation between TREM DEGs and AD vs. HC vs. MCI microglia using GSEA

GSEA results between TREM DEGs and signed P value of AD vs. HC, MCI vs. HC, and AD vs. MCI in microglia of ROSMAP syn18485175 data.

*FDR q-value indicates FDR-adjusted P value of GSEA

TREM2, triggering receptor expressed on myeloid cells 2; DEG, differentially expressed genes; AD, Alzheimer's disease; HC, healthy control; MCI, mild cognitive impairment; GSEA, gene set enrichment analysis; NES, normalized enrichment scores; FDR, false discovery rate; cogdx, clinical consensus diagnosis of cognitive status at the time of death; MMSE, Mini-Mental State Examination; ROSMAP, Religious order Study and the Memory and Aging Project.

Dataset	TREM2 DEG	NES	FDR q-value*
Correlation of Braak	TREM2 Up	-1.527	θ
Correlation of CERAD	TREM2 Up	-1.458	0.009
Correlation of CERAD	TREM2 Down	-0.957	0.439
Correlation of MMSE	TREM2 Down	0.975	0.472
Correlation of MMSE	TREM2 Up	1.043	0.562
Correlation of Braak	TREM2 Down	0.849	0.788

Table 6. Correlation between TREM2 DEGs and clinical scores of AD using GSEA

GSEA results between TREM DEGs and clinical score of AD of ROSMAP syn18485175 data.

*FDR q-value indicates FDR-adjusted P value of GSEA

TREM2, triggering receptor expressed on myeloid cells 2; DEG, differentially expressed genes; AD, Alzheimer's disease; GSEA, gene set enrichment analysis; NES, normalized enrichment scores; FDR, false discovery rate; CERAD, Consortium to Establish a Registry for Alzheimer's Disease; MMSE, Mini-Mental State Examination; ROSMAP, Religious order Study and the Memory and Aging Project.

Pathway Total			Cogdx AD vs. HC			MMSE AD vs. HC		
		FDR-	In	Genes	FDR-	In Data	Genes	
		adjusted	Data		adjusted			
		P value			P value			
Development_PEDF signaling	49	8.718E-	3	Fra-2, c-IAP1, c-	2.497E-	2	JAK1, c-IAP2	
		03		IAP ₂	02			
Development_G-CSF signaling	49	8.718E-	3	JAK1, c-IAP2,	2.562E-	$\mathbf{2}$	c-IAP1, c-IAP2	
		03		CXCR4	02			
Signal transduction_NF-kB activation pathways	51	9.348E- 03	3	c-IAP1. NIK(MAP3K14),	$2.588E -$ 02	$\overline{2}$	JAK1, c-IAP2	
				c -IAP2				
response_IL-5 Immune	56	1.176E-	3	MKP-1, JAK1, c-	2.588E-	2	c-IAP1, c-IAP2	
signaling via JAK/STAT		02		IAP ₂	02			
Cytoskeleton	16	1.923E-	\overline{c}	Tubulin $G-$ α,	2.588E-	\overline{c}	JAK1,	
remodeling_Substance P		02		$\alpha-12$ protein	02		NIK(MAP3K14)	
mediated membrane blebbing				family				
Stem cells_CD30 signaling in	18	2.341E-	$\overline{2}$	TRAF5,	2.588E-	$\overline{2}$	c-IAP1, c-IAP2	
transformed embryonic stem		02		NIK(MAP3K14)	02			
cells								
CHDI_Correlations from	79	2.820E-	3	CD83,	2.588E-	$\overline{2}$	c-IAP1, c-IAP2	
Replication data_Causal		02		NIK(MAP3K14),	02			
network (positive correlations)				CXCR4				
Development_Role of G-CSF	21	2.950E-	2	JAK1, CXCR4	2.588E-	$\overline{2}$	STAT4, JAK1	
in hematopoietic stem cell		02			02			
mobilization								
SLE genetic marker-specific	84	3.115E-	3	STAT4, JAK1,	2.653E-	$\overline{2}$	TRAF5,	
pathways in antigen-presenting		02		NIK(MAP3K14)	02		NIK(MAP3K14)	
cells (APC) response_IL-2 Immune	25	3.751E-	2	STAT4, JAK1	2.653E-	$\mathbf{2}$	c-IAP1, c-IAP2	
signaling via JAK/ STAT		02			02			
Development_ERBB-family	39				4.341E-	3	HB-EGF, TGF-	
signaling					03		α,	
							NIK(MAP3K14)	
signaling of Non-genomic	53				5.949E-	3	$HB-$	
ESR2 (membrane) in lung					03		EGF(mature),	
cancer cells							HB-EGF, TGF- α	
Development_EGFR signaling	71				1.297E-	3	HB-EGF, TGF-	
pathway					02		α , JAK1	
TLR EGFR-induced and	22				2.077E-	$\overline{2}$	HB-EGF, TGF- α	
signaling inflammatory in					02			
normal and asthmatic airway								
epithelium Neurogenesis_NGF/ TrkA	105				2.497E-	3	C3G, HB-EGF,	
MAPK-mediated signaling					02		PLAUR (uPAR)	
Pancreatic cell cancer	27				2.497E-	$\mathfrak{2}$	HB-EGF, TGF- α	
resistance to Tarceva (erlotinib)					02			
Development_Dopamine-	$\overline{31}$				2.588E-	$\sqrt{2}$	HB-EGF, TGF- α	
transactivation induced of					02			
EGFR in SVZ neural stem cells								
Immune response_IL-11	34				2.588E-	$\overline{2}$	JAK1, Pim-3	
signaling via JAK/STAT					02			
Plasminogen activators	35				2.588E-	2	HB-EGF,	
signaling in pancreatic cancer					02		PLAUR (uPAR)	
Cigarette smoke-induced	36				2.588E-	\overline{c}	HB-EGF, TGF- α	
inflammatory signaling in					02			
airway epithelial cells								
PR action in breast cancer:	36				2.588E-	$\mathfrak{2}$	HB-EGF, JAK1	
stimulation of cell growth and					02			
proliferation								

Table 7. Pathway enrichment analysis of genes enriched in GSEA between TREM2 up and AD microglia (2/4)

Table 7. Pathway enrichment analysis of genes enriched in GSEA between TREM2 up and AD microglia (3/4)

Pathway	Total	Cogdx AD vs. HC			MMSE AD vs. HC		
		FDR-	In	Genes	FDR-	In Data	Genes
		adjusted	Data		adjusted		
		P value			P value		
Development_Oligodendrocyte	38				2.653E-	2	HB-EGF, TGF-α
differentiation (general					02		
schema)							
Cell adhesion_PLAU signaling	39				2.653E-	2	PLAUR (uPAR),
					02		JAK1
response_TSLP Immune	39				2.653E-	$\overline{2}$	STAT4, JAK1
signalling					02		
Immune response_Th1 and Th2	40				2.656E-	$\overline{2}$	STAT4, JAK1
cell differentiation					02		
The role of UV radiation in	40				2.656E-	$\mathbf{2}$	HB-EGF, TGF- α
melanoma development					02		
Apoptosis and survival_Anti-	42				2.791E-	$\overline{2}$	TRAF5,
apoptotic TNFs/NF-kB/Bcl-2					02		NIK(MAP3K14)
pathway							
Inhibition of apoptosis in	42				2.791E-	$\overline{2}$	c-IAP1, c-IAP2
gastric cancer					02		
and Apoptosis	43				2.796E-	$\overline{2}$	c-IAP1, c-IAP2
survival_TNFR1 signaling					02		
pathway							
Immune response_BAFF-	43				2.796E-	\overline{c}	c-Rel $(NF-kB)$
induced $NF-kB$ canonical					02		subunit),
signaling							NIK(MAP3K14)
EGFR signaling in Prostate	46				2.997E-	\overline{c}	HB-EGF, TGF- α
Cancer					02		
Immune response_Induction of	47				3.022E-	2	C3G, JAK1
apoptosis and inhibition of					02		
proliferation mediated by IFN-							
γ							
signaling_TC21 G-protein	25	3.751E-	2	C3G, G-protein			
regulation pathway		02		α -12 family			
Immune response_IFN- α/β	94	3.856E-	3	RSAD2, JAK1,			
signaling via PI3K and NF-kB		02		NIK(MAP3K14)			
pathways							
Transcription_HIF-1 targets	95	3.856E-	3	PLAUR TfR1,			
		02		(uPAR), CXCR4			
Apoptosis and survival_IL-17-	28	4.059E- 02	2	TRAF5,			
induced CIKS-dependent NF-				NIK(MAP3K14)			
signaling kВ and mRNA stabilization							
Development Role of CNTF	28	4.059E-	2	JAK1, c-IAP2			
and LIF in regulation of		02					
oligodendrocyte development							
Role of IFN- β in activation of T	29	4.059E-	2	c-IAP1, c-IAP2			
apoptosis in multiple cell		02					
sclerosis							
Apoptosis and	29	4.059E-	2	Fyn, FKHR			
survival_nAChR in apoptosis		02					
inhibition cell and cycle							
progression							
Histone deacetylases in	29	4.059E-	2	Tubulin α, FKHR			
Prostate Cancer		02					
Role of CNTF and LIF in	30	4.224E-	2	JAK1, c-IAP2			
regulation of oligodendrocyte		02					
development in multiple							
sclerosis							
Apoptosis and survival_Role of IAP-proteins in apoptosis	31	4.389E- 02	2	c-IAP1, c-IAP2			

Pathway	Total	Cogdx AD vs. HC FDR-		Genes	MMSE AD vs. HC FDR- In Data Genes		
		adjusted	In Data		adjusted		
		P value			P value		
ACTH of Activation	32	4.439E-	2	JAK1,			
production in pituitary gland in major depressive disorder		02		NIK(MAP3K14)			
Cytoskeleton	32	4.439E-	$\overline{2}$	Tubulin α,			
remodeling_Reverse signaling by Ephrin-B		02		CXCR4			
Resistance of pancreatic cancer cells to death receptor signaling	33	4.492E- 02	2	c-IAP1, c-IAP2			
$SDF-1$ axis in endothelial progenitor cell recruitment in	33	4.492E- 02	2	FKHR, CXCR4			
healing myocardial infarction							
Role of Apo-2L(TNFSF10) in Prostate Cancer cell apoptosis	34	4.548E- 02	2	c-IAP1, c-IAP2			
signaling_RhoA G-protein	34	4.548E-	2	Fyn, G-protein α -			
regulation pathway		02		12 family			
Development Growth	35	4.708E-	2	Fyn, C3G			
hormone signaling via STATs and PLC/IP3		02					
response IL-22 Immune signaling pathway	36	4.867E- 02	$\overline{2}$	STAT4, JAK1			
Immune response_Generation	37	5.027E-	2	FKHR, JAK1			
of memory CD4+ T cells		02					
Development_SDF-1 signaling in hematopoietic stem cell	38	5.037E- 02	2	C3G, CXCR4			
homing							
Apoptosis and survival_APRIL	39	5.037E-	2	TRAF5,			
and BAFF signaling		02		NIK(MAP3K14)			
Apoptosis and	39	5.037E-	2	c-IAP1, c-IAP2			
survival_Ubiquitination and phosphorylation in TNF- α -		02					
induced NF-kB signaling							

Table 7. Pathway enrichment analysis of genes enriched in GSEA between TREM2 up and AD microglia (4/4)

Table 8. Comparison of TREM2 expression levels between AD vs. HC vs. MCI microglia

*FDR-adjusted P value from comparison test between AD vs. HC, AD vs. MCI, and MCI vs. HC of ROSMAP syn18485175 data.

*FDR-adjusted P value from correlation between TREM2 gene and MMSE, Braak, or CERAD of ROSMAP

syn18485175 data.

Donor ID	Age at death	$MMSE*$	Braak	CERAD	Cogdx	Classification by MMSE	Classification by cogdx
10298957	82.4	10.0	3	$\overline{2}$	$\overline{4}$	AD	AD
15121461	$90+$	16.2	5	$\mathbf{1}$	$\overline{4}$	AD	AD
15144878	86.2	7.0	5	$\mathbf{1}$	$\overline{4}$	AD	AD
15178486	$90+$	30.0	$\overline{4}$	$\overline{4}$	$\mathbf{1}$	HC	HC
15179365	83.6	17.0	3	$\mathbf{1}$	$\overline{4}$	AD	AD
15196848	$90+$	28.0	\mathfrak{Z}	$\overline{4}$	$\mathbf{1}$	MCI	HC
20240514	89.7	30.0	\mathfrak{Z}	$\overline{4}$	$\mathbf{1}$	HC	HC
20280666	$90+$	27.6	$\overline{4}$	$\overline{4}$	$\mathbf{1}$	MCI	HC
20371236	$90+$	14.0	5	$\mathbf{1}$	$\overline{4}$	AD	AD
20535564	82.7	$0.0\,$	5	$\mathbf{1}$	$\overline{4}$	AD	AD
20800682	84.8	30.0	3	$\overline{4}$	$\mathbf{1}$	HC	HC
20897173	89.3	21.4	$\sqrt{3}$	$\overline{4}$	$\mathbf{1}$	AD	HC
20911508	$90+$	$0.0\,$	5	$\mathbf{1}$	$\overline{4}$	AD	AD
20959216	$90+$	12.0	5	$\overline{2}$	$\overline{4}$	AD	AD
20963578	81.9	28.0	$\overline{4}$	$\overline{4}$	$\mathbf{1}$	MCI	HC
21272396	87.2	28.0	$\mathbf{1}$	$\overline{4}$	1	MCI	HC
21403995	86.1	15.0	3	1	$\overline{4}$	AD	AD
30544882	89.4	13.0	3	\overline{c}	$\overline{4}$	AD	AD
34779151	86.3	25.0	$\sqrt{2}$	$\overline{4}$	$\mathbf{1}$	MCI	HC

Table 10. Clinical profiles of donors from ROSMAP syn21125841 data

*Missing items were imputed based on other variables in cases where a participant refused to answer one to four MMSE

items or was physically unable to answer one or more items
Chapter 2: TNFR2 pathways are fully active in cancer regulatory

T cells

Abstract

Tumor necrosis factor receptor 2 (TNFR2), a membrane-bound tumor necrosis factor receptor expressed by regulatory T cells (Tregs), participates in Treg proliferation. Although a specific TNFR2 pathway has been reported, the signaling mechanism has not been completely elucidated. This study sought to clarify TNFR2 signaling in human Tregs using amplicon sequencing and single-cell RNA-sequencing to assess Tregs treated with a TNFR2 agonist antibody. Pathway enrichment analysis based on differentially expressed genes highlighted tumor necrosis factor α signaling via nuclear factor-κ B, interleukin-2 signal transducer and activator of transcription 5 signaling, interferon-g response, and cell proliferation-related pathways in Tregs after TNFR2 activation. *TNFR2*-high Treg-focused analysis found that these pathways were fully activated in cancer Tregs, showing high TNFR2 expression. Collectively, these findings suggest that TNFR2 orchestrates multiple pathways in cancer Tregs, which could help cancer cells escape immune surveillance, making TNFR2 signaling a potential anticancer therapy target.

Introduction

Regulatory T cells (Tregs) are a subset of T cells that act as negative regulators of cytotoxic T cells immune response [111]. Tregs are required for the maintenance of peripheral tolerance to self and non-toxic antigens; for example, the loss of Tregs can contribute to autoimmune deficiency, polyendocrinopathy, enteropathy, and X-linked diseases [112]. Dysfunction or reduction in the number of Tregs is also observed in

autoimmune diseases such as systemic lupus erythematosus and type-1 diabetes [112]. Conversely, excessive Treg activation is observed in cancer tissues, where it can cause cytotoxic T cells to fail to recognize cancer antigens and lead to cancer growth [113, 114]. These findings suggest that the regulation of Treg function and proliferation could be an effective treatment strategy for autoimmune diseases and cancers.

Proliferation of Tregs is initiated by the activation of, and subsequent signaling via, the T cell receptor by costimulatory receptors such as inducible T cell costimulatory (ICOS), tumor necrosis factor receptor 2 (TNFR2), which is a receptor for TNF α and has antiinflammatory activities [115], OX40 (TNF receptor superfamily member 4, TNFRSF4), and 4-1BB (TNF receptor superfamily member 9, TNFRSF9) [114]. In Tregs, the role of TNFR2 as a co-stimulator has been evaluated using selective TNFR2 agonist antibodies or TNFR2 ligands [116-119]. Human peripheral blood mononuclear cell (PBMC)-derived Tregs can be expanded via treatment with a TNFR2 agonist antibody [116]. Treatment with a TNFR2-selective ligand increases Treg expansion *in vivo* [118] and improves symptoms in animal models of immunological disease, such as collagen-induced arthritis [119] and graft versus host disease [117]. Conversely, inhibition of TNFR2 signaling using an antagonist antibody, and the subsequently reduced Treg proliferation, reduce cancer growth in a syngeneic mouse model by enhancing immune responses in cancer tissue [120]. These studies support the hypothesis that modulation of TNFR2 has therapeutic potential for autoimmune diseases and cancers.

Several studies have described the mechanisms of TNFR2 stimulation during Treg proliferation by focusing on specific signaling pathways. Upon activation of TNFR2,

TNFR2-associated signaling cascade molecules, including TNF receptor-associated factor 2 (TRAF2), cellular inhibitor of apoptosis protein-1 (cIAP-1), and cIAP-2 interact with the C-terminus of TNFR2 [115]. cIAP1 and cIAP2 activation is an initial step in gene transcription via nuclear factor-κ B (NF-κB) [115]. Additionally, treatment with a mitogen-activated protein kinase (MAPK) inhibitor suppresses TNFR2 signal-induced proliferation of mouse Tregs [121]. Expression of histone methyltransferase and enhancer of zeste homolog 2 (EZH2), which enhances the stability of Tregs, is induced by TNFR2 agonist antibodies [122]. Specifically, TNFR2 agonist antibodies can expand Tregs in human blood and upregulate the expression of various genes, including those encoding adenosine monophosphate kinase and carnitine transferase 1A, which are involved in the Krebs cycle and fatty acid supply [123]. However, none of the studies have comprehensively investigated all TNFR2 signals in Treg.

TNFR2-expressing Tregs have been previously associated with cancer: in ovarian cancer patients, TNFR2 expression is high in Tregs [124] and a correlation has been reported between the number of TNFR2-high Tregs in pleural effusion and the prognosis of lung cancer patients [125]. TNFR2 is also used as a marker of highly suppressive Tregs as TNFR2-high Treg populations showed higher suppressive activity against cytotoxic T cells compared to TNFR2-low Tregs [126]. However, it remains to be elucidated whether TNFR2 signals are active in such TNFR2-expressing Tregs in cancer patients.

In this study, to understand the entire TNFR2 biological pathway, I performed amplicon sequencing (Ampli-seq) analysis to identify highly upregulated pathways in Tregs in response to TNFR2 activation. I further clarified the relationship between TNFR2

expression and Treg gene expression profiles using single-cell RNA-seq analysis. Comparison of my sequencing datasets with public databases allowed me to further characterize the roles of TNFR2 in the functional regulation of cancer Tregs.

Materials and Methods

Isolation and culture of human Tregs

All human cell protocols used in this study were approved by the Takeda Institutional Ethical Committee (Protocol No. CS-00100155) and followed the guidelines of the Declaration of Helsinki. Human peripheral blood samples were collected from healthy volunteers. Whole blood was mixed with phosphate-buffered saline (PBS; FUJIFILM Wako Pure Chemical, Osaka, Japan) containing 2 mM ethylenediaminetetraacetic acid (EDTA; Invitrogen, Waltham, MA, USA) and added to a tube containing Ficoll (GE Healthcare, Tokyo, Japan). After centrifuging at $400 \times g$ for 40 min, the PBMC layer (between the PBS and Ficoll layers) was collected and washed twice with 2 mM EDTA-PBS. CD4⁺CD25⁺ Tregs were isolated using Regulatory CD4⁺CD25⁺ T Cell Dynabeads (Thermo Fisher Scientific, Waltham, MA, USA) following the manufacturer's instructions.

The purity of Tregs was monitored by measuring CD4, CD25, and forkhead box P3 (FOXP3) expression by fluorescence-activated cell sorting (FACS) using a Treg detection kit (Miltenyi Biotec, Bergisch Gladbach, Germany). Twenty thousand cells were seeded into a round-bottom 96-well plate and cultured in RPMI-1640 (FUJIFILM Wako Pure Chemical) containing 10% fetal bovine serum and 500 IU/mL interleukin-2 (IL-2; R&D

Systems, Minneapolis, MN, USA) in a humidified $CO₂$ incubator at 37 °C. Dynabeads Treg expander (Invitrogen) was added at a bead: cell ratio of 1: 2. TNFR2 activation was achieved using an MR2-1 TNFR2 agonist antibody (Hycult Biotech, Uden, Netherlands). As control treatment, mouse IgG_1 (R&D Systems) was used. After 5–7 days of culture, FOXP3 expression was measured by FACS using the Treg detection kit containing anti-FOXP3 antibody (Miltenyi Biotec); cultured cells without anti-FOXP3 antibody staining were used as the negative control. Treg proliferation was determined by measuring the ATP content of each well using CellTiter-Glo (Promega, Madison, WI, USA).

Ampli-seq analysis

Ampli-seq libraries were constructed and sequenced using the Ion Proton platform (Thermo Fisher Scientific) according to the manufacturer's instructions. Briefly, 10 ng total RNA isolated from cultured Tregs were reverse transcribed using the SuperScript VILO cDNA synthesis kit (Thermo Fisher Scientific), followed by library generation using the Ion Ampli-seq transcriptome human gene expression kit (Thermo Fisher Scientific). The libraries were diluted to 45 pM, and equal volumes from five individual samples were combined into a pooled sample. The pooled libraries were multiplexed, clonally amplified using the Ion Chef system (Thermo Fisher Scientific), and sequenced on Ion PI chips using an Ion Proton sequencing system (Thermo Fisher Scientific). The data were first analyzed using Torrent Suite with the Ampli-seqRNA analysis plugin to generate count data. Principal component analysis (PCA) was performed using the "promp" function of the stats package in R (R default package). A test for equal means in a one-way layout was conducted to compare PC1 in each group using the "oneway.test" of stats package in R. Differentially expressed genes (DEGs) were identified based on the gene-wise negative binomial generalized linear model with the quasi-likelihood method using the edgeR package in R [127, 128]. Heatmaps were created using the ComplexHeatmap package in R [129]. All Ampli-seq data were deposited in the Gene Expression Omnibus (GEO) repository at http://www.ncbi.nlm.nih.gov/geo (accession number: GSE185145).

Single-cell RNA-seq analysis

A single-cell RNA-seq library was prepared from cultured Tregs using a Chromium Single Cell 3' Library Kit v2 $(10 \times$ Genomics, Pleasanton, CA, USA) following the manufacturer's instructions. The libraries were sequenced using the Illumina HiSeq system at a depth of 100,000 reads per cell to generate binary base call (bcl) files. The initial analysis was carried out using the 10X Genomics Cell Ranger version 3 pipeline. Using the Cell Ranger "count" software, the bcl files were converted to FASTQ format, filtered, and mapped to the GRCh38 reference genome. Mapped reads data were counted and normalized to generate a matrix containing normalized gene counts. Using the Cell Ranger "aggr" software, count data from multiple samples were aggregated, normalized to the same sequencing depth, and recomputed to the feature-barcode matrix. Downstream analysis was conducted primarily using the Seurat version 3 package [57,130] in R. Low-quality cells (< 200 genes/cell and > 10% mitochondrial genes) and doublet cells were excluded using the Seurat and DoubletFinder packages [131],

respectively, in R. Count data were further normalized with the global-scaling normalization method, loge-transforms, and linear transformation to remove mitochondrial contamination and the Hamming-corrected unique molecular identifier (UMI) count variations using the Seurat function "NormalizeData" and "ScaleData".

The resulting top 2,000 variable genes were used for PCA with the Seurat function "FindVariableFeatures" and "RunPCA". The first nine principal components adopted to visualize the uniform manifold approximation and projection (UMAP) were color-coded by each sample condition using the Seurat function "RunUMAP" and "DimPlot". The gene expression levels of *TNFR2* (Gene symbol: *TNFRSF1B*) in each cell were visualized in UMAP using the Seurat function "FeaturePlot". The cells were divided into two groups based on *TNFR2* expression level according to the valley of the bimodal distribution (high, \geq 0; low, < 0 of log_e-normalized expression value). DEGs between the *TNFR2* high and low groups were identified with the non-parametric Wilcoxon rank sum test using the Seurat function "FindMarkers". The P values from the statistical tests were converted into false discovery rate (FDR)-adjusted P values using the "p.adjust" function in the stats (R default) package. Heatmaps were generated using the ComplexHeatmap [129] and RColorBrewer packages [132]. All single-cell RNA-seq data were deposited in the GEO repository at http://www.ncbi.nlm.nih.gov/geo (accession number: GSE185144).

Cancer Treg single-cell RNA-seq data analysis

Single-cell RNA-seq data from patients with hepatocellular carcinoma (HCC) (GSE98638) [133], non-small cell lung cancer (NSCLC) (GSE99254) [134], and

colorectal cancer (CRC) (GSE108989) [135] were downloaded from the GEO repository. The datasets consisted of T cells from cancer patients isolated by FACS analysis into different subtypes: $CD8^+$ T cells ($CD3^+$ and $CD8^+$), T helper cells ($CD3^+$, $CD4^+$, and CD25⁻), and Tregs (CD3⁺, CD4⁺, and CD25^{high}), which were profiled by Smart-seq2 and sequenced on the HiSeq system. Counts and annotation data for each cell were downloaded and normalized by the global-scaling normalization method, logetransformed, and linearly transformed to remove mitochondrial contamination and UMI count variations using the Seurat functions "NormalizeData" and "ScaleData".

Statistical analysis was conducted using the non-parametric Wilcoxon rank sum test with the Seurat function "FindMarkers" for each dataset to identify DEGs between cancer and normal Tregs. After normalization of the expression data, the original datasets were collected into clusters that were then used in my analysis: Cancer Treg: Cluster 8 in HCC, Cluster 9 in NSCLC, and Cluster 12 in CRC; Normal Treg: Cluster 7 in HCC, Cluster 8 in NSCLC, and Cluster 10 in CRC. The P values from the statistical tests were converted to FDR-adjusted P values using the "p.adjust" function in the stats (R default) package. Violin plots were constructed using the Seurat function "VlnPlot."

Pathway enrichment analysis

The DEGs identified from Ampli-seq or single-cell RNA-seq were used for pathway enrichment analysis. Briefly, pathway enrichment analysis was conducted by Fisher's exact test using the "fisher.test" function of the stats package in R with "hallmark gene sets" from the Molecular Signatures Database [136-138]. The criterion for pathway enrichment analysis was set at P value ≤ 0.01 .

Results

Expansion of human Tregs with TNFR2 agonist antibody treatment

We first confirmed the activity of the TNFR2 agonist antibody (clone MR2-1) by monitoring Treg proliferation. Tregs were isolated from PBMCs of healthy volunteers and stimulated with the TNFR2 agonist antibody in the presence of anti-CD3/CD28. After 7 days of culture, Treg proliferation increased by 57.1% in response to 10 µg/mL TNFR2 agonist antibody when compared to that in the control group. The antibody expanded Tregs in a dose-dependent manner with an EC_{50} value of 45.4 ng/mL, and its maximum effect was observed at $\geq 3 \mu$ g/mL (Figure 5A). Therefore, I used 3 μ g/mL TNFR2 agonist antibody for subsequent studies. The percentage of FOXP3-positive cells in the TNFR2 agonist antibody treatment group was tested to confirm Treg purity after proliferation. There was 91.0% FOXP3 expression on day 0 before TNFR2 agonist antibody treatment, which was then maintained at 90.9% after TNFR2 agonist antibody treatment (Figure 5B), similar to that after control IgG treatment (87.6%). These results suggested that the Treg purity was maintained after the TNFR2 agonist antibody induced cell expansion. FOXP3 expression was also maintained after TNFR2 agonist antibody treatment as compared to that after control treatment, as demonstrated by measuring a representative sample.

Ampli-seq identification of pathways upregulated by TNFR2 agonist antibody treatment Ampli-seq analysis was conducted using Tregs treated with the TNFR2 agonist antibody. I first confirmed the difference between the gene expression profiles of the TNFR2 agonist antibody and control IgG treatment groups using PCA of the Ampli-seq transcriptome data (Figure 6A). The results of the PCA indicated a clear difference between the expression profiles of the TNFR2 agonist antibody and IgG treatment groups, shown by a clear separation in PC1. Next, I extracted the upregulated DEGs between the Tregs treated with TNFR2 agonist antibody or IgG, which were then used in pathway enrichment analysis with the hallmark gene set [138]. Ten pathways were significantly enriched by the upregulated DEGs (Figures. 6B-I): cell proliferation- and cell cyclerelated pathways ("E2F targets," "G2M checkpoint," "Myc targets v1," "DNA repair," and "mitotic spindle"); downstream signaling of the cytokine receptor ("TNF α signaling via NFκB," "IFNγ response," and "IL-2 STAT5 signaling"); and "mTORC1" and "androgen response" pathways. Thus, my Ampli-seq findings clearly identified pathways regulated by TNFR2 activation.

Upregulation of NF-κB, IL-2 STAT5, and IFNγ response pathways in Treg with high TNFR2 expression

We next performed single-cell RNA-seq analysis to analyze the TNFR2 pathways in Treg subpopulations. After treatment with the TNFR2 agonist antibody, Tregs were subjected to single-cell RNA-seq. For this analysis, I used non-treatment as a negative control, instead of IgG, and TNFR2 agonist antibody because 1) IgG did not affect the proliferation of Tregs (Figure 5A); 2) Fcγ receptors are not expressed in human Tregs [139], which was confirmed by my Ampli-seq data (data not shown), and therefore, the

TNFR2-independent IgG effect through Fcγ receptors was negligible; and 3) in singlecell RNA-seq analysis, the number of genes detected per cell was generally much lower than that in bulk cell analysis, such as Ampli-seq, suggesting that gene expression could largely affect pathway enrichment data if IgG can cause off-target gene expression changes. My analysis successfully detected the difference in the entire gene expression profiles of *TNFR2*-high and *TNFR2*-low Tregs treated with the TNFR2 agonist antibody, which were visualized by UMAP (Figure 7A) and used to extract upregulated DEGs from *TNFR2*-high Tregs.

To evaluate whether the expression level of *TNFR2* was associated with the pathways identified in my sequencing analyses, I performed pathway enrichment analysis to compare the DEGs between *TNFR2*-high and *TNFR2*-low Tregs (*TNFR2*-high, log_e) 0; *TNFR2*-low, $log_e < 0$) (Figure 7B). DEGs from the *TNFR2*-high Treg population showed enrichment in downstream cytokine receptor signaling, such as the "IFNγ response," "TNFα signaling via NFκB," "IFNα response," "IL-2 STAT5 signaling," and "IL-6 JAK-STAT3 signaling" pathways. Additionally, the pathways related to intracellular signaling, such as "mTORC1 signaling," "PI3K AKT mTOR signaling," and, "androgen response" pathways were significantly enriched by DEGs in *TNFR2*-high Tregs.

Upregulation of TNFR2 pathways in cancer Tregs

To evaluate the involvement of TNFR2 signaling in disease conditions, I analyzed transcriptome data from cancer tissues in which cancer-associated Tregs caused cancer

cells to escape immune surveillance [140]. I specifically focused on single-cell RNA-seq data that allowed for cell-type specific analysis and found three single-cell RNA-seq data available for HCC (GSE98638) [133], NSCLC (GSE99254) [134], and CRC (GSE108989) [135]. Each dataset included Tregs isolated from cancer tissues and adjacent normal tissue and peripheral blood. I found that *TNFR2* expression was higher in cancer Tregs than in normal Tregs from HCC (FDR-adjusted P value of 3.1×10^{-30}), NSCLC (FDR-adjusted P value of 7.3 \times 10⁻³⁷), and CRC (FDR-adjusted P value of 1.9 $\times 10^{-60}$) (Figures 8A–C). These results revealed that TNFR2 could transform Tregs into cancer Tregs.

Pathway enrichment analysis was performed using DEGs extracted from *TNFR2*-high cancer Tregs that were commonly upregulated in the HCC, NSCLC, and CRC datasets. Similar to the pathway enrichment results from the single-cell RNA-seq analysis of TNFR2 agonist antibody-stimulated Tregs, cell proliferation-related pathways ("Myc targets v1", "G2M checkpoint", "E2F targets", "mitotic spindle", and "DNA repair"), downstream pathways of cytokine receptors ("IFNγ response," "IFNα response," "TNFα signaling via NFκB," "IL-2 STAT5 signaling," "IFNα response," and "IL-6 JAK STAT3 signaling"), cell metabolism pathways ("glycolysis" and "oxidative phosphorylation"), and other intracellular signaling pathways ("mTORC1 signaling," "PI3K AKT mTOR signaling," and "androgen response") were significantly correlated with the upregulated DEGs (Figure 8D). These results suggested that TNFR2 signals were enhanced in *TNFR2*-high cancer Tregs.

Discussion

TNFR2 plays a critical role in regulating Treg function, which in turn, can modulate disease progression. Thus, functional modulation of TNFR2 has been thought to have therapeutic potential for various diseases, including cancers, autoimmune diseases, and neurological diseases, which has been reviewed elsewhere [115]. Moreover, transcriptome analysis identified genes with upregulated expression upon TNFR2 activation in mouse Tregs treated with TNFR2-selective ligand [141]. However, this analysis did not fully characterize how TNFR2 controls cellular signals in Tregs, particularly in TNFR2-high Tregs. Therefore, for a comprehensive understanding of the downstream signaling of TNFR2, in this study, I analyzed Ampli-seq and single-cell RNA-seq data of Tregs treated with a TNFR2 agonist antibody, followed by pathway enrichment analysis, by focusing on *TNFR2*-high Tregs.

In my study, upregulation of "TNFα signaling via the NF-κB" pathway was identified by TNFR2 agonist antibody-treated and *TNFR2*-high Tregs. A previous *in vitro* study showed that phosphorylation of NF-κB and transcriptional activity of NF-κB is enhanced by TNFα stimulation in Tregs [142]. Meanwhile, another report showed that activation of TNFR2 by an agonist activates the degradation of the nuclear factor of the κ light polypeptide gene enhancer in the B-cells inhibitor α (I κ B α), indicating activation of the NF-κB pathway in Tregs upon TNFR2 activation [143]. My pathway enrichment data from transcriptome data on TNFR2 agonist antibody-treated Tregs precisely captured TNFR2 activation, consistent with previous findings produced by different methods, as described below. A closer examination of individual genes in the "TNFα signaling via the

NF-κB" pathway showed that the expression levels of *NFKB2* and *RELB* were elevated. TNFR2 is known to activate non-canonical NF-κB signaling via activation of NF-κB inducing kinase (NIK), responsible for processing the C-terminal region of p100, which is encoded by *NFKB2* [144]. The processing of p100 induces translocation of the transcription factor RelB (encoded by *RELB*), followed by induction of target gene transcription by the RelB/p52 transcription factor [144]. My transcriptome data clearly showed activation of the non-canonical NF-κB pathway in Tregs by stimulation with a TNFR2 agonist. Taken together, these findings suggest that TNFR2 activation is likely to promote Treg proliferation through non-canonical NF-κB signaling.

The "IL-2 STAT5 signaling" pathway was also upregulated in TNFR2 agonist antibodytreated and *TNFR2*-high Tregs. The IL-2 receptor is expressed in Tregs and activates STAT5, which then promotes the activation and proliferation of Tregs [145]. Activation of TNFR2 by the TNFR2 agonist antibody enhanced Treg proliferation when combined with IL-2 [116]. In addition to its involvement in proliferation, IL-2 induces FOXP3 expression [146]. Meanwhile, STAT5 functions downstream of IL-2 and enhances transcription of *FOXP3* by binding its promoter region [146]. My *in vitro* data confirmed that the IL-2 signaling pathway was enhanced by the TNFR2 agonist, resulting in Treg proliferation. These results were consistent with previous studies reporting that activation of TNFR2 in mouse Tregs can induce *TNFR2* expression but not *TNFR1* through TNFαdependent phosphorylation of STAT5 by IL-2 [145], and TNFR2 agonist antibody elevated *STAT5* expression in Tregs [141]. Moreover, my results demonstrated that the "IL-6 JAK STAT3" pathway was activated in *TNFR2*-high Tregs. A previous study indicated that activation of the STAT3 transcription factor enhances *FOXP3* expression in Tregs [146], suggesting that "IL-2 STAT5 signaling" and "IL-6 JAK STAT3" are likely to regulate Treg proliferation pathways.

My data showed that the "IFNγ response" was upregulated in Tregs treated with the TNFR2 agonist antibody and in *TNFR2*-high Tregs. Interestingly, the TNFR2 agonist antibody decreased the ratio of IFNγ-positive Tregs [147]. Hence, the highlighted IFNγ response pathway in my analysis likely did not increase the abundance of IFNγ-positive Tregs but rather enhanced IFNγ signaling. TNFR2 activates AKT and PI3K [148], which affect the phosphorylation of STAT1 and was consistent with my identification of the "PI3K AKT mTOR signaling" pathway in the *TNFR2*-high Tregs. This "IFNγ response" pathway may also indicate that TNFR2 transmits signals to STAT1 via AKT-PI3K, which agrees with the findings of another study that also showed the IFNγ pathway is involved in the generation of Tregs [149]. Furthermore, the activation of the "IFN α response" pathways could be due to the activation of STAT1 as IFN α induces gene transcription via STAT1 [150]. A previous report showed that IFN α signaling promotes the development of Tregs in the thymus and survival in the peripheral tissues [151]. Hence, activation of the "IFNγ pathway" and "IFNα pathway" could represent one mechanism by which TNFR2 activation stimulates Treg proliferation.

My single-cell RNA-seq analysis highlighted not only the inflammation- and cytokinerelated pathways discussed above but also Treg metabolism by TNFR2 signaling. As shown in Figure 7B, "glycolysis" and "oxidative phosphorylation" pathways were pronounced in *TNFR2*-high Tregs. In thymus-derived Tregs, TNFR2 induced glycolysis through PI3K-mTOR signaling [152] and my data also captured this aspect.

From single-cell RNA-seq analysis of TNFR2 agonist antibody-stimulated Tregs, I identified a total of 32 pathways (Figure 7B). Meanwhile, cancer Tregs had 43 highlighted pathways (Figure 8D). Interestingly, 31 out the 32 pathways from TNFR2 agonist antibody-stimulated Tregs were included in the 43 pathways of cancer Tregs. This finding strongly suggests that TNFR2 signaling is fully active in cancer Tregs. Furthermore, pathway enrichment analysis of cancer Tregs was performed using DEGs extracted that were commonly upregulated in *TNFR2-*high cancer Tregs of HCC, NSCLC, and CRC. This suggests that the upregulation of TNFR2 signaling in cancer Tregs is a common feature in these cancer types. In fact, a previous report showed that the level of TNFR2 expression in Tregs was elevated in ovarian cancer patients, especially in patients with ascites [124]. Meanwhile, another report showed a correlation between the number of TNFR2-high Tregs in pleural effusion and the prognosis of lung cancer patients. The survival rate was significantly lower in patients with TNFR2-high Tregs [125]. Moreover, TNFR2 expression levels in Tregs within the peripheral blood correlate with the clinical pathology of lung cancer patients [153].

Similar analyses will reveal that pronounced TNFR2 signaling also occurs in these cancer types in which the increased number of TNFR2-high Treg is evident or possibly determines the prognosis of patients. Six out of the 11 pathways in cancer Tregs not overlapped with TNFR2 agonist antibody-stimulated Tregs were cell proliferation-related pathways such as: "Myc targets v1," "G2M checkpoint," "E2F targets," "mitotic spindle," "Myc targets v2," and "mitogenesis." I speculate that this is because cancer Tregs could

chronically receive TNFR2 activation stimuli under the cancerous environment that may activate TNFR2-dependent proliferation pathways in cancer Tregs. This phenomenon may occur by the enhanced expression of TNFR2 ligand, TNFα, which was also identified as an upregulated gene in my cancer Treg analysis. Indeed, the expression of TNF α is elevated in human cancer tissues, such as gastric and colorectal cancers, compared to adjacent normal tissues [154]. TNF α is also known to upregulate TNFR2 expression [155]; therefore, TNFR2 signaling may be further enhanced in cancer Tregs. Although pathway enrichment analysis with single-cell RNA-seq data of TNFR2 agonist antibodystimulated Tregs failed to show the cell proliferation pathways, "G2M checkpoint" and "E2F targets" were top two pathways in the pathway enrichment analysis with Ampli-seq data (Figure 6B). For example, *EZH2* expression was upregulated and included in the "E2F target" and "G2M checkpoint" pathways in the Ampli-seq (Figure 6C and D), and EZH2 expression is reportedly upregulated by TNFR2 stimulation [156] and involved in Treg stability after TNFR2 activation [157]. Taken together, the two pathways "E2F target" and "G2M checkpoint" may capture the proliferative phenotype of *TNFR2*-high Tregs, in response to *in vitro* TNFR2 agonist antibody stimulation, but genes encoding such cell proliferation pathways were not collectively detected upregulated in *TNFR2*-high vs *TNFR2*-low Tregs *in vitro.* However, it is noteworthy that the single-cell RNA-seq identified the larger number pathways compared to the Ampli-seq, implying that the significance of my study that for the first time has fully uncovered TNFR2 signaling in *TNFR2*-high Treg by using single-cell RNA-seq.

Aside from cancer, changes in Treg function or their reduced abundance also represent

features of other diseases. For instance, Treg dysfunction or reduced abundance has been reported in various autoimmune diseases, including systemic lupus erythematosus and type-1 diabetes [112]. Moreover, recent studies have demonstrated an altered Treg population in neurodegenerative diseases such as Alzheimer's disease and Parkinson's disease [158]. By completely identifying all TNFR2 pathways, the determination of whether TNFR2 is active or inactive in Tregs in the above-mentioned diseases will become possible. In addition, the overall proportion of TNFR2-high Tregs may serve as a diagnostic marker as well as a marker of TNFR2 therapy efficacy. However, these postulations must be confirmed by analyzing TNFR2 expression profiles and investigating the proportion of *TNFR2*-low and *TNFR2*-high populations in these diseases. In addition, recent single-cell RNA-seq studies based on clinical samples from cancer patients identified Treg subtypes by their gene expression profiles and function [134-136, 159]. Thus, by increasing the size of patient cohort and analyzing the detailed relationship between TNFR2 expression levels and Treg subsets in the future studies, it may be possible to characterize the specific Treg subsets more deeply responsible for TNFR2 signaling.

Thus, my results provide evidence that TNFR2 signaling is activated in TNFR2-high cancer Tregs and that TNFR2-activated Tregs may help cancer cells escape immune surveillance, making TNFR2 signaling a potential anticancer therapy.

Figures and Tables

Figure 5. Treg expansion by treatment with TNFR2 agonist antibody

A Treg expansion by TNFR2 agonist antibody treatment. Tregs were isolated from healthy donor PBMCs and cultured in the presence of the control IgG or TNFR2 agonist antibody for 7 d. Treg proliferation in response to the control IgG or TNFR2 was detected by measuring ATP content and calculated as a percentage of the non-treatment group. Data points represent the mean + standard deviation, acquired in triplicate. **B** FOXP3 protein expression in Tregs treated with the control IgG or TNFR2 agonist antibody. FOXP3 expression was measured by FACS. Data was obtained from a representative sample from each group. All data are representative of at least two independent experiments.

Figure 6. Pathway enrichment analysis using Ampli-seq transcriptome data from Tregs treated with the TNFR2 agonist antibody Ampli-seq analysis was performed using Tregs treated with a TNFR2 agonist antibody

A A scatter plot of the first and second principal components in the PCA. **B** Enriched pathways of the upregulated DEGs identified in Tregs treated with the TNFR2 agonist antibody. Significantly enriched pathways with a P value < 0.01 are shown. Bars indicate the -log¹⁰ (P value) in each pathway. **C-I** Heatmaps of individual DEG expression values associated with each pathway. These pathways included **C** E2F Target, **D** G2M checkpoint, **E** TNFα signaling via NFκB, **F** IL-2 STAT5 signaling, **G** IFNγ response, **H** mTORC1 signaling, and **I** androgen response. The expression levels for each gene are shown as z-scaling log₂ counts per million (CPM) values in the heatmaps.

Figure 7. Pathway enrichment analysis using single-cell RNA-seq transcriptome data from Tregs treated with the TNFR2 agonist antibody

A Loge-normalized *TNFR2* expression levels are shown in the UMAP plot. **B** Pathway enrichment of DEGs between *TNFR2*-high and *TNFR2*-low Tregs. Significantly enriched pathways with a P value < 0.01 are shown. Bars indicate the -log₁₀ (P value) for each pathway.

Figure 8. Enhanced *TNFR2* expression and signaling in cancer Tregs

A-C Violin plots showing loge-normalized expression levels of *TNFR2* in **A** HCC (hepatocellular carcinoma), **B** NSCLC (non-small cell lung cancer), and **C** CRC (colorectal cancer). **D** Pathway enrichment by DEGs between cancer and normal Tregs that were commonly upregulated in the three cancers. Significantly enriched pathways with a P value < 0.01 are shown, and bars indicate the -log¹⁰ (P value) for each pathway. The DEGs between cancer and normal Tregs were extracted and commonly upregulated DEGs across three datasets (GSE98638, GSE99254, and GSE108989) were used for pathway enrichment analysis.

General Discussion

The identification of the gene signature that constitute pathologic pathways by comprehensive gene expression analyses allows for new associations of disease and pathologic genes that would be difficult to prove by examining specific genes in past studies.

As concrete examples, in the case of Chapter 1, by comparing the gene signatures after TREM2 activation identified by RNA-seq of iPS-microglia treated with anti-TREM2 agonist antibody and the gene signatures extracted from microglia of AD patients by snRNA-seq, I found for the first time that TREM2 activation was lower in microglia of AD than in microglia of healthy subjects, and was further reduced with disease progression, suggesting that the lower TREM2 activation in microglia of AD patients may allow anti-TREM2 agonist antibodies may be able to control AD progression because TREM2 activation is low in microglia of AD patients. In the case of Chapter 2, My comparisons between (i) the gene signatures of TNFR2-activated Tregs by RNA-seq and scRNA-seq and (ii) those of cancer Tregs revealed that TNFR2 regulates multiple pathways in cancer Tregs that may help cancer cells escape immune surveillance. Combined, I proposed that inhibition of TNFR2 signaling could be a target for anticancer therapy. Although the diseases in the above two cases are completely different, they are considered to be successful cases in which the relationship between the disease-causing genes and the disease was clarified by identifying the gene signatures that constitute the

pathologic pathways using comprehensive gene expression analysis.

In this section, I would like to discuss the commonalities between my two studies and the factors that led me to identify the gene signatures that comprise the pathologic pathways using comprehensive gene expression analysis. First, in both cases, I clearly defined the gene signature, which is controlled by the presence or absence of expression of the gene of interest, by performing in-vitro experiments and exhaustive gene expression analyses that specifically regulate the expression of pathologic genes alone. Next, I unified the cell types used in the experiments with the cell types in which disease-specific gene signatures appear, and extracted the gene signatures regulated by the pathologic genes. This unification of cell types allowed direct comparison of the gene signatures regulated by the pathologic genes and those of the disease, eliminating potential factors unrelated to the phenomena of interest. Furthermore, in the comparison of the gene signatures, I incorporated biological interpretation using pathway and GO enrichment analysis to each gene signature and compared overlaps on pathway and GO levels. This method confirms that biologically important functions in disease were regulated by a pathologic gene. The common factors mentioned above enabled us to identify the gene signatures constituting the pathologic pathways using comprehensive gene expression analysis and even suggested the possibility of drug discovery.

Based on the above discussion, I would like to further discuss some points to be noted in

conducting this research method and promote the effective use of this research method in the future. First, it is important to note that studies using comprehensive gene expression analysis are required to handle a huge number of results, for example, approximately 26,000 genes for human, as many as the number of genes, and the interpretation of the gene signatures obtained from such studies is intensive. Therefore, it is important to have a precise plan in the research planning phase that allows the acquisition of the gene signatures focused only on the specific phenomenon to be elucidated without confounding factors. In addition to basic knowledge of the hypothesis to be proved, the interpretation of the gene signature requires a comprehensive and objective evaluation, integrating expert knowledge of the vast number of genes and their populations, such as pathways, omics, and bioinformatics. Knowledge bias toward a particular gene population or pathway sometimes runs the risk of creating arbitrary bias in the interpretation of the gene signature. To avoid this risk, it is useful to use biological information from mechanical methods such as enrichment analysis using GO and pathway databases and GSEA as a source of interpretation when interpreting the gene signature [64]. On the other hand, those bioinformatic analysis methods calculate importance scores based on gene overlap and ranking, so it is not always clear whether the highlighted pathways contain biologically key genes. Therefore, human curation after analysis is also important. Since it is difficult for one researcher to do all of the

interpretation covering all of the above specialties, it is also said that the ideal research structure for the future is to have various specialists collaborate on the interpretation, since it is difficult for a single researcher to do all of the interpretation covering all of the above specialties [160].

Finally, I would like to describe the significance of this study. I here proposed the method that is based on comprehensive gene expression analyses and allows us to interpret the relationship between the pathologic gene and the disease comprehensively, beyond the extent to which conventional studies have only examined certain aspects of the pathologic gene. This method may increase the speed of identifying the pathogenesis of diseases and the probability of success in drug discovery. In addition, this research approach is applicable to basic biology. When you wish to verify a complex phenomenon in a difficult-to-obtain species, you may first extract the gene signatures that are reliably regulated by the target gene in an in-vitro experiment in a closely related model species, and feedback the data from the model organism to the species of the primary interest. In conclusion, based on the above considerations, if the identification of the gene signature that constitutes pathologic pathways by comprehensive gene expression analyses can be performed with high accuracy, many new insights into the relationship between disease and pathway genes, which have been difficult to prove by simply

examining specific genes, will be realized. I hope that such this method will accelerate

precise drug discovery research directly related to the pathology of diseases.

Acknowledgements

I am most grateful to Professor Yuji Inagaki for being in charge of this dissertation, and for his valuable guidance and encouragement through my doctoral program.Also, I am sincerely grateful to Professors Ryusuke Niwa, Kaori Ishikawa and Yukihiko Toquenaga for guiding my work and valuable discussions.

I also thank Dr. Shuji Sato in Takeda Pharmaceutical Company Limited for his encouragement and helpful guidance in my research work.

Acknowledgements are also made to Dr. Yo Muraki in Takeda Pharmaceutical Company Limited for his kind cooperation and advice in my research work.

Further, I thank Associate Director Shuuichi Miyakawa and Dr. Yusuke Kikukawa, current supervisors in Takeda Pharmaceutical Company Limited, for endorsement of participation in the graduate program.

Finally, I would like to appreciate my family for supporting my life in University of Tsukuba.

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