Iron Responsive Element (IRE)-mediated responses to iron dyshomeostasis in Alzheimer's disease

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Abstract

Background: Iron trafficking and accumulation is associated with Alzheimer's disease (AD)
pathogenesis. However, the role of iron dyshomeostasis in early disease stages is uncertain.
Currently, gene expression changes indicative of iron dyshomeostasis are not well
characterized, making it difficult to explore these in existing datasets.

Objective: To identify sets of genes predicted to contain Iron Responsive Elements (IREs)
and use these to explore possible iron dyshomeostasis-associated gene expression
responses in AD.

Methods: Comprehensive sets of genes containing predicted IRE or IRE-like motifs in their
3' or 5' untranslated regions (UTRs) were identified in human, mouse, and zebrafish
reference transcriptomes. Further analyses focusing on these genes were applied to a range
of cultured cell, human, mouse, and zebrafish gene expression datasets.

Results: IRE gene sets are sufficiently sensitive to distinguish not only between iron
overload and deficiency in cultured cells, but also between AD and other pathological brain
conditions. Notably, changes in IRE transcript abundance are amongst the earliest
observable changes in zebrafish familial AD (fAD)-like brains, preceding other AD-typical
pathologies such as inflammatory changes. Unexpectedly, while some IREs in the 3'
untranslated regions of transcripts show significantly increased stability under iron deficiency
in line with current assumptions, many such transcripts instead display decreased stability,
indicating that this is not a generalizable paradigm.

Conclusion: Our results reveal IRE gene expression changes as early markers of the
pathogenic process in fAD and are consistent with iron dyshomeostasis as an important

58 driver of this disease. Our work demonstrates how differences in the stability of IRE-

59 containing transcripts can be used to explore and compare iron dyshomeostasis-associated

60 gene expression responses across different species, tissues, and conditions.

Keywords

63 Iron responsive element, iron homeostasis, Alzheimer's disease, gene expression,

64 Computational Biology, Transcriptomics, familial Alzheimer's disease

Introduction

The pathological processes underlying Alzheimer's Disease (AD) commence decades

before symptoms become evident [1,2]. Since the early days of AD research, iron trafficking

and accumulation has been observed to be altered in AD [3–7]. However, it is still unclear

whether iron dyshomeostasis represents a late symptom or an early pathological driver of

AD. Iron homeostasis is closely linked to many critical biological processes including cellular

respiration, hypoxia, and immune responses, all of which are disrupted in AD. Consistent

with this, discoveries over the past decade have shown that disruptions to iron homeostasis

can drive feedback loops that worsen AD pathology [8,9]. However, evidence for iron

dyshomeostasis as an early driver of the disease is only just emerging. While iron

accumulation associated with amyloid plaque formation has been observed in various

transgenic mouse models of AD [10–13], the age at which iron dyshomeostasis first occurs

is uncertain [14].

Currently, gene expression patterns representing responses to iron dyshomeostasis are not

well-characterized. Cellular responses to iron dyshomeostasis are complex and involve

several systems and layers of regulation. The stability of the transcription factor HIF1α, (a

component of HIF1, a master regulator of responses to hypoxia) is regulated by an iron-

dependent mechanism so that transcriptional responses to iron deficiency can resemble

hypoxia responses [15]. However, cellular iron homeostasis is also regulated at the post-

transcriptional level by the IRP/IRE system [16–18]. In this system, altered levels of available

ferrous iron (Fe^{2+}) cause Iron Regulatory Proteins (IRP1 or IRP2) to change conformation or

stability respectively [19,20]. This alters their ability to bind *cis*-regulatory Iron Responsive

Element (IRE) stem-loop motifs in the 3' or 5' untranslated regions (UTRs) of genes

encoding products related to iron metabolism. Only a few IRE-containing genes have been

characterized in detail, including transferrin receptor 1 (*TFR1*; 3' UTR IRE), divalent metal

transporter 1 (*DMT1* or *SLC11A2*; 3' UTR IRE), ferritin heavy chain and ferritin light chain (

FTH1 and *FTL*; both 5' UTR IRE), and ferroportin (*SLC40A1*; 5' UTR IRE) [18]. In general,

these previously-characterized IRE-containing genes suggest that IRPs binding to 3' IREs

tend to stabilize transcripts to increase protein translation, while binding to 5' IREs

suppresses translation [17]. It is important to note that while the ancestral ferritin IRE is

present even in lower metazoans (including sponges), IRE elements in other genes have

likely arisen more recently through convergent evolution [21]. Perhaps because of this, the

properties of IRE genes can vary in different ways. For example, *SLC11A2* is stabilized by

IRP1 binding to a greater extent than by IRP2 binding (as its 3' IRE has a greater affinity for

IRP1) [22]. Similarly, while *CDC42BPA* and *TFRC* both possess 3' IREs, *CDC42BPA* is

stabilized to a greater extent than *TFRC* under iron deficiency [23]. There are also IRE-

containing genes that bind only IRP1 or IRP2 exclusively, at least in mice [24]. However,

global gene expression changes mediated by genes with IREs have not yet been well-

defined, and the overall expression patterns of IRE-containing genes have not been

explored in the context of AD. In addition, it is unclear how expression of these genes might

differ between AD and other neurodegenerative diseases, or how AD risk factors such as

aging and hypoxia might contribute.

In this study, we utilized the SIREs (Searching for Iron Responsive Elements) tool [25] to

predict and identify sets of IRE-containing genes in human, mouse, and zebrafish. We then

applied these gene sets to explore overall IRP/IRE-mediated iron dyshomeostasis-

associated responses in datasets involving: (1) a cultured cell line subjected to iron overload

and deficiency treatments, (2) a cohort of AD patients, healthy controls, and two other

pathological conditions affecting the brain, (3) 5XFAD mice used to model the amyloid and

tau pathology seen in AD, and (4) a zebrafish knock-in model possessing a familial AD

(fAD)-like mutation.

Our IRE gene sets displayed significant enrichment in AD, the 5XFAD mouse model, and an

fAD-like zebrafish model, demonstrating for the first time the early and extensive

involvement of IRP/IRE-mediated iron dyshomeostasis-associated gene expression

responses in the context of AD. IRE gene sets were sufficiently sensitive to distinguish not

only between iron overload and deficiency in a cultured cell line dataset, but also between

AD and other pathological conditions affecting the brain (pathological aging and progressive

supranuclear palsy), implying that the dysregulation of IRE-containing genes in AD may

differ from other conditions. Changes in IRE gene expression were already evident in young

adult brains of animal models of AD (3-month-old 5XFAD mice, 6-month-old fAD-like

zebrafish). Overall, our observations do not support the current assumption that IRP binding

to 3' IREs generally stabilizes transcripts as, under most conditions, we observed both

increases and decreases in the abundances of transcripts with either 3' or 5' IREs.

Methods

Defining IRE gene sets for human, mouse, and zebrafish

We extracted all 3' and 5' UTR sequences from the human, mouse and zebrafish genome

assemblies using the Bioconductor packages BSgenome.Hsapiens.UCSC.hg38,

BSgenome.Mmusculus.UCSC.mm10 and BSgenome.Drerio.UCSC.danRer11, and gene

definitions from the Ensembl 94 release. Note that potential IREs have also been identified

within protein coding sequences [24,26], but were not included in our analyses under the

initial assumption that the classic IRE paradigm was valid, as their possible effects on

transcript stability are unknown. Each set of UTR sequences was then submitted into the

SIREs web server (v.2.0 [25]). The SIREs algorithm assigns quality scores to predicted IREs

taking into account whether the sequence is canonical, whether it contains any mismatches

and bulges, and the free energy of the secondary structure. Canonical sequences are

tagged by SIREs as being high-quality, while IRE-like sequences are tagged as low or

medium quality. Given that high-quality IRE predictions miss the majority of true IREs, this

enables a more comprehensive sampling of IRE motifs. For human, mouse, and zebrafish,

we separately defined the following four gene sets: *HQ 3' IREs* and *HQ 5' IREs*

(representing genes with high-quality predicted IREs), along with *all 3' IREs* and *all 5' IREs*,

which included genes containing any predicted IRE in the respective UTR. Comparisons

between gene sets were performed using the UpSetR package (v.1.4.0 [27]) with gene ID

mappings between species obtained by BioMart [28].

Over-representation of IRE gene sets in existing MSigDB gene sets

We downloaded the following gene set collections from MSigDB (v.6.0 [29]): Hallmark, C2

(gene sets from online pathway databases and biomedical literature, including KEGG and

the REACTOME databases), C3 (motif gene sets based on regulatory targets), and C5

(gene sets defined by Gene Ontology terms). We excluded the following collections from

analysis: C1 (specific to human chromosomes and cytogenetic bands, while our analysis

involves different species), C4 (computationally-defined cancer-focused gene sets), C6

(oncogenic signatures) and C7 (immunologic signatures). C4, C6, and C7 were not included

as the level of detail in the gene sets in these specific collections is more domain-specific

rather than broad-level. We used Fisher's exact test to determine whether any IRE gene set

was significantly over-represented in each MSigDB gene set. Gene sets were defined as

having significant enrichment for IRE gene sets if the FDR-adjusted *p*-value from Fisher's

exact test was below 0.05. UpSet plots were produced using the UpSetR package (v.1.4.0

[27]) while network representations were produced in Gephi (v.0.9.3 [30]). To produce

network visualizations, we first exported node and edge tables from R. The nodes table

contained the following gene sets: top 15 gene sets (ranked by Fisher's exact test *p*-value),

Hallmark Heme Metabolism gene set, **all 3' IREs**, **all 5' IREs**, and all genes contained within

these gene sets. The edges table contained gene – gene set edges which indicated the

gene set(s) that genes belonged to. To create the network plots in Gephi, we used "Force

Atlas 2" as the initial layout algorithm, followed by the "Yifan Hu" [31] layout algorithm to

improve visual separation between distinct groupings of genes.

177 Over-representation analysis of transcription factor motifs in IRE gene

178 promoters

Defining promoter regions as being 1500 bp upstream and 200 bp downstream of the

transcription start site for each gene, we used the findMotifs.pl script from HOMER (v.4.11)

[32,33] to search for known transcription factor binding site (TFBS) motifs in the promoters of

each IRE gene set. The HOMER Motif database contains 363 vertebrate transcription factor

binding motifs based on analysis of high-quality public ChIP-seq datasets

(http://homer.ucsd.edu/homer/motif/HomerMotifDB/homerResults.html). We considered

TFBS motifs as being significantly enriched in a gene set if the FDR-adjusted p-value (q-

value as provided in HOMER output) was less than 0.05.

Gene set enrichment testing

We performed all gene set enrichment tests in R v3.6.1 [34] using *fry* [35,36], *camera* [37],

and *fgsea* [38,39]. For *fry*, and *camera,* we used model fits obtained using *limma* [40,41],

whilst for *fgsea*, a ranked list was obtained using *moderated t*-statistics taken from *limma*. All

genes were used in gene set enrichment tests (i.e. not just DE genes). We combined the

raw p-values from *fry, camera*, and *fgsea* using Wilkinson's method [42] with default

parameters, followed by FDR-adjustment. When performing gene set enrichment testing on

the MSigDB Hallmark gene sets, we applied FDR-adjustment to combined p-values and

defined significant enrichment as gene sets having an adjusted p-value < 0.05. When

performing gene set enrichment on the four IRE gene sets (**all 3' IREs**, **all 5' IREs**, **HQ 3'**

IREs, **HQ 5' IREs**), we applied Bonferroni-adjustment to combined p-values to further

protect against Type I errors and defined significant enrichment as gene sets having an

adjusted p-value < 0.05. Depending on the species in the dataset being analyzed, we used

the respective IRE gene sets defined for human, mouse, or zebrafish.

Analysis of the Caco-2 cultured cell line dataset

We downloaded processed microarray data from GEO (accession number: GSE3573). This

study investigated gene expression responses to iron treatments, including iron deficiency

(cells in iron-free medium vs. cells cultivated in ferric ammonium nitrate, and iron overload

(cells cultivated in DMEM-FBS medium with hemin vs. cells in DMEM-FBS medium) [43].

We performed differential gene expression analysis using the "lmFit" and eBayes" functions

in *limma* [40]. Genes were defined as differentially expressed when their FDR-adjusted p-

value < 0.05.

Analysis of the Mayo Clinic RNA-seq dataset

No experiments of human subjects were performed in this study as all human data was accessed from public databases and was anonymous. We downloaded processed CPM count data from Synapse (https://www.synapse.org/#!Synapse:syn5550404). We matched cerebellum and temporal cortex samples by their patient ID, and only retained genes which were present across all samples and patients for which there were both cerebellum and temporal cortex samples (n=236 patients with measurements for cerebellum and temporal cortex, 472 samples in total). We performed analysis using *limma* [40,41] and determined differentially expressed genes between conditions. In addition, we used the "duplicateCorrelation" function in *limma*, setting the "block" parameter to the patient ID. Genes were considered differentially expressed if their FDR-adjusted *p*-value < 0.05.

Zebrafish husbandry and animal ethics

All zebrafish work was conducted under the auspices of the Animal Ethics Committee (permit numbers S-2017-089 and S-2017-073) and the Institutional Biosafety Committee of the University of Adelaide. Tübingen strain zebrafish were maintained in a recirculated water system.

fAD-like *psen1*^Q96_K97del/+ zebrafish

The isolation of the *psen1*^Q96_K97del mutation has previously been described [44]. Zebrafish mutations were only analyzed in the heterozygous state in this study.

Acute hypoxia treatment of zebrafish

235 *psen1*^{Q96_K97del/+} mutants and their wild-type siblings were treated in low oxygen levels by

236 placing zebrafish in oxygen-depleted water for 3 hours (oxygen concentration of 6.6 ± 0.2

237 mg/L in normoxia and 0.6 ± 0.2 mg/L in hypoxia.

Whole brain removal from adult zebrafish

240 After normoxia or hypoxia treatment adult fish were euthanized by sudden immersion in an

241 ice water slurry for at least ~30 seconds before decapitation and removal of the entire brain

242 for immediate RNA or protein extraction. All fish brains were removed during late

243 morning/noon to minimize any influence of circadian rhythms.

RNA extraction from whole brain

Total RNA was isolated from heterozygous mutant and WT siblings using the *mir*Vana

miRNA isolation kit (Thermo Fisher). RNA isolation was performed according to the

manufacturer's protocol. First a brain was lysed in a denaturing lysis solution. The lysate

was then extracted once with acid-phenol:chloroform leaving a semi-pure RNA sample. The

sample was then purified further over a glass-fiber filter to yield total RNA. Total RNA was

DNase treated using the DNA-free™ Kit from Ambion, Life Technologies according to the

manufacturer's instructions. Total RNA was then sent to the Genomics Facility at the South

Australian Health and Medical Research Institute (Adelaide, Australia) to assess RNA quality

and for subsequent RNA sequencing *(using poly-A enriched RNA-seq technology, and*

estimated gene expression from the resulting single-end 75 bp reads using the reference

GRCz11 zebrafish assembly transcriptome)

Pre-processing of the fAD-like *psen1*^{Q96_K97del/+} zebrafish dataset:

RNA-seq libraries contained single-end 75bp Illumina NextSeq reads. We performed quality

trimming with *AdapterRemoval* using default parameters. Trimmed reads were pseudo-

aligned to the reference zebrafish transcriptome using *Kallisto* (v.0.45) [45] and transcript

descriptions from Ensembl release 94. The "catchKallisto" function from *edgeR* [46] was

used to import and summarise counts from transcript-level to gene-level, with all subsequent

analyses performed at the gene-level.

Differential gene expression analysis for fAD-like zebrafish dataset

For differential gene expression analysis, we retained all genes with expression of at least 1

cpm in 4 or more samples, and used voomWithQualityWeights to downweight lower quality

samples [41]. Contrasts were defined to include all relevant pairwise comparisons between

conditions, and genes were considered as differentially expressed using an FDR-adjusted *p*-

value < 0.05. The *limma* model used to create the design matrix for this dataset included

biological sex as a variable (~0 + biologicalSex + group, where biologicalSex is either male

or female and group refers to the combination of age, hypoxia treatment, and genotype of

the samples) to minimize any sex-specific effects in the gene expression analysis. More

details regarding the modest effects of biological sex in this dataset are provided in

Supplementary Text 1.

Estimation of spliced and unspliced gene expression in fAD-like zebrafish dataset

For spliced transcripts in Ensembl release 94, we additionally defined unspliced genes

including intronic regions. Unspliced transcripts were appended to the end of the reference

transcriptome and used to build a new Kallisto [45] index. Estimated counts for spliced

transcripts and unspliced genes were imported into R using the "catchKallisto" function from

edgeR [46].

Gene set enrichment tests for other zebrafish datasets

Please refer to ref. [44] for details on RNA-seq data processing and analysis of the non-fAD-

like dataset, and ref. [47] (GEO accession: GSE148631) for details on RNA-seq data

processing and analysis of the 7-day-old Q96_K97del/+ dataset. In the current work, we

used the gene expression counts matrix with *limma*. The voom, design, and contrasts

objects produced as part of the *limma* analysis were used for gene set enrichment analysis

with the zebrafish IRE gene sets we defined as well as the MSigDB Hallmark gene sets.

Significantly enriched Hallmark gene sets had FDR-adjusted *p*-value < 0.05 while IRE gene

sets were considered significantly enriched if the Bonferroni-adjusted *p*-value < 0.05.

Differential transcript stability analysis

The estimated spliced and unspliced transcript count estimates from *kallisto* [45] were

imported into R using the catchKallisto function from *edgeR* [46]. We used *limma* [40] to

determine the logFC of spliced transcripts and unspliced transcripts for each comparison. To

test for whether there was a significant difference in the logFC of the spliced and unspliced

transcripts, we used Welch's *t*-test with the *s2.prior* values from *limma* as the variances of

the spliced and unspliced transcripts. We defined the null (no stabilization of transcript) and

alternate (stabilization of transcript) hypotheses for each gene as follows, where s and u

refer to the spliced and unspliced versions of a particular gene:

$$H_0: \ \mathrm{logFC_s} = \mathrm{logFC_u}$$

$$H_a: \ \mathrm{logFC_s} \neq \mathrm{logFC_u}$$

We defined genes with FDR-adjusted *p*-values < 0.05 as having differential stability.

Checks that observed gene expression differences are not artifacts of differences in proportions of cell types

The Mayo Clinic RNA-seq study, 5XFAD mice, and fAD-like zebrafish datasets are bulk RNA-seq datasets. To confirm that any gene expression changes were likely due to altered transcriptional programs rather than changes in cell type proportions, we compared expression of marker genes for four common neural cell types (astrocytes, neurons, oligodendrocytes, microglia) in conditions within each dataset. The marker genes for astrocytes, neurons, and oligodendrocytes were obtained from MSigDB gene sets from [48] which were based on studies in mice. The marker genes for microglia were derived from [49] which was based on studies in human and mouse. All gene IDs were converted to human, mouse, or zebrafish Ensembl IDs using BioMart [28] for each dataset. Please refer to **Supplementary Text 2** for details.

Expression of previously validated IRE genes in cell line datasets

Gene symbols from Figure 2 and Supplementary Tables S1 and S2 of Sanchez et al. [50] were matched to corresponding Ensembl gene identifiers using the *biomaRt* R package [28], and filtered to include only genes present in **HQ 3' IRE** and **HQ 5' IRE** gene sets for human and/or mouse. Processed cell line microarray datasets were downloaded from GEO and included a human Caco-2 cell line dataset (GEO accession GSE3573), and mouse splenic B cell dataset (GEO accession GSE77306). The datasets were filtered for validated IRE genes and boxplots were used to visualize expression between groups. *t*-tests were used to test for differences in expression between groups, with *p*-values ≤ 0.05 considered statistically significant. The Sankey plot was produced using the *networkD3* R package [51].

Results

Defining sets of genes containing Iron Responsive Elements (IREs)

We utilized the SIREs (Searching for Iron Responsive Elements) tool, to define species-specific IRE gene sets by searching for IRE and IRE-like motifs in the 3' and 5' untranslated regions (UTRs) of the reference transcriptomes of human (hg38), mouse (mm10), and zebrafish (z11). *SIREs* assigns a quality-score to all detected IREs, with "high-quality" scores corresponding to canonical IREs and "medium-quality" or "low-quality" scores reflecting deviations from the canonical IRE (alternative nucleotide composition in the apical loop, one bulge at the 3' or one mismatch in the upper stem) that would still produce an IRE-like motif with potential to be functional [25,52–55]. **Figure 1** summarizes the IRP/IRE interaction effects on transcripts and gives examples of canonical and non-canonical IREs.

We defined four gene sets for each species as follows: ***HQ 3' IREs*** (high-quality predicted 3' IRE genes), ***HQ 5' IREs*** (high-quality predicted 5' IRE genes)*, **all 3' IREs*** (including all low, medium, and high-quality predicted 3' IRE genes), and ***all 5' IREs*** (including all low, medium, and high-quality predicted 5' IRE genes). The size of these gene sets for each species and the overlap present is shown in **Figure 2** and the gene sets are provided in **Supplementary Table 1**. Overall, searching through human UTRs uncovered the largest number of predicted IRE genes, followed by mouse, and then zebrafish. Overlap between homologous genes from the IRE gene sets of different species was generally poor. The largest sets of genes shared between species were consistently found between human and mouse, which is reflective of their closer evolutionary divergence.

While not many high-quality IRE genes were identified across all three species, the few we identified are consistent with known and well-characterized IREs in the literature [56,57]. For example, the single ***HQ 3' IRE*** gene shared between the three species was *TFRC*

(transferrin receptor), while the **_HQ 5' IRE_** genes shared between the three species included

FTH1 (ferritin heavy chain 1) and _ALAS2_ (5'-aminolevulinate synthase 2). We note that the

scoring of genes for the **_HQ 3' IRE_** and **_HQ 5' IRE_** sets is considered stringent (i.e. only

canonical IREs). These two gene sets recover known IRE genes in human, including

CDC14A (3' IRE; [50]), _CDC42BPA_ (3' IRE; [23,58], _SLC40A1_ (5' IRE; [59]), and _FTL_ (5'

IRE; [60]). These genes are also recovered in the **_All 3' IRE_** and **_All 5' IRE_** sets across

mouse and zebrafish too. In addition, the 3' IRE of _SLC11A2_ (also known as _DMT1_) [22]

which is only found in mammals, was also recovered in the human **_HQ 5' IREs_** set and

mouse **_All 3' IREs_** set (but not for zebrafish). The expression of these previously

characterized IRE genes across the human, mouse, and zebrafish datasets analyzed in this

current work is described in **Supplementary Text 3** and discussed further in the analyses

we later describe.

373 IRE gene sets are over-represented within up-regulated AD genes, but

374 overall not well-represented in existing gene sets

We explored the biological relevance of the predicted IRE gene sets described above by

testing whether genes within them are over-represented in existing gene sets from the

Molecular Signatures Database (MSigDB; available at https://www.gsea-

msigdb.org/gsea/msigdb). MSigDB represents one of the largest publicly-available

collections of gene sets collated from existing studies and other biological databases [29].

We limited our analysis to gene sets from the following collections: Hallmark (non-redundant

sets of ~200 genes each representing various biological activities), C2 (gene sets from

databases including KEGG and Reactome and published studies), C3 (gene sets containing

genes with motif elements), and C5 (gene sets based on gene ontology terms) (see

Methods). We performed over-representation analysis for the predicted IRE gene sets (**_all_**

3' IREs and **_all 5' IREs_**) separately for each species (human, mouse, zebrafish), and used

Wilkinson's meta-analytic approach to determine gene sets that were significantly over-

represented across the three species' IRE gene sets. Our results indicated that 1,148 of

10,427 tested gene sets displayed over-representation of IRE gene sets across all three

species (Bonferroni-adjusted Wilkinson's p-value < 0.05) (**Figure 3**; **Supplementary Table**

2). The bar plots in **Figure 3** show the 15 MSigDB gene sets with the most significant

enrichment for human, mouse, and zebrafish. Remarkably, the "Blalock Alzheimer's Disease

Up" gene set from the C2 collection was significantly over-represented in both the sets of ***all***

3' IREs (Bonferroni-adjusted Wilkinson's p-value = 3.9e-14) and ***all 5' IREs*** (Bonferroni-

adjusted Wilkinson's p-value = 2.1e-26) in the meta-analysis, and was also the gene set with

the most significant over-representation of the human ***all 3' IREs*** set (Bonferroni-adjusted

Fisher's exact test p-value = 7.8e-58) (**Supplementary Table 2**). This supports that

disturbance of iron homeostasis particularly distinguishes Alzheimer's disease from other

disease conditions and pathways represented within the C2 collection. In addition, the top 15

MSigDB gene sets showing the most significant over-representation generally differed

between species. However, in all cases, a large proportion of IRE genes from the predicted

IRE gene sets were not contained within any of these top-ranked MSigDB gene sets or

within the Heme Metabolism gene set belonging to the Hallmark collection (**Figure 3**). This

is visualized through the network plots of **Figure 3**, which show that the predicted IRE genes

we defined are not fully captured by existing gene sets. This suggests that IRE sets may be

uniquely useful for investigating gene expression changes during the IRE-IRP response to

iron dyshomeostasis.

Involvement of transcription factor regulation within IRE gene sets

To be confident that IRE gene sets accurately capture information about IRP/IRE-mediated

responses, we needed to investigate possible co-ordinate regulation by other factors. As a

starting point, we examined whether known binding motifs for transcription factors were

significantly over-represented in the promoter regions of genes within each IRE gene set (*all*

3' IREs, *all 5' IREs*, *HQ 3' IREs*, and *HQ 5' IREs*) for each species. We detected significant

over-representation of several transcription factors including the Klf14 motif in the zebrafish

all 3' IREs set (FDR-adjusted *p*-value = 0.049), the E2F motif in the human *all 5' IREs* set

(FDR-adjusted *p*-value = 0.049) and the Bach1 (FDR-adjusted *p*-value = 0.012), Nrf2 (FDR-

adjusted *p*-value = 0.013), and NF-E2 (FDR-adjusted *p*-value = 0.019) motifs in the

zebrafish *HQ 5' IREs* set (**Supplementary Table 3**). This suggests that the following results

should be interpreted with the knowledge that expression of subsets of genes in some of the

IRE gene sets may be influenced by factors other than iron ions.

Gene set enrichment testing approach

Our predicted IRE gene sets can be used in any standard gene set enrichment testing

approach to detect potential changes in iron homeostasis between conditions. Our workflow,

which we later apply to human, mouse, and zebrafish datasets, is shown in **Figure 4**. Due to

variability in the results produced by different gene set enrichment testing methods, we were

inspired by the EGSEA framework [61] to combine the results from different methods. Based

on an initial analysis using EGSEA, we chose *fry/mroast* [35,36], *camera* [37], and *fgsea*

[38,39] as the representative methods to use. (See **Supplementary Figure 2** for a principal

component analysis of results from different gene set enrichment analysis approaches.) A

summary of the different characteristics of the three methods is shown in **Table 1**. The raw

enrichment *p*-values from these approaches can be combined to obtain an overall

enrichment *p*-value for each gene set. In accordance with EGSEA default parameters, we

used Wilkinson's method to combine raw *p*-values, and then applied adjustment for multiple

testing on all combined *p*-values. Along with performing this gene set enrichment testing on

our IRE gene sets, we also recommend using the same method to test for enrichment for the

MSigDB Hallmark gene sets as the diverse biological activities they represent help to

provide context for interpreting the IRE enrichment results. To explore further the results of

IRE gene set enrichment analysis, we use UpSet plots to display the overlap between sets

of "leading-edge" genes in the *all 3' IREs* and *all 5' IREs* gene sets. The leading-edge

genes can be interpreted as the core (often biologically important) genes of a gene set that

account for the significant enrichment as calculated by GSEA [39].

Differences in IRE gene set enrichment during iron deficiency and iron

overload in a cultured cell line

We first tested how our enrichment approach illuminated the effects of iron overload and

deficiency in a cultured cell line microarray dataset from Caco-2 cells (GEO accession:

GSE3573). As only one cell type contributed to this dataset, interpretation of the IRE

enrichment results is simplified by not having to consider the differing iron requirements of

different cell types. This allowed us to focus on whether the iron dyshomeostasis treatments

(iron overload and iron deficiency) could be detected and distinguished in terms of their

IRP/IRE system-driven transcript abundance response. Because the dataset was from a

microarray experiment, we performed only the differential gene expression and gene set

enrichment testing portions of our workflow. The results of Principal Component Analysis

and differential gene expression analysis are provided in **Supplementary Figure 3**. We note

that this particular dataset was chosen despite not being derived from a central nervous

system cell type, as maintaining iron homeostasis is fundamental to all cell types (regardless

of their tissue of origin). In addition, this particular dataset included iron deficiency and iron

overload treatments in the same batch and with sufficient sample number, and no other

cultured cell line gene expression dataset was publicly available at the time that fulfilled

these criteria.

In general, we found iron deficiency and iron overload treatments resulted in different gene

expression responses. In terms of classic IRE genes such as *TFRC, FTL,* and *FTH1*, iron

deficiency is associated with increased expression of *TFRC* (consistent with increased

transcript stabilization of this 3' IRE gene) and decreased expression of the 5' IRE genes

FTL and *FTH1,* and these changes are in the opposite direction during iron overload (see

Supplementary Text 3 and **Supplementary Figure 1A**). Differential gene expression

across all detected genes in the dataset additionally revealed that iron deficiency was

associated with 96 differentially expressed genes of which 10 possessed predicted IREs

while iron overload was associated with 212 differentially expressed genes (FDR-adjusted *p*-

value from *limma* < 0.05) of which 33 possessed predicted IREs (**Supplementary Figure**

3B). There were 17 differentially expressed genes in common between iron deficiency and

iron overload treatments, and all moved in opposite directions according to the treatment

(i.e. increased abundance under iron deficiency and decreased abundance under iron

overload, or vice versa). These clear differences between iron deficiency and iron overload

were reflected in gene set enrichment analyses using the MSigDB Hallmark gene sets,

where the gene sets involved and the proportions of gene transcripts with increased or

decreased abundance differed (**Figure 5A**). As expected, IRE gene sets also showed

significant enrichment under iron deficiency and overload conditions (**Figure 5B**) (Bonferroni

adjusted *p*-value < 0.05).

We expected that iron deficiency would result in increased expression of genes with 3' IREs

under the IRP/IRE paradigm similar to the *TFRC* gene as seen in **Supplementary Text 3**.

However, both the 3' and 5' IRE gene sets displayed mixed patterns of increased and

decreased expression under both the iron deficiency and iron overload treatments (**Figure**

5B). This indicates it would be difficult to distinguish between these conditions based purely

on overall increases or decreases in the expression of IRE gene sets. Despite this, we see

that the iron deficiency and iron overload treatments can be distinguished by their "leading-

edge" genes (those genes contributing most to the enrichment signal for the predicted IRE

gene sets (*all 3' IREs* and *all 5' IREs*) (**Figure 5C**). This supports that gene set enrichment

using predicted IRE gene sets may be sufficiently sensitive to detect whether iron

dyshomeostasis is present and potentially more informative than individual IRE genes in

distinguishing between different IRP-IRE system-mediated gene expression responses in

iron deficiency and iron overload treatments in this cell line.

497   A distinct iron homeostasis response in human AD patients compared to

498   other neuropathologies

Given that IRE gene sets could distinguish between iron overload and deficiency in a

cultured cell line, we next tested our gene sets on a more complex dataset including

cerebellum and temporal cortex tissue samples from post-mortem human brains. The brains

originated from either healthy controls or patients afflicted with one of three conditions:

Alzheimer's disease (AD); pathological aging (PA), a condition involving amyloid pathology

but no significant dementia symptoms; or progressive supranuclear palsy (PSP), a

tauopathy without amyloid pathology [62]. An important characteristic of the dataset is that

both cerebellum and temporal cortex tissue samples were available from each patient. A

summary of the 236 patients whose data we included in this analysis is shown in **Table 2**

and the results of differential gene expression analysis and IRE gene set enrichment

analysis are shown in **Table 3** and **Figure 6A**, and summarised in comparison to the mouse

and zebrafish datasets later analysed in **Table 5**. The expression of classic IRE genes

including *TFRC, FTL,* and *FTH1* in this dataset is shown in **Supplementary Text 3** and

Supplementary Figure 1B-C. In our analyses, we focus mainly on comparing conditions

within each tissue rather than between tissues. This is because we found significant

differences in the AD vs. control comparison in the temporal cortex compared to the

cerebellum (see **Supplementary Figure 4**).

Overall, our IRE enrichment analyses indicate significant enrichment of IRE gene sets in all

pathological conditions (AD, PA or PSP) compared to healthy controls within the cerebellum

and temporal cortex (**Figure 6A**). In all pathological conditions, 3' and 5' IRE gene

transcripts show overall mixed patterns of abundance (e.g. increased and decreased).

Further examination of the leading-edge genes from these IRE gene sets gives more insight

regarding potential differences and similarities between AD, PA, and PSP (**Figure 6B**).

Overall, AD, PSP, and PA appear to involve distinct yet partially overlapping IRE gene

expression responses in a tissue-specific manner. Within the temporal cortex, there are 435

3' IRE leading-edge genes and 178 5' IRE leading-edge genes exclusively present in the

"AD vs. control" comparison. These are greater numbers than for the other two conditions.

Interestingly, AD and PA share only relatively small numbers of leading-edge genes despite

the fact that many regard PA as a prodrome of AD [63]. Also interesting is that, in the

cerebellum, while AD and PSP share many 3' and 5' IRE leading-edge genes, PA is

associated with a large number of unique leading-edge 3' and 5' IRE genes, further

emphasizing its difference from AD and also PSP. These observations are supported when

considering expression of previously characterized IRE genes individually (see

Supplementary Text 3 and **Supplementary Figure 1B-C**). The results in this

Supplementary Text suggest that, in particular, some 3' IRE genes (e.g. *TFRC*, *CAV3*,

CDC14A, *CDC42BPA, SERTAD2, TRAM1*) show increased expression in AD (relative to

controls) whereas PA and PSP do not. Overall, our results suggest that IRP-IRE system-

mediated gene expression changes may be sufficiently sensitive to discern and identify

potential differences in the way iron homeostasis is regulated in AD compared to PA and

PSP.

Age-dependent disruption of IRE-driven iron homeostasis in the 5XFAD mouse model

Alzheimer's disease is thought to develop over decades [64–66]. However, detailed molecular studies of AD brains can only be based on post-mortem tissues. To reveal the early molecular changes that initiate the progression to AD we must study the brains of animal disease models. Given that the IRE gene sets appear to work well in human datasets, we then tested our mouse IRE gene sets on an RNA-seq dataset derived from brain cortex tissue of the 5XFAD transgenic mouse AD model (GEO: GSE140286). The 5XFAD mouse is one of the most common systems used to model the amyloid beta histopathology of AD brains and, in a concordance analysis, brain gene expression patterns in this model were previously shown to resemble those of human AD brains to a greater degree than for four other mouse models (3xTg, CK-p25, J20, and Tg2576) [67]. 5XFAD mice possess two transgenes that include a total of five different mutations, each of which individually causes fAD in humans. In this dataset, the mice analyzed were either 3, 6 or 12 months of age. We acknowledge that the small sample size of this particular dataset means that results should be interpreted tentatively (see Discussion).

Using gene set enrichment testing methods as before, we observed significant enrichment of the *all 3' IREs* and *all 5' IREs* gene sets in several comparisons. These included 5XFAD vs. wild type comparisons and wild type aging comparisons (Bonferroni-adjusted enrichment p-value < 0.05) (**Figure 7**). Notably, even the youngest age group of 5XFAD mutant mice (3 months) displayed significant enrichment of genes containing 3' or 5' IREs compared to age-matched wild types. This is consistent with an enrichment of immune-related Hallmark gene sets that we observed in this age group (see **Figure 7B**) and with a previous transcriptome analysis suggesting immune activation in 5XFAD mice as early as 2-4 months [68]. UpSet

plots of overlapping leading-edge genes suggest that the IRE responses due to aging and

due to the 5XFAD transgenes may involve partially overlapping gene expression changes

(**Figure 8**). In addition, the UpSet plots reveal subsets containing large numbers of IRE-

containing genes which uniquely contribute to enrichment of IRE gene sets in only one

comparison (e.g. 256 3' IRE genes only contribute to enrichment in the "*5xFAD vs WT at 6*

months" comparison). Notably, there are 126 shared 3' IRE genes contributing to enrichment

in the "*5xFAD vs WT at 6 months*" and "*5xFAD vs WT at 3 months*" comparisons, but no

genes shared between these comparisons and the "*5xFAD vs WT at 12 months*"

comparison. These 126 genes were found to show over-representation of Gene Ontology

terms including "Hsp70 protein binding" and "nuclear import signal receptor" (FDR-adj. *p*-

value < 0.05) (**Supplementary Table 4**), suggesting that subsets of leading-edge genes

may have biological relevance, and that these may give insight into the biologically distinct

age-dependent iron dyshomeostasis responses caused by the 5XFAD transgenes. Although

beyond the scope of our current analysis, further investigation into these subsets of genes

may contribute to definition of differences in iron dyshomeostasis responses under different

biological conditions of interest.

Similarities in IRE-driven iron homeostasis responses during hypoxia

and from a familial AD-like mutation in a zebrafish model

Concerns have been raised over the relevance of transgenic mouse models in modelling the

early stages of AD (reviewed by [69]). Meanwhile, knock-in models of familial AD (fAD) (that

possess a single, heterozygous mutation in an endogenous gene like the human version of

the disease) only exhibit subtle pathological changes with little to no visible amyloid or tau

pathology present [70]. Despite the comparatively more subtle pathology seen in

heterozygous, single fAD-like mutation knock-in models, since they closely mimic the

genetic state of fAD, analysis of their brain gene expressionthem may reveal molecular

changes relevant to early fAD states in human brains. We had access to a whole-brain RNA-

seq dataset from a knock-in zebrafish model of fAD possessing a heterozygous, single fAD-

like mutation in its endogenous *psen1* gene (*psen1*^{Q96_K97del}/+) (henceforth referred to as the

"fAD-mutation-like" model in this paper). Previous analysis of a subset of this dataset

involving young adult (6-month-old) brains revealed gene expression changes related to

energy metabolism and mitochondrial function, especially ATP synthesis and other ATP-

dependent functions including lysosomal acidification [44]. (In contrast, the 3-month-old

young adult 5XFAD mouse brain dataset is dominated by immune/inflammation responses,

Figure 7B). Considering the critical role of iron homeostasis in energy metabolism, we

decided to revisit this zebrafish dataset. We performed IRE gene set enrichment on the

entire dataset in order to include exploration of the effects of aging and acute hypoxia (two

important risk factors for sporadic late onset AD) and to analyze how these effects interact

with the fAD-like *psen1*^{Q96_K97del}/+ mutant genotype. The experimental design and the results

of the differential gene expression analyses and gene set enrichment tests are summarized

in **Figure 9**.

We first turned our attention to the comparison between young adult (6-month-old)

psen1^{Q96_K97del}/+ mutant zebrafish and their wild-type siblings. At this age, gene expression

changes in the mutant fish likely represent early stresses driving the development of fAD in

humans. Gene set enrichment tests in this comparison identify alteration of energy

metabolism-related Hallmark gene sets (e.g. OXIDATIVE PHOSPHORYLATION,

GLYCOLYSIS) (**Figure 9B**) which is consistent with a previous analysis of gene ontology

terms with this dataset [44]. In addition, we see enrichment of other gene sets including

FATTY ACID METABOLISM, PI3K AKT MTOR SIGNALLING, MTORC1 SIGNALLING, and

HEME METABOLISM. All of these gene sets showing enrichment in 6-month-old

psen1^{Q96_K97del}/+ mutants relative to wild-type siblings are also enriched in 24-month-old

("middle-aged") *psen1Q96_K97del*/+ mutants relative to their wild-type siblings (**Figure 9B**). This

supports that the biological activities represented in these gene sets are amongst the

earliest altered in this particular fAD mutation model.

In Lumsden et al. [14] we predicted that fAD mutations in the major locus *PSEN1* might

cause an early cellular deficiency of ferrous iron due to the observation of insufficient

acidification of the endolysosomal pathway in in-vitro *PSEN1* mutation studies [71,72]. In

Newman et al. [44] we saw that Gene Ontology enrichment analysis of 6-month-old

psen1Q96_K97del/+ zebrafish brains supported that lysosomal acidification was affected.

Therefore, we applied our IRE enrichment analysis to test for evidence of iron

dyshomeostasis in these fish. The enrichment of the ***all 3' IREs*** gene set in 6-month-old

psen1Q96_K97del/+ zebrafish brains supports that iron dyshomeostasis is an important stress in

the early stages of fAD (**Figure 10A**).

While almost all pairwise comparisons in the zebrafish dataset show significant enrichment

of at least one IRE gene set (**Figure 10A**), the expression of IRE genes appears to differ in

terms of the proportions of IRE-containing transcripts which show increased versus

decreased abundance (**Figure 10B**). In addition, the Principal Component Analysis plot of

expression of the ***all 3' IREs*** gene set over all samples shown in **Figure 10C** suggests that

different conditions appear to drive distinct patterns of expression of these genes. Across the

first principal component, different age groups (6- and 24-month-old brains) differ in their

expression of predicted 3' IRE genes, while the second principal component appears to

separate *psen1*Q96_K97del/+ mutants from their wild-type siblings. This separation between

*psen1*Q96_K97del/+ mutants and wild type siblings is even more pronounced when both are

exposed to hypoxia.

To gain more insight into the similarities and differences between the IRE responses in the

psen1^Q96_K97del/+ vs. wild type comparison, we plotted UpSet plots of overlapping leading-

edge genes (**Figure 10D**). These plots suggest that the IRE responses during hypoxia,

during aging, and due to this fAD-like mutation, are mostly distinct from each other with

unique leading-edge genes. However, similarities in the IRE responses between different

conditions are suggested by the existence of some shared leading-edge genes. For

example, for the set of **all 3' IREs**, the "*6-month-old psen1^Q96_K97del/+ vs. wild type*"

comparison shares 19 leading-edge genes with the "*24-month-old psen1^Q96_K97del/+ vs. wild*

type" comparison. As an initial exploration of the biological relevance of these genes, we

submitted them to the STRINGR tool. This indicated that the proteins products of these

genes were significantly associated with each other (e.g. in terms of text-mining from

PubMed articles, experimentally determined interactions, and co-expression). These

proteins were significantly over-represented in the gene sets "MAPK pathway", "AP-1

transcription factor", "Jun-like transcription factor", and "signaling by TGF-beta family

members" (FDR-adjusted over-representation p-value < 0.05; **Supplementary Figure 5**).

The AP-1 and MAPK pathways have previously been shown to be stimulated by iron

depletion [73,74]. Therefore, mechanistically, it is possible that the IRE-IRP response to iron

dyshomeostasis in the fAD-like zebrafish mutant involves these pathways.

The fact that aging, hypoxia, and a fAD-like mutation all cause changes in the abundance of

IRE-containing transcripts in zebrafish raised concerns regarding the specificity of such

changes. Therefore, as a negative control, we examined changes in IRE transcript

abundance in a brain transcriptome dataset derived from zebrafish heterozygous for a *psen1*

mutation now thought not to be fAD-like, *psen1^K97fs* [75]. In this dataset, *psen1^K97fs/+*

zebrafish are compared to their wild type siblings at 6 and 24 months. We tested this dataset

for enrichment using our zebrafish 3' and 5' IRE gene sets but found no significant

enrichment of any of our predicted IRE gene sets in *psen1*[K97fs]/+ vs. wild type comparisons

at any age (**Table 4**; **Supplementary Figure 6**). Reassuringly, we still observed significant

enrichment of both 3' and 5' IRE gene sets during wild type aging (*24-month-old* wild types

vs. 6-month-old wild types), consistent with the equivalent comparison in the

psen1[Q96_K97del]/+ dataset. These results support that IRE-containing transcript abundance

changes are sufficiently sensitive to reflect differences in iron homeostasis between different

mutation models.

Simultaneous stabilization of some 3' IRE transcripts and destabilization

of others

In the cultured cell line dataset analyzed above, we noticed that even a straightforward iron

deficiency treatment resulted in the simultaneous increase and decrease in expression of 3'

IRE-containing genes. These findings are difficult to reconcile with the current paradigm that

stabilization of 3' IRE-containing genes occurs under iron deficiency and suggest that the

current model of the IRP/IRE system may be incomplete or insufficient for describing the

regulation of a broader collection of IRE genes. Given that many predicted 3' IRE genes with

non-canonical IREs (e.g. in the ***all 3' IREs*** set) displayed enrichment and different gene

expression patterns in the different genotype/age/oxygenation groups of the fAD-like

zebrafish dataset, we decided to explore further the stability changes of these genes by

comparing the expression of spliced and unspliced transcripts for each gene

(**Supplementary Text 4**). We found that transcripts of some predicted 3' IRE genes were

significantly increased in stability while others were significantly decreased in stability

(**Supplementary Figure 7**; **Supplementary Table 5**).

Some validated IRE genes demonstrate expression changes

inconsistent with the classic IRE paradigm

The work described above discovered both increased and decreased stability of transcripts

predicted to possess IREs in fAD-like zebrafish brains relative to wild-type brains. However,

it did not address directly whether such changes in stability occur in transcripts confirmed as

targets of IRP binding and in systems subjected to disturbance of iron homeostasis. To

support that our sets of 5'- and 3'-IRE-containing genes include both transcripts that

increase in abundance and transcripts that decrease in abundance as iron levels change,

we examined several IRE genes previously demonstrated by Sanchez et al. [24] to produce

transcripts bound by IRPs (see below). We examined these transcripts in transcriptome

datasets produced from cell lines subjected to changes in iron levels (**Figure 11**).

In Sanchez et al. [24], a total of 258 mRNAs were identified that immunoprecipitated with

mouse IRP1 and/or IRP2 (44 immunoprecipitating with both IRP1 and IRP2, 113

immunoprecipitating exclusively with IRP1, and 101 immunoprecipitating exclusively with

IRP2). We filtered these mRNAs for those with high-quality IREs (as predicted using SIREs)

in the UTR of either the human or the mouse Ensembl gene model (**Figure 11A**). We found

30 mRNAs with high-quality IREs in human Ensembl gene models, and 50 mRNAs with

high-quality IREs in mouse Ensembl gene models. These were then separated into those

with IREs in their 3' UTRs and those with IREs in their 5' UTRs (see **Figure 11A** for more

details), since transcripts with 3' IREs are expected to show altered abundance under the

classic IRE paradigm while the abundance of transcripts containing 5' IREs is not expected

to change (see **Figure 1**). Lists of experimentally-validated IRE genes filtered using these

steps are available in **Supplementary Table 6**.

We then examined the expression of these experimentally-validated IRE-containing genes in

transcriptome datasets from human and mouse cells subjected to iron level-altering

treatments. We sought to observe whether transcript abundance differences were consistent

with those predicted under the classic IRE paradigm. The datasets included the human

Caco-2 cultured cell line dataset (previously described above), and a mouse splenic B cell

dataset [76] (GEO Accession: GSE77306).

The Caco-2 dataset includes both iron overload (DMEM-FBS Medium + Hemin vs. DMEM-

FBS Medium) and iron deficiency (Iron-free Medium vs. Iron-free Medium +FAC) treatments,

while the mouse B cell dataset includes only a treatment with deferoxamine (DFO) to create

iron deficiency (DFO-treated cells vs. control). We note that the DFO and control samples in

the mouse B cell dataset are not directly comparable within each group, due to the

unstimulated or stimulated anti-IgM or LPS treatments also used in this study. However, a

Principal Component Analysis plot of the samples shows that the DFO-treated samples

apparently separate from the control samples across Principal Component 2, indicating that

DFO-treatment is likely to be one of the main causes of differential gene expression in this

dataset (**Supplementary Figure 8**).

Overall, in the mouse B cells and human Caco-2 cells affected by changes in iron levels,

approximately half of the genes identified with validated IREs show significant differential

expression. Of those, similar proportions show increased or decreased transcript abundance

in either the 3' IRE or 5' IRE groups and, of those, there are numerous genes showing

changes in expression inconsistent with the IRE paradigm. In particular, in the Caco-2 cells,

three 3' IRE genes (*EIF4EB2, LAS1L,* and *ZNF207*) show decreased expression in cells

treated to create iron deficiency (**Figure 11B**; t-test *p*-values ≤ 0.05). In the mouse B cells,

DFO-treatment to cause iron deficiency increases the abundance of transcripts of four 3'

IRE-containing genes, including *Tfrc,* in accordance with the classic paradigm (**Figure 11C**;

t-test *p*-values ≤ 0.05). In contrast, transcripts of four such 3' IRE genes show decreased

abundance (*Bub3, Cxcl16*, *Gstm6*, *Zfp71-rs1*) (**Figure 11C**; *t*-test *p*-values ≤ 0.05).

Although these sample sizes are small, they clearly indicate that the presence of an IRE in

either the 5' or 3' UTR of a transcript cannot, by itself, be used to predict how the abundance

of the transcript will change in response to iron availability.

Discussion

In this study we identified comprehensive sets of genes predicted to contain IREs in

humans, mice, and zebrafish. The idea of analysing gene expression datasets using gene

sets is not novel, with many well-established techniques for gene set testing [35–39] that

offer the opportunity to analyze the behavior of large groups of genes to detect statistically

significant changes in state, even though these may be quite subtle for individual genes.

Table 5 summarises representative enriched Hallmark gene sets (representing common

biological pathways/activities) across the human, mouse, and zebrafish datasets analysed in

this work. Surprisingly, we found that IRE gene sets are generally not well-represented in

existing gene sets. The existing gene set in which IRE genes are most highly represented is

one previously shown to be up-regulated in AD brains (the "Blalock Alzheimer's Disease Up"

gene set from MSigDB). This supports a unique importance of IRE genes in AD.

Consequently, the IRE gene sets identified here represent a novel resource for researchers

interested in exploring iron dyshomeostasis gene expression responses in detail in different

species, conditions, and treatments. In our results, we demonstrate that IRE gene sets are

sufficiently sensitive to reveal broad differences across different conditions (both in human

AD and animal models), while also offering the opportunity to study individual

genes/transcripts contributing to enrichment in more detail. IRE gene sets displayed

significant enrichment in postmortem brains from a human AD cohort, the 5XFAD mouse

model, and a zebrafish model of a fAD-like mutation. Taken together, our results

demonstrate, for the first time, the involvement of coordinated IRP/IRE-mediated gene

expression responses associated with AD.

Overall, IRE gene sets were sufficiently sensitive to reveal several interesting phenomena.

The relatively tightly controlled conditions in the mouse and zebrafish model datasets

revealed strongly age-dependent effects on the transcript abundances of these predicted

IRE-containing genes. Notably, 3' IRE gene expression changes were amongst the earliest

changes observable in the zebrafish heterozygous single fAD-like mutation model alongside

changes in energy metabolism. These 3' IRE gene expression changes preceded other

signals of pathological change in the transcriptome (such as altered expression of

inflammatory response pathways) commonly associated with AD. Our findings raise the

question of how early IRE gene expression changes, and iron dyshomeostasis more

broadly, may begin in fAD brains. In a recent analysis of transcriptome data from pools of 7-

day-old zebrafish larvae heterozygous for the fAD-like mutation *psen1*$^{Q96\_K97del}$ (compared to

wild type half-siblings), we observed over-representation of the GO term "iron ion transport"

without significant changes in 3' IRE or 5' IRE transcript abundance [47]. This supports that

the 3' IRE transcript abundance signal in 6-month-old brains of this mutant line reflects

changes in ferrous iron abundance that develop with age in response to an underlying defect

in cellular iron regulation.

In relation to our findings associated with the 5XFAD mouse model, we acknowledge that

low sample number is a limitation in this analysis and constrains interpretation of our results.

Unfortunately, to our knowledge, no other publicly-available 5XFAD mouse dataset was

available containing (1) both young and aged adults in the same batch (where young mice

are defined as ~2-4 months old as this is when the earliest signs of pathology are observed

for this model [77,78]), (2) 5XFAD and WT genotype mice in the same batch, (3) information

about biological sex for each sample (so that sex-specific effects could be accounted for in

the statistical model for differential gene expression), and (4) separation of groups by

biological factors (e.g. age, genotype) rather than by unidentifiable batch effects when

inspected through Principal Component Analysis. Our original rationale for analyzing the

5XFAD mouse model came from results from an independent concordance analysis of

various mouse models and human AD [67]. In that study, it was found that 5XFAD mouse

brain transcriptomes showed greatest (although still fairly poor) concordance to human AD

compared to other mouse models including the 3xTg model. However, we also acknowledge

the limitations associated with only analyzing the 5XFAD mouse model here. It would be

useful to analyze other mouse models of AD in the future to compare the involvement of IRE

genes across different models. Likewise, we anticipate that further analysis of fAD-like

mutation models in general will help to extend our knowledge of the early molecular changes

contributing to the development of AD.

Notably, both classic IRE genes (e.g. *TFRC*, *FTL*, and *FTH1*) and the IRE gene sets were

sufficiently sensitive to distinguish not only between iron overload and deficiency in a

cultured cell line dataset, but also between AD and other neuropathologies (i.e. PA and

PSP). This suggests that the dysregulation of IRE-containing genes, (and iron homeostasis

in general), in AD may differ from other neuropathological conditions. The differences in both

classic IRE genes and IRE gene set expression between AD and PA are of particular

interest. Considering that presence of amyloid pathology is required to diagnose individuals

with AD [79,80] and contributes to diagnosis of preclinical AD [1,2], it will be interesting to

explore further the biological relevance and impact of these IRE gene expression differences

using other techniques to gauge whether PA is a prodrome of, or a separate pathological

condition to, AD.

One of our original intentions for IRE gene set analysis of the human AD and animal model

datasets was to gain insight into whether these brains were in a state of iron deficiency or

overload using gene expression-level evidence. Unfortunately, it became clear that

interpretation of IRE gene expression changes was more complex than expected, both

because of the use of bulk brain tissue samples in the human and animal model datasets

(which obscures differences between cell type and tissue types) and because the regulation

of both 3' and 5' IRE-containing genes we observed did not follow the expected paradigm.

To address the former issue, future work should expand the use of IRE gene sets to single-

cell RNA-seq (scRNA-seq) datasets so that the IRE gene expression patterns of different

cell types can be deconvoluted. Recently, a large-scale scRNA-seq study of AD brains

indicated highly cell-type specific changes related to inflammation during early stages of

disease progression within the prefrontal cortex [81], highlighting the importance of studying

iron homeostasis responses at the single-cell level in the context of AD. The failure of 3' IRE

genes to follow the expected expression paradigm is a limitation we did not anticipate when

we began this work. In particular, our observations indicating that (1) the stability of some 3'

IRE transcripts (rather than their "expression"/"levels" as addressed in preceding analyses)

is significantly different under different conditions in zebrafish, and that (2) validated 3' IRE

genes show both increased and decreased expression under iron deficiency in two cell line

datasets (suggesting they are not stabilized as predicted by the IRE paradigm), challenge

the simplistic generalisation that 3' IREs stabilise transcripts under ferrous iron deficiency.

Previous research found that, under iron deficiency, the transcripts of 3' IRE-containing

genes such as *TFRC* are stabilized causing increased expression [20] to increase ferrous

iron availability. However, our findings reveal that this principle (the "classic IRE paradigm")

does not necessarily apply to other 3' IRE-containing genes, including those with canonical

IREs (e.g. *SLC11A2* in the Caco-2 cultured cell line), and genes with IRE-like elements

deviating from the canonical IRE sequence. Interestingly, Tybl et al. [82] found that the 3'

IRE in *SLC11A2* (*DMT1)* appears to influence transcript abundance in a development-

specific manner in mice, by promoting transcript expression during postnatal growth and

suppressing expression in adulthood. Together with our findings, this demonstrates that the

regulation of IRE genes is more complex than commonly appreciated.

Aside from 3' IRE genes, 5' IRE genes also showed unexpected behavior in the datasets we

analyzed. In general, the classic IRE paradigm holds that binding of IRPs to 5' IREs blocks

translation but is not expected to change transcript abundance. We initially sought to

investigate 5' IRE transcripts as a negative control group to which changes in the stability of

the 3' IRE transcripts could be compared. Unexpectedly, our results indicated that 5' IRE

gene sets are significantly enriched under various conditions. Upon reflection, this is not

unreasonable, considering that binding of any protein to a transcript must, inevitably,

changes the transcript's stability to some degree. However, the direction of that stability

change is difficult to predict as there is no generalizable cellular "rule" for the outcome of

protein binding. This is consistent with the reality that each gene represents a largely

independently evolving system constrained only by cells' requirements for its functionality.

For example, inactivation of RNA-binding proteins has been demonstrated previously to

cause both up- and down-regulation of different genes simultaneously [83]. In addition, the 5'

canonical IRE and surrounding acute box sequences of the H-ferritin (*FTH*) transcript have

been shown to stabilize it, which might appear contrary to the expected function of a 5' IRE

(of decreasing protein translation under iron deficient conditions) [84]. H-ferritin is one of the

better-characterised IRE genes, and it is possible that other, yet-to-be characterised

regulatory mechanisms involving 5' IREs could contribute to stability changes in other

transcripts. Aside from 3' IREs, other 3' UTR regulatory motifs are known that bind to

proteins to regulate multiple biological activities (e.g. AU-rich 3' UTR motifs as described in

[85]). Therefore, mechanistically, it is reasonable to assume that IRE-based regulation of

transcript stability may be co-opted for other biological activities beyond iron homeostasis

(and see below). Alternative splicing of IRE genes may be one mechanism for this, where a

non-IRE-containing isoform is expressed in certain tissues or conditions, as is the case for

mammalian *DMT-1* (*SLC11A2*) [22]. Differential transcript isoform inclusion of IREs is

beyond the scope of our current work, but will be important to explore in future. We expect

our findings to provide a starting point for further research involving IRE genes and their

complex regulation beyond the classic paradigm.

It is important to acknowledge that some of the complexity involved with IRE gene

expression, and the large number of genes identified with putative IREs, may reflect the

involvement of IREs in functions other than iron homeostasis. These functions include

regulation of oxidative stress [86–88]), oxidative phosphorylation [89], and cell cycle control

[90,91]. In 2019, it was proposed that the tricarboxylic acid cycle (TCA) may have evolved

around the reactivity of iron [92], and TCA intermediates themselves also perform important

cellular regulatory functions [93]. In addition, our analyses identified several transcription

factor motifs potentially associated with other biological pathways as over-represented in

IRE gene sets. Similarly, although beyond the scope of our current work, a regulatory role

for micro RNAs (miRNAs) in binding IRE structures is emerging [94–97]. This may be

particularly relevant to AD, as a miRNA has been described that can bind the 5' IRE-like

structure in AβPP transcripts to up-regulate AβPP its expression [98]. Co-regulation of IRE-

containing genes within other biological pathways may explain some of the IRE gene set

enrichment observed in the datasets we analyzed, and some of the unexpected expression

changes (e.g. decreased expression of 3' IRE genes in conditions where stabilization of their

transcripts might be expected, and increased expression of 5' IRE genes even when no

change in stability would be expected). Hence, the changes in expression of predicted IRE

genes we observed must be interpreted carefully as reflecting not only iron dyshomeostasis

responses, but also other co-occurring changes in linked processes. This was particularly

evident in our analysis of the Caco-2 cultured cell line dataset where even straightforward

iron overload and iron deficiency treatments resulted in significant enrichment of gene sets

related to reactive oxygen species and hypoxia pathways. We note that the relationship

between iron homeostasis and hypoxia would be interesting to explore in future work,

particularly their similarities at the the level of gene expression. Previous research has

demonstrated that desferrioxamine (that induces iron deficiency) can also induce HIF-1

activity, which activates erythropoietin (important for red blood cell formation to carry

oxygen) [99]. This supports that iron deficiency and hypoxia involve similar molecular

changes in cells (i.e. the view that iron deficiency generates a form of "pseudohypoxia"). We

expect that future work deconvoluting the expression of IRE genes at the cellular level will

be required to determine to what extent such expression changes are influenced by cell /

tissue type compared to other linked biological activities.

Most previous work has assumed that accumulation of iron in the brain with age (a

phenomenon observed broadly across animal phyla [100,101]) is indicative of cellular iron

overload driving oxidative stress [102]. Indeed, iron accumulation and oxidative stress

apparently contribute to the insolubility of amyloid plaques and neurofibrillary tangles in AD

brains [103]. However, a recent publication by Yambire et al. [104] showed disturbed

lysosomal function leading to increased lysosomal pH and causing a deficiency of functional

ferrous iron (Fe^{2+}) while non-functional ferric iron (Fe^{3+}) accumulated in lysosomes. The

deleterious effects of this on the brains of mice (defective mitochondrial biogenesis and

function and stimulation of inflammatory responses) could be alleviated by dietary iron

supplementation. The observations of Nixon and colleagues that acidification of the

endolysomal pathway is affected both by fAD mutations in *PSEN1* [71] and excessive

dosage of the amyloid beta A4 precursor protein (*AβPP*) gene [105], together with our

observations from our fAD-mutation-like *psen1*$^{Q96\_K97del}$/+ mutant zebrafish in both this study

and in ref. [44] (where gene expression changes associated with lysosome and mitochondria

for this model were first described), support the possibility that AD brains may suffer a

ferrous iron deficiency in a background of ferric iron overload. This is discussed further

below.

Although the evidence from human AD brains is more tentative at this stage, our findings of

increased expression of *TFRC* expression and other well-characterized 3' IRE genes in the

temporal cortex tissue of human AD brains is consistent with the existence of a cellular

ferrous iron deficiency, although more research is required to confirm this at the single-cell

level. Intriguingly, the greatest genetic risk factor for late onset AD, the ε4 allele of the gene

APOE, appears to increase lysosomal pH [106] but ε4's increased risk of AD is alleviated in

individuals who possess the *HFE* 282Y allele that predisposes to the iron overload disease

hemochromatosis [107]. Given that many other risk loci for sporadic late onset AD also

affect endolysosomal pathway function (reviewed in [108]), it is reasonable to suggest that

disturbed iron homeostasis may afflict brains with this disease.

Our work provides evidence consistent with Yambire et al. [104] and Lee et al. [71] to

suggest that fAD mutations may drive a ferrous iron deficiency that contributes to AD

pathology. However, iron export is a complex process, and it remains unclear whether iron

deficiency or overload is more relevant to the pathology seen in AD. Much of the existing

research has focused on the role of AβPP and its contributions to elevating iron levels within

cells and to increasing iron export to the cerebral interstitium in AD. For example,

Venkataramani et al. [109] demonstrated that decreased AβPP levels resulted in

stabilisation of ferroportin, resulting in increased iron export from neuroblastoma cells in two

mouse models. Later work by McCarthy et al. [110] proposed a mechanism for this

phenomenon, involving a motif in sAβPPa (cleavage product of AβPP) binding to ferroportin

and increasing iron export from cells through increasing the number of ferroportin molecules

in the plasma membrane but not their activity. A complicating factor is that ferroportin-

mediated iron export from cells requires both (1) stabilisation of ferroportin in the membrane,

and (2) ferroxidase activity (provided by either haephaestin or ceruloplasmin) [110]. The role

of haephestin as a ferroxidase in this process of iron export from cells has sometimes been

overlooked, despite that it is well-established as complexing with, and stabilizing, ferroportin

to export iron [111–113]). For example, recently Tsatsanis et al. [114] described the effects

on intracellular iron and iron export of changes in amyloidogenic cleavage (via β-secretase)

and non-amyloidogenic cleavage (via γ-secretase) of AβPP. It was observed that

amyloidogenic cleavage of AβPP led to destabilisation of ferroportin on the cell surface and

increased iron retention in cells. In addition, inhibiting β-secretase mitigated this effect,

increasing ferroportin stabilization and decreasing iron retention in cells. However, an

alternative explanation not considered by those authors is that haephestin may also be

cleaved by β-secretase (see Figure 7 in [115]), so it is possible that reduced β-secretase

activity could increase the haephestin available and also contribute to the effects on iron

export observed. Overall, the situation around iron export from cells is a complex area of

ongoing research involving many cellular factors, and it will be increasingly important in

future work to understand these mechanisms more completely in the context of AD.

We have previously noted that all the fAD mutations of AβPP (including gene duplications)

are expected to have the singular quality of increasing the abundance of the amyloidogenic

β-CTF / C99 fragment of AβPP (see Figure 2 in Lumsden et al. [14]). Recently Jiang et al.

[105] showed that increased β-CTF reduces lysosomal acidification. According to the results

of Yambire et al. cited above, this would be expected to reduce cellular ferrous iron levels

(while causing accumulation of ferric iron in lysosomes). This idea is consistent with the

existence of an IRE in the 5' UTR of AβPP transcripts that inhibits AβPP translation (and

hence β-CTF production) when cytosolic ferrous iron levels are low [116]. Thus, AβPP may

influence cellular ferrous iron levels by modulating lysosomal pH to regulate importation of

ferrous iron into the cytosol, rather than by modulating ferroportin stability to regulate iron

export from the cytosol.

Overall, our results demonstrate for the first time the involvement of a coordinated IRP/IRE-

mediated gene expression response in the context of AD. By searching entire human,

mouse, and zebrafish transcriptomes for all genes containing potential IREs, we formed

comprehensive gene sets applicable to the analysis of any human, mouse, or zebrafish

gene expression dataset. For the first time, our work suggests the existence of gene

expression changes associated with the IRP/IRE system in the young, pre-pathology brains

of *PSEN1* fAD mutation carriers, and is consistent with the idea of iron dyshomeostasis as

an early contributor to the disease process. It also reinforces the critical importance of IRE

genes in general in the development of the late onset, sporadic form of AD. More broadly,

our approach highlights how changes in the stability and abundance of IRE-containing

transcripts can be used to give insight into iron dyshomeostasis-associated gene expression

responses in different species, tissues, and conditions.

Tables

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1002 **Table 1. Summary of gene set testing approaches used in our analyses.**

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Method	Hypothesis	Focused / battery approach	Accounts for inter-gene correlation	R implementation
Fry / Roast	Self-contained null hypothesis (genes within a set have no association with experimental condition)	Focused (each gene set is tested on its own terms, and multiple testing adjustment is applied afterwards)	Yes	"fry" and "mroast" functions in the *limma* Bioconductor package [35,36]
Camera	Competitive null hypothesis (genes within a set do not have a stronger association with experimental condition compared to a random gene set)	Focused (each gene set is tested on its own terms, and multiple testing adjustment is applied afterwards)	Yes	"camera" function in the *limma* Bioconductor package [37]
fgsea (fast implementation of GSEA in R)	Self-contained null hypothesis (genes within a set have no association with experimental condition)	Battery (gene sets are pitted against each other to determine which ones are more significantly enriched)	No	"fgsea" function in the *fgsea* Bioconductor package [38,39]

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1007 **Table 2. Samples analyzed from Mayo Clinic RNA-seq study.**

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Group	Total number	% Female	Mean age ± s.d (years)	Diagnosis
Alzheimer's disease (AD)	134	56.7	82.6 ± 7.3	Braak Stage ≥ 4, diagnosis according to NINCDS-ADRDA criteria
Control	130	46.2	82.9 ± 8.3	Braak Stage ≤ 3, No or sparse CERAD neuritic and cortical plaque density, no diagnoses for any neurodegenerative disease
Pathological Aging (PA)	44	54.5	84.5 ± 4.3	Braak Stage ≤ 3, CERAD neuritic and cortical plaque density of 2 or more, no diagnoses for any neurodegenerative disease or mild cognitive impairment
Progressive supranuclear palsy (PSP)	164	40.2	73.8 ± 6.5	Braak Stage ≤ 3, no or sparse CERAD neuritic and cortical plaque density

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 Table 3. Differential gene expression and IRE gene set enrichment results from Mayo

 Clinic RNA-seq study. Asterisks (*) indicate significant enrichment (Bonferroni-adjusted

 Wilkinson's *p*-value from *fry*, *camera*, and *fgsea* < 0.05).

	Comparison	No. of DE genes (FDR p-value < 0.05 and abs(logFC) > 0.5)	All 3' IREs enrichment p-value	All 5' IREs enrichment p-value	HQ 3' IREs enrichment p-value	HQ 5' IREs enrichment p-value
Effect of Alzheimer's disease	AD vs. control (cerebellum)	Down: 1,422 Up: 1,308	0.0109*	0.128	0.770	0.770
	AD vs. control (temporal cortex)	Down: 1,650, Up: 1,929	9.03E-15*	2.44E-14*	4.50E-15*	8.95E-08*
Effect of pathological aging (amyloid pathology, no dementia symptoms)	PA vs. control (cerebellum)	Down: 254, Up: 463	0.000116*	0.00139*	0.0201*	0.770
	PA vs. control (temporal cortex)	Down: 466, Up: 512	0.000521*	0.0461*	0.000065*	0.0000682*
Effect of progressive supranuclear palsy (PSP)	PSP vs. control (cerebellum)	Down: 2,550, Up: 1,080	1.81E-22*	3.45E-22*	1.43E-12*	0.0399*
	PSP vs. control (temporal cortex)	Down: 1,271, Up: 622	3.58E-11*	5.17E-13*	1.39E-06*	0.0399*
Differences between Alzheimer's disease and pathological aging	AD vs. PA (cerebellum)	Down: 1,728, Up: 1,006	0.000116*	0.00139*	0.0201*	0.770
	AD vs. PA (temporal cortex)	Down: 2,633, Up: 2,174	0.000521*	0.0461*	0.000065*	0.0000682*
Differences between Alzheimer's disease and progressive supranuclear palsy	AD vs. PSP (cerebellum)	Down: 108, Up: 659	0.0019*	0.00184*	0.158	0.158
	AD vs. PSP (temporal cortex)	Down: 2,052, Up: 2,354	9.12E-22*	2.10E-22*	5.35E-16*	0.040*
Differences between cerebellum and temporal cortex tissue	Cerebellum vs. temporal cortex in controls	Down: 10,925, Up: 9,302	0.00E+00*	0.00E+00*	2.82E-269*	1.60E-81*
	Cerebellum vs. temporal cortex in AD	Down: 11,966, Up: 9,950	0.00E+00*	0.00E+00*	7.71E-302*	9.35E-92*
	Cerebellum vs. temporal cortex in PA	Down: 10,200, Up: 8,737	1.87E-153*	5.88E-160*	1.22E-89*	1.31E-88*
	Cerebellum vs. temporal cortex in PSP	Down: 11,552, Up: 9,576	0.00E+00*	0.00E+00*	0.00E+00*	4.74E-104*

Table 4. Enrichment of Iron Responsive Element (IRE) gene sets in fAD-like zebrafish dataset. Raw *p*-values from *fry, camera* and *fgsea* were combined with Wilkinson's method, with combined *p*-values then Bonferroni-adjusted for multiple testing. The same process was repeated for the K97fs/+ dataset, which involves an independent family of fish (†).

	Comparison	All 3' IREs enrichment *p*-value	All 5' IREs enrichment *p*-value	HQ 3' IREs enrichment *p*-value	HQ 5' IREs enrichment *p*-value
Effect of *psen1* mutation	6-month-old Q96_K97del/+ vs. 6-month-old +/+ all under normoxia	0.0109	0.128	0.770	0.770
	6-month-old Q96_K97del/+ vs. 6-month-old +/+ all under hypoxia	9.03E-15	2.44E-14	4.50E-15	8.95E-08
	24-month-old Q96_K97del/+ vs. 24-month-old +/+ all under normoxia	0.000116	0.00139	0.0201	0.770
	24-month-old Q96_K97del/+ vs. 24-month-old +/+ all under hypoxia	0.000521	0.0461	0.000065	0.0000682
	6-month-old K97fs/+ vs. 6-month-old +/+ all under normoxia †	0.199	0.289	0.0197	0.289
	24-month-old K97fs/+ vs. 24-month-old +/+ all under normoxia †	0.116	0.115	0.00000118	0.979
Effect of hypoxia	6-month-old +/+ under hypoxia vs. 6-month-old +/+ under normoxia	1.10E-18	1.10E-18	8.19E-13	1.27E-08
	24-month-old +/+ under hypoxia vs. 24-month-old +/+ under normoxia	3.67E-15	7.98E-11	2.94E-07	3.31E-05
	6-month-old Q96_K97del/+ under hypoxia vs. 6-month-old Q96_K97del/+ under normoxia	1.13E-24	9.88E-22	2.28E-13	2.86e- 3
	24-month-old Q96_K97del/+ under hypoxia vs. 24-month-old Q96_K97del/+ under normoxia	0.000521	0.015	0.128	0.770
Effect of aging	24-month-old +/+ vs. 6-month-old +/+ all under normoxia	6.80E-35	4.82E-27	3.41E-18	1.26E-21
	24-month-old +/+ vs. 6-month-old +/+ all under hypoxia	1.55E-35	6.84E-31	2.36E-20	7.40E-23
	24-month-old Q96_K97del/+ vs. 6-month-old Q96_K97del/+ all under normoxia	1.85E-27	1.03E-21	8.09E-17	1.07E-17
	24-month-old Q96_K97del/+ vs. 6-month-old Q96_K97del/+ all under hypoxia	3.77E-30	1.59E-23	2.11E-19	2.46E-16
	24-month-old +/+ vs. 6-month-old +/+ all under normoxia (K97fs family) †	1.69E-10	3.96E-08	5.95E-10	4.59E-06
	24-month-old K97fs/+ vs. 6-month-old K97fs/+ all under normoxia †	0.199	0.289	0.0197	0.289

Table 5. Summary of enriched gene sets from the MSigDB Hallmark Gene Set
Collection in Datasets Analyzed. Gene sets shown here are representative enriched gene
sets from the MSigDB Hallmark Collection (Bonferroni-adjusted Wilkinson's *p*-value from *fry,*
camera, and *fgsea* < 0.05). For full lists of enriched gene sets, see relevant figures or
Supplemental Tables). For gene sets which had a significant direction, an up (↑) or down (↓)
arrow is used to indicate whether most of the genes in the gene set are increased or
decreased in expression. No arrow indicates gene sets involving both increased and
decreased expression from different subsets of genes.

Dataset	Comparison	Hallmark Gene Sets Enriched*
Caco-2 cell line (see **Fig. 5**)	Iron Overload	↓ Interferon Gamma Response ↑ Reactive Oxygen Species Pathway
	Iron Deficiency	↑ Interferon Gamma Response ↓ Reactive Oxygen Species Pathway
Human Mayo-Clinic RNA-seq Study (see Supplementary Table 7)	AD vs. control (Temporal Cortex)	↓ Oxidative Phosphorylation ↑ TNFA signalling via NFKB ↑ Interferon Alpha Response ↑ Inflammatory Response ↑ Interferon Gamma Response
	AD vs. control (Cerebellum)	↑ G2M Checkpoint ↑ Mitotic Spindle ↑ PI3K AKT MTOR Signalling ↑ Hypoxia
	PA vs. control (Temporal Cortex)	Estrogen Response Heme Metabolism Complement Adipogenesis Inflammation
	PA vs. control (Cerebellum)	Estrogen Response Glycolysis Hypoxia Unfolded Protein Response
	PSP vs. control (Temporal Cortex)	↓ Interferon Alpha Response ↑ Reactive Oxygen Species Signalling Pathway ↑ Glycolysis ↑ Hypoxia ↑ Estrogen Response
	PSP vs. control (Cerebellum)	↑ Myc Targets ↑ G2M Checkpoint ↑ Mitotic Spindle ↑ Heme Metabolism ↑ Hypoxia ↓ Fatty Acid Metabolism
Mouse 5XFAD model (see **Fig. 7**)	5XFAD vs. WT (3 months old)	↑ Interferon Gamma Response ↑ Interferon Alpha Response ↑ Cholesterol Homeostasis
	5XFAD vs. WT (6 months old)	Above also enriched + many other gene sets, see Fig. 7 for more details)
	5XFAD vs. WT (12 months old)	Above also enriched + many other gene sets, see Fig. 7 for more details)
Zebrafish *psen1*Q96K97del/+ model (see **Fig. 9**)	Q96K97del/+ vs. WT (6 months)	↓ Oxidative Phosphorylation ↓ Fatty Acid Metabolism MTORC1 signalling PI3K AKT MTOR signalling
	Q96K97del/+ vs. WT (24 months)	Above also enriched + many other gene sets, see Fig. 9 for more details)

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Declarations

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Conflict of Interest / Disclosure Statement

The authors have no conflict of interest to report.

Ethics approval and consent to participate

No experiments of human subjects were performed in this study as all human data was accessed from public databases and was anonymous. All zebrafish work was conducted under the auspices of the Animal Ethics Committee (permit numbers S-2017-089 and S-2017-073) and the Institutional Biosafety Committee of the University of Adelaide.

Consent for publication

All authors give consent for publication of the manuscript.

Datasets and Data Articles

The fAD-like zebrafish dataset supporting the conclusions of this article is available in the GEO repository with accession number GSE149149.

Authors' contributions

NH performed the bioinformatics analysis and drafted the manuscript. MN generated the mutant zebrafish, isolated brain RNA and protein, drafted the description of this and edited the manuscript. SP directly supervised NH, guided the analysis, and edited the manuscript. ML conceived the project, supervised all aspects of it, and edited the manuscript. All authors read and approved the manuscript.

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Figure Legends

Figure 1. Iron Responsive Element (IRE) background. A. The classical paradigm of altered transcript stability due to the IRP/IRE system under iron dyshomeostasis. When cellular iron levels (through FeS) are low, Iron Regulatory Proteins (IRP1 or IRP2) bind IREs in the 5' or 3' untranslated regions (UTRs) of genes involved in iron homeostasis. In general, genes with IREs in their 3' UTRs will be stabilised and hence increased in expression while genes with IREs in their 5' UTR will have repressed translation from IRP binding. However, when cellular iron levels are high, IRP1 undergoes a conformation change and is now unable to bind IREs. IRP1 now acts as a cytosolic aconitase (ACO1). IRP2 is degraded in high iron conditions and is also unable to bind IREs. Without IRPs binding to IREs, genes with 5' IREs will have increased translation, while those with 3' IREs will have decreased mRNA stability, causing their expression to be decreased. **B. Consensus IRE secondary structure and examples of high-quality and IRE-like motifs predicted by SIREs.** IRE-like motifs with non-canonical structure can be detected by SIREs if they have up to one mismatch pair in the upper stem (e.g. *Hao1*) or 1 unpaired bulge nucleotide on the 3' strand of the upper stem (e.g. *EPAS1*). For more details on the prediction of non-canonical IRE motifs, please refer to Figure 1 of Campillos et al. [25].

Figure 2. Overlap between predicted IRE gene sets for human, mouse, and zebrafish. The number of genes in the gene set for each species is shown at the bottom-left bars of each UpSet plot, while genes with shared homologs across species are indicated in the main plot region. IRE genes in mouse and zebrafish gene sets were excluded from this plot if they did not have a human homolog.

Figure 3. MSigDB gene sets showing over-representation of predicted 3' and 5' IRE genes in human, mouse, and zebrafish. The top 15 MSigDB gene sets ranked by Fisher's

exact test *p*-value (testing for over-representation of the ***all 3' IREs*** and/or ***all 5' IREs*** sets)

are shown for each species. In the network plots, the top 15 MSigDB gene sets are shown

as large nodes, with genes represented as small nodes. Edges connecting genes to gene

sets indicate the gene set(s) that a gene belongs to. Overall, the ***all 3' IREs*** and ***all 5' IREs***

gene sets have a large proportion of genes which are not included in any of the top ranked

MSigDB gene sets for each species.

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1509   **Figure 4. IRE-containing gene expression analysis workflow.** The section including

1510   identification of candidate 3' IRE genes stabilized under iron deficiency was only applied to

1511   the fAD-like zebrafish dataset due to unavailable raw RNA-seq reads for the other datasets

1512   needed to identify expression of unspliced genes.

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Figure 5. Analysis of Caco-2 cultured cell line microarray dataset. A. Gene set

enrichment testing results for human predicted IRE gene sets for the iron overload

and iron deficiency treatments. Dots indicate if a gene set was considered significantly

enriched (Bonferroni-adjusted *p*-value < 0.05) in the iron overload (on left) or iron deficiency

(on right) treatment. **B. Gene set enrichment testing results for MSigDB Hallmark gene**

sets in the iron overload and iron deficiency treatments. Dots indicate if a gene set was

considered significantly enriched (FDR-adjusted *p*-value < 0.05) in the iron overload (on left)

or iron deficiency (on right) treatments. **C. UpSet plots showing overlap between iron**

overload and iron deficiency treatments in GSEA leading-edge genes for the *All 3'*

***IREs* and *All 5' IREs* gene sets**. The bars to the lower-left indicate the number of the

leading-edge genes for iron overload and iron deficiency treatments, while the bars in the

main plot region indicate the number of leading-edge genes which are unique or shared

between the treatments.

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Figure 6. Analysis of Mayo Clinic RNA-seq dataset with human IRE gene sets. A.

Enrichment analysis results of IRE gene sets in comparisons of AD (Alzheimer's

Disease), PA (Pathological Ageing) and PSP (Progressive Supranuclear Palsy) vs.

control. The proportions of IRE genes within each IRE gene set with increased, decreased,

or unchanged expression are indicated as coloured bars. The dots indicate that the IRE

gene set was significantly enriched (Bonferroni-adjusted enrichment p-value < 0.05). **B.**

UpSet plots showing overlap between leading-edge IRE genes in comparisons of AD

(Alzheimer's Disease), PA (Pathological Aging), and PSP (Progressive Supranuclear

Palsy) vs. control. The bars to the lower-left region of each UpSet plot indicate the number

of leading-edge IRE genes for each comparison, while bars in the main plot region indicate

the number of leading-edge IRE genes which are unique or shared between comparisons.

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Figure 7. Analysis of 5XFAD mouse dataset. A. Experimental design and results of

IRE gene set enrichment analysis. The gene sets *all 3' IREs* and *all 5' IREs* derived from

searching for IRE sequences in the UTRs of genes in the reference mouse genome mm10

are represented here as "3' IRE" and "5' IRE" respectively. Asterisks (*) indicate that the

gene set was significantly enriched in a particular comparison (Bonferroni-adjusted p-value $<$

0.05). **B. Proportions of genes in IRE and MSigDB Hallmark gene sets which are**

increased (t > 2) or decreased (t < -2) in expression in all "5XFAD vs. wild type"

comparisons. A dot next to a bar indicates that the gene set was significantly enriched

(FDR-adjusted p-value < 0.05).

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1550   **Figure 8. UpSet plots showing the overlap in GSEA leading-edge genes between all**

1551   **comparisons in the 5XFAD mouse datasets for the gene sets all 3' IREs and all 5'**

1552   **IREs**. Numbers of genes for each intersection are shown above intersection bars.

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Figure 9. Differential gene expression and gene set enrichment analysis in the fAD-like zebrafish dataset. A. Results of differential gene expression analysis. Genes which were significantly increased or decreased in expression are indicated in boxes. These differentially expressed genes have FDR-adjusted *p*-value < 0.05. **B. Gene set enrichment with MSigDB Hallmark gene sets.** The comparisons between Q96_ K97del/+ fAD-like mutants and their wild-type siblings are shown for the 6-month-old (young adult) and 24-month-old (infertile adult) age groups. Dots indicate gene sets which are significantly enriched (FDR-adjusted *p*-value < 0.05).

Figure 10. Iron Responsive Element (IRE)-containing gene expression in the fAD-like zebrafish dataset. A. Results of gene set enrichment testing using predicted IRE gene sets. We represent the gene sets all 3' IREs and all 5' IREs derived from searching for IRE and IRE-like sequences from z11 reference zebrafish gene UTRs as "3' IRE" and "5' IRE" in the panel. **B. Proportions of predicted IRE genes which are increased (t > 2) or decreased (t < -2) in expression for each pairwise comparison in the dataset. C. Principal component analysis of all genes in the sets all 3' IREs and all 5' IREs for all samples.** Circles on the 3' IRE plot show that different conditions generally have distinct expression of genes in the *all 3' IREs set* but not in the *all 5' IREs* set. **D. UpSet plot showing overlap in leading-edge genes for the *all 3' IREs* gene set for select comparisons.**

Figure 11. Expression of validated IRE genes in two cell line datasets. A. Summary of workflow. mRNAs found to bind mouse IRP1 and/or IRP2 via immunoprecipitation in Sanchez et al. [24] were filtered for those which contained a high-quality IRE in their 3' or 5' UTR in human and mouse Ensembl gene models. Expression of these validated IRE genes was examined in a mouse splenic B cell dataset and a human Caco-2 cell line dataset.

Within each dataset, *t*-tests were used to test for significant expression differences of

validated IRE genes between iron deficiency-treated cells and control cells. *t*-test *p*-values ≤

0.05 were considered to indicate statistically significant differences. Statistically significant 3'

IRE genes were categorized as either "consistent with the IRE paradigm" (increased

expression in iron deficiency-treated cells) or "inconsistent with the IRE paradigm"

(decreased expression in iron deficiency-treated cells). 5' IRE genes were not expected to

show significant differences according to the IRE paradigm, but 5' IRE genes showing

significant differences in either direction in iron deficiency-treated cells were also recorded

and plotted. **B. Expression of validated IRE genes showing statistically significant**

differences in iron deficiency-treated human Caco-2 cells. Iron deficiency-treated cells

refers to the "Iron-free Medium" cells relative to "Iron-free Medium + FAC" cells. Numbers

over boxplots are *p*-values from *t*-tests between groups. **C. Expression of validated IRE**

genes showing statistically significant differences in iron deficiency-treated mouse

splenic B cells. Iron deficiency-treated cells refers to the deferoxamine (DFO)-treated cells

relative to control cells. *p*-values are from *t*-tests between DFO-treated and control cells.

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1596

Supplementary Information

Supplementary Text

- **Supplementary Text 1.** Effects of biological sex on gene expression in the fAD-mutation-like zebrafish dataset.
- **Supplementary Text 2.** Neural cell type proportions in the gene expression datasets analyzed in this paper.
- **Supplementary Text 3.** Expression of previously characterized 3' and 5' IRE genes in the gene expression datasets analyzed in this paper
- **Supplementary Text 4.** Identifying predicted 3' IRE genes with altered stability.

Supplementary Tables

- **Supplementary Table 1.** Iron Responsive Element (IRE) gene sets defined from human, mouse, and zebrafish transcriptomes. The untranslated regions (UTR) of all known genes were searched for IRE and IRE-like motifs. Four gene sets are included for each species: *all 3' IREs* (all genes with predicted IRE in their 3' UTR), *all 5' IREs* (all genes with predicted IRE in their 5' UTR), *HQ 3' IREs* (genes with high-quality predicted IRE in 3' UTR), and *HQ 5' IREs* (genes with high-quality predicted IRE in 5' UTR). Genes are provided as ENSEMBL gene identifiers.
- **Supplementary Table 2.** Molecular Signature Database (MSigDB) gene sets with significant over-representation of IRE gene sets in human, mouse, and zebrafish. Gene sets were defined to have significant over-representation of IRE gene sets if the FDR-adjusted Fisher's exact test p-value was < 0.05.
- **Supplementary Table 3**. Promoter motif over-representation analysis results for all IRE gene sets in human, mouse, and zebrafish. Promoter regions were defined as being 1500 bp upstream and 500 bp downstream of genes. See Methods for details. We define significant over-representation as FDR-adjusted enrichment p-value < 0.05.
- **Supplementary Table 4.** Gene ontology (GO) analysis results for leading edge genes shared between the "5XFAD vs. WT (3-months-old)" and "5XFAD vs. WT (6-months-old)" comparisons. Significant over-representation of GO terms was determined as GO terms having an FDR-adjusted p-value < 0.05.

1645 ## Supplementary Figures

1664   association between IRE gene expression and the *psen1*[K97fs/+] mutant genotype.

1665   • **Supplementary Figure 7.** Predicted 3' IRE-containing transcripts with significant

1666   differences in stability between conditions in the fAD-like zebrafish dataset.

1667   • **Supplementary Figure 8.** Principal Component Analysis (PCA) plot of splenic

1668   mouse B cell dataset (GEO Accession: GSE77306).

1669

A

Low Iron Conditions

Decreases mRNA translation

IRP1/2

IRP1/2

Increases mRNA stability to <u>increase</u> translation

Gᵐ

5' UTR

Start

// mRNA Stop

3' UTR

AAAAAAAAAA

High Iron Conditions

IRP2 (degraded)

FeS

IRP1 as ACO1

FeS FeS

FeS

Translational activation (<u>Increases</u> mRNA translation)

Decreases mRNA stability to <u>decrease</u> translation

Gᵐ

5' UTR

Start

// mRNA Stop

3' UTR

AAAAAAAAAA

C

Loop

G^3

A^2 U^4

C^1 ······· G^5

N^6

Upper stem

N – N
N – N
N – N
N – N
N – N

Bulge   C

N – N
N – N
Lower stem
N – N
N – N
N – N

5' – N – N – 3'

consensus IRE

FTL

Example of a high-quality (canonical) predicted IRE

EPAS1

Unpaired bulge nucleotide

Hao1

Mismatch

Examples of predicted IRE-like motifs

All predicted 3' IRE genes

All predicted 5' IRE genes

High-quality predicted 3' IRE genes

High-quality predicted 5' IRE genes

Human

Mouse

Zebrafish

Inputs   Results

Gene counts matrix → **Differential gene expression analysis with *limma***
- Differentially expressed genes
- *limma* objects (design, contrasts, and either fit and expression matrix, or voom-adjusted counts)

- Predicted IRE gene sets
- MSigDB Hallmark gene sets

→ **Gene set enrichment tests with *mroast/fry*, *camera*, and *fgsea***

Combine raw *p*-values with Wilkinson's method + adjustment for multiple tests →

Significantly enriched gene sets
- Leading edge genes contributing to *fgsea* enrichment signal for IRE gene sets
- Proportions of genes in each gene set showing increased or decreased expression

Gene counts matrix including both spliced and unspliced genes → **Identification of candidate 3' IRE genes stabilized under iron deficiency**

Welch's *t*-test on logFC of spliced and unspliced genes to determine if changes in stability between experimental conditions are significant →

3' IRE genes showing significant increase in expression and stability

A

Iron overload
(DMEM-FBS Medium +
Hemin vs. DMEM-FBS Medium)

Iron deficiency
(Iron-free Medium vs.
Iron-free Medium +FAC)

HEDGEHOG SIGNALING	
APICAL SURFACE	
ANGIOGENESIS	
NOTCH SIGNALING	
CHOLESTEROL HOMEOSTASIS	
MYC TARGETS V2	
TGF BETA SIGNALING	
ANDROGEN RESPONSE	
PROTEIN SECRETION	
PANCREAS BETA CELLS	
WNT BETA CATENIN SIGNALING	
PEROXISOME	
REACTIVE OXYGEN SPECIES PATHWAY	
UNFOLDED PROTEIN RESPONSE	
PI3K AKT MTOR SIGNALING	
G2M CHECKPOINT	
UV RESPONSE DN	
BILE ACID METABOLISM	
E2F TARGETS	
IL6 JAK STAT3 SIGNALING	
FATTY ACID METABOLISM	
EPITHELIAL MESENCHYMAL TRANSITION	
MTORC1 SIGNALING	
SPERMATOGENESIS	
MITOTIC SPINDLE	
DNA REPAIR	
COAGULATION	
GLYCOLYSIS	
ADIPOGENESIS	
ESTROGEN RESPONSE EARLY	
MYOGENESIS	
MYC TARGETS V1	
HEME METABOLISM	
APOPTOSIS	
IL2 STAT5 SIGNALING	
P53 PATHWAY	
ESTROGEN RESPONSE LATE	
HYPOXIA	
UV RESPONSE UP	
INTERFERON ALPHA RESPONSE	
OXIDATIVE PHOSPHORYLATION	
APICAL JUNCTION	
COMPLEMENT	
XENOBIOTIC METABOLISM	
KRAS SIGNALING UP	
INFLAMMATORY RESPONSE	
KRAS SIGNALING DN	
TNFA SIGNALING VIA NFKB	
INTERFERON GAMMA RESPONSE	
ALLOGRAFT REJECTION	

Number of genes

Number of genes

- Not significant
- Decreased in expression (t < -2)
- Increased in expression (t > 2)

● indicates significant enrichment of gene set (Bonferroni-adjusted *p*-value < 0.05)

B

Iron overload
(Cells cultured in DMEM-FBS Medium
+ Hemin vs. DMEM-FBS Medium)

Iron deficiency
(Cells cultured in Iron-free Medium
vs. Iron-free Medium +FAC)

High-quality 5' IRE genes
High-quality 3' IRE genes
All predicted 5' IRE genes
All predicted 3' IRE genes

Number of genes

Number of genes

- Not significant
- Decreased in expression (t < -2)
- Increased in expression (t > 2)

● indicates significant enrichment of gene set (Bonferroni-adjusted *p*-value < 0.05)

C

All predicted 3' IRE genes

All predicted 5' IRE genes

A

Temporal Cortex

Cerebellum

Not significant   Decreased in expression (t < -2)   Increased in expression (t > 2)

B

Temporal Cortex

Leading-edge genes in all predicted 3' IRE genes   Leading-edge genes in all predicted 5' IRE genes

Cerebellum

Leading-edge genes in all predicted 3' IRE genes   Leading-edge genes in all predicted 5' IRE genes

A

Test for enrichment of IRE-containing mouse genes

-log2(p)
20
10
0

B

Gene set

	3 months (5XFAD vs. wild type)	6 months (5XFAD vs. wild type)	12 months (5XFAD vs. wild type)
Canonical 5' IRE genes			
Canonical 3' IRE genes			
All predicted 5' IRE genes			
All predicted 3' IRE genes			

Expression change
- No significant change
- Decreased ($t < -2$)
- Increased ($t > 2$)

Number of genes

Gene set

3 months (5XFAD vs. wild type)   6 months (5XFAD vs. wild type)   12 months (5XFAD vs. wild type)

NOTCH SIGNALING
ANGIOGENESIS
HEDGEHOG SIGNALING
PANCREAS BETA CELLS
WNT BETA CATENIN SIGNALING
APICAL SURFACE
REACTIVE OXYGEN SPECIES PATHWAY
MYC TARGETS V2
TGF BETA SIGNALING
CHOLESTEROL HOMEOSTASIS
IL6 JAK STAT3 SIGNALING
PROTEIN SECRETION
ANDROGEN RESPONSE
PI3K AKT MTOR SIGNALING
PEROXISOME
UNFOLDED PROTEIN RESPONSE
INTERFERON ALPHA RESPONSE
BILE ACID METABOLISM
SPERMATOGENESIS
COAGULATION
UV RESPONSE DN
DNA REPAIR
UV RESPONSE UP
APOPTOSIS
FATTY ACID METABOLISM
MYC TARGETS V1
HEME METABOLISM
P53 PATHWAY
KRAS SIGNALING DN
EPITHELIAL MESENCHYMAL TRANSITION
MYOGENESIS
TNFA SIGNALING VIA NFKB
G2M CHECKPOINT
E2F TARGETS
MTORC1 SIGNALING
COMPLEMENT
ESTROGEN RESPONSE EARLY
OXIDATIVE PHOSPHORYLATION
MITOTIC SPINDLE
GLYCOLYSIS
HYPOXIA
XENOBIOTIC METABOLISM
INFLAMMATORY RESPONSE
APICAL JUNCTION
IL2 STAT5 SIGNALING
ADIPOGENESIS
ALLOGRAFT REJECTION
INTERFERON GAMMA RESPONSE
ESTROGEN RESPONSE LATE
KRAS SIGNALING UP

Number of genes

Expression change
- No significant change
- Decreased ($t < -2$)
- Increased ($t > 2$)

Aging

253 / 396

1386 / 1362

Hypoxia

912 / 1156

982 / 815

271 / 130

511 / 247

24 months

733 / 468

958 / 960

249 / 296

Normoxia

1136 / 1303

1209 / 1020

6 months

135 / 143

Mutation

+/+   psen1 Q96K97/+

Hypoxia

B

Normoxia
6 month old Q96K97/+ vs. wild-type

Normoxia
24 month old Q96K97/+ vs. wild-type

	Pathway	
-	PANCREAS BETA CELLS	-
-	ANGIOGENESIS	-
●	NOTCH SIGNALING	●
-	HEDGEHOG SIGNALING	●
-	REACTIVE OXIGEN SPECIES PATHWAY	●
-	WNT BETA CATENIN SIGNALING	●
-	MYC TARGETS V2	-
-	APICAL SURFACE	-
-	TGF BETA SIGNALING	●
-	IL6 JAK STAT3 SIGNALING	-
-	CHOLESTEROL HOMEOSTASIS	●
-	INTERFERON ALPHA RESPONSE	●
-	ANDROGEN RESPONSE	●
●	PROTEIN SECRETION	●
-	BILE ACID METABOLISM	●
-	PEROXISOME	●
●	UNFOLDED PROTEIN RESPONSE	●
-	COAGULATION	●
●	PI3K AKT MTOR SIGNALING	●
-	SPERMATOGENESIS	●
-	DNA REPAIR	●
-	APOPTOSIS	●
●	UV RESPONSE DN	●
●	FATTY ACID METABOLISM	●
-	INFLAMMATORY RESPONSE	-
-	ALLOGRAFT REJECTION	-
-	KRAS SIGNALING DN	●
●	E2F TARGETS	●
●	HEME METABOLISM	●
-	UV RESPONSE UP	●
-	INTERFERON GAMMA RESPONSE	-
●	ESTROGEN RESPONSE EARLY	●
-	XENOBIOTIC METABOLISM	●
-	TNFA SIGNALING VIA NFKB	●
-	ESTROGEN RESPONSE LATE	●
-	COMPLEMENT	●
-	KRAS SIGNALING UP	●
●	MYC TARGETS V1	●
●	OXIDATIVE PHOSPHORYLATION	●
●	GLYCOLYSIS	●
-	P53 PATHWAY	●
●	G2M CHECKPOINT	●
-	IL2 STAT5 SIGNALING	●
-	HYPOXIA	●
-	APICAL JUNCTION	●
-	MTORC1 SIGNALING	●
●	ADIPOGENESIS	●
-	MYOGENESIS	●
●	EPITHELIAL MESENCHYMAL TRANSITION	●
-	MITOTIC SPINDLE	●

250   200   150   100   50   0   0   50   100   150   200   250

Number of genes   Number of genes

☐ Non-significant
■ Decreased expression ($t < -2$)
■ Increased expression ($t > 2$)