A multi-omics analysis of human fibroblasts overexpressing an *Alu* transposon reveals widespread disruptions in aging-associated pathways

Juan I. Bravo,[1,8] Eyael Tewelde,[2,3,8] Christina D. King,[4] Joanna Bons,[4] Samah Shah,[4] Jacob

Rose,[4] Judith Campisi,[4] Birgit Schilling,[4] and Bérénice A. Benayoun[1,2,5,6,7,9,*]

[1]Leonard Davis School of Gerontology, University of Southern California, Los Angeles, CA 90089,

USA.

[2]Alfred E. Mann School of Pharmacy and Pharmaceutical Sciences, University of Southern

California, Los Angeles, CA 90033, USA.

[3]Graduate program in Pharmaceutical and Translational Sciences, University of Southern

California, Los Angeles, CA 90033, USA.

[4]Buck Institute for Research on Aging, Novato, CA 94945, USA.

[5] Cancer Biology Department, USC Keck School of Medicine, Los Angeles, CA 90033, USA.

[6]USC Norris Comprehensive Cancer Center, Epigenetics and Gene Regulation, Los Angeles, CA

90033, USA.

[7]USC Stem Cell Initiative, Los Angeles, CA 90089, USA.

[8]These authors contributed equally

[9]Lead contact

*Correspondence: bbenayou@usc.edu

SUMMARY

During aging and cellular senescence, repetitive elements are frequently transcriptionally derepressed across species and cell types. Among these, the most abundant repeats by copy number in the human genome are *Alu* retrotransposons. Though *Alu* elements are often studied for their mutagenic potential, there is increasing appreciation for their contributions to other biological functions, including pro-inflammatory signaling and mitochondrial dysfunction. However, a comprehensive analysis of *Alu*-driven molecular changes remains to be conducted, and *Alu*'s potential contributions to aging features remain incompletely characterized. Here, we show that overexpression of an *AluJb* transposon in human primary IMR-90 fibroblasts leads to large-scale alterations across the transcriptome, cellular proteome, and secretome. Functional genomics analyses reveal alterations in aging/senescence pathways, broadly, and mitochondrial metabolism, proteostasis, cell cycle, and extracellular matrix pathways, more specifically. Our results demonstrate that *Alu* transcriptional upregulation is sufficient to drive widespread disruptions to cellular homeostasis that mirror aging-associated alterations.

KEYWORDS

Aging, Retrotransposons, *Alu*, Fibroblasts, Mitochondria, Cell Cycle, Proteostasis, Transcriptomics, Proteomics, Secretome

INTRODUCTION

Transposable elements (TEs), often informally referred to as "jumping genes", are genetic elements that can mobilize within a genome. Depending on mobilization mechanisms, TEs can be classified as DNA transposons, which operate through a "cut-and-paste" mechanism, or retrotransposons, which operate through a "copy-and-paste" mechanism (Kidwell, 2002). Historically, transposable elements have been largely ignored in biological studies because of (1) biases that considered TEs "junk" DNA and (2) the extreme difficulty of working with multi-copy, highly repetitive genomic sequences. Thus, there is frequently a gap in our understanding of the relationship between TEs and biological processes of interest, such as cellular senescence or aging.

Technological advancements over the past two decades (including next generation sequencing) have facilitated the study of TEs, including in the context of aging and aging-associated diseases [reviewed in (Bravo et al., 2020)]. For example, age-related de-repression of TEs has been observed across diverse model systems, including *Caenorhabditis elegans* (Dennis et al., 2012), *Drosophila* (Chen et al., 2016; Li et al., 2013; Wood et al., 2016), and *Mus musculus* (Benayoun et al., 2018; De Cecco et al., 2013b), and in senescent cells (De Cecco et al., 2013a; De Cecco et al., 2019; Wang et al., 2011). Importantly, TE de-repression has also been observed across age-associated pathologies, e.g. cell senescence, cancer (Di Ruocco et al., 2018; Iskow et al., 2010; Luca et al., 2015; Rodić et al., 2014), and Alzheimer's disease (Guo et al., 2018; Sun et al., 2018). These findings suggest that aging biology and transposon biology are tightly intertwined. However, whether TEs are drivers of aging and aging phenotypes or whether they are mere "innocent" bystanders of the aging process is still unknown.

In the human genome, the two most abundant families of TEs are the retrotransposons long interspersed element 1 (*LINE-1* or *L1*) and *Alu*. *Alu* transposons, in particular, have the largest number of copies, with ~1.1 million loci occupying ∼9-11% of the genome (Lander et al., 2001; Venter et al., 2001). These retrotransposons are short (~300 base pairs) and require the *LINE-1* machinery for their own mobilization (Dewannieux et al., 2003; Rubin et al., 1980; Wallace et al., 2008). Further, the *Alu* family can be segregated into three subfamilies depending on evolutionary age: *AluJ* is the oldest lineage and likely immobile in humans, *AluS* is the middle-aged lineage containing some mobile copies, and *AluY* is the youngest lineage with the most functionally intact copies (Bennett et al., 2008). Evolutionarily, *Alu* elements are believed to have originated from 7SL RNA (Rubin et al., 1980; Ullu and Tschudi, 1984) which plays important roles in (1) co-translationally directing proteins to the endoplasmic reticulum as part of the protein

secretory pathway (Nyathi et al., 2013; Walter and Blobel, 1982; Wild et al., 2002) and (2)

orchestrating a cellular response to thermal stress that involves transcription and translation arrest

(Bujisic et al., 2025). Its evolutionary history suggests that *Alu* may play important roles in

regulating proteostasis, although this has not been thoroughly evaluated, and the breadth of *Alu*-

regulated pathways remains unclearly defined.

Thus far, the effects of elevated *Alu* expression in a non-diseased and non-senescent

background are ill-defined, and whether *AluJb* overexpression is sufficient to recapitulate

senescence or aging phenotypes is an open question. To address these gaps, we generated a

multi-omic resource encompassing transcriptomic, proteomic, and secretomic profiles of "healthy"

human primary IMR-90 fibroblasts overexpressing an *AluJb* retrotransposon, an element which

naturally becomes transcriptionally upregulated in human primary aging fibroblasts. We

demonstrate that this overexpression induces widescale remodeling of the transcriptome, cellular

proteome, and secretome, and that this remodeling partially reflects remodeling observed during

aging and senescence. On both a molecular and functional level, we observe *AluJb*-induced

alterations in mitochondrial metabolic activity, cell proliferation, and proteostasis—all pathways

that become mis-regulated during aging. Our results suggest that *AluJb* overexpression is

sufficient to promote senescence and aging-associated molecular and functional changes, and,

therefore, *AluJb* may partially promote senescence or aging phenotypes when de-repressed

under physiological conditions with aging.

RESULTS

Aging upregulates repetitive elements, including *Alu* transposons, in primary human fibroblasts

To systematically characterize the effects of aging on the repetitive transcriptome, we leveraged publicly available mRNA-sequencing data for human aging primary fibroblasts (Fleischer et al., 2018) (**Figure 1A**). Though others have explored the relationship between aging and transposon expression in these samples (LaRocca et al., 2020; Pabis et al., 2024), we note that our sample selection criteria were more stringent. To minimize batch effects and isolate aging effects without confounding effects from development, the final sample set we utilized included 76 samples with the following characteristics: male and female adults were aged between 20 and 96 years old, adults were of Caucasian ethnicity, and all fibroblasts were derived from skin on the arm.

Differential gene expression analysis identified 395 repeat subfamilies that increased with age and 33 subfamilies that decreased with age at an FDR < 0.05 (**Figure 1B, Supplementary Table S1A**). These effects were not specific to any repeat class, as specific DNA transposons, long interspersed elements (LINEs), short interspersed elements (SINEs), and long terminal repeat (LTR) transposons changed with age (**Supplementary Table S1A**). Because SINEs are a relatively understudied class of transposons despite being one of the most abundant classes in the human genome, we chose to focus on one of its subfamilies and characterize it further. Though a few SINE subfamilies changed with age, we decided to concentrate on the *AluJb* subfamily of retrotransposons, whose total expression increased with age (FDR = 1.02E-2, **Figure 1C**). After quantifying expression levels at individual repeat loci and aggregating counts by genomic context [as previously done in (Bravo et al., 2024)] (**Supplementary Table S1B**), we observed that intergenic *AluJb* copies within 5 kilobases of a gene (FDR = 2.03E-5) and exon-overlapping copies (FDR = 7.52E-3) both increased with age (**Figure 1C**). These results reiterate that transposon control mechanisms become dysregulated with age, and *Alu* transposon expression becomes elevated with age. Moreover, these results leave open the possibility that *AluJb* may exert cellular aging-associated effects either through its own independent transcripts or by incorporating itself into the transcripts of hosting genes.

To identify candidate pathways that may become mis-regulated in response to elevated *AluJb* expression, we carried out differential gene expression analysis across total *AluJb* expression levels (**Supplementary Table S1C**) followed by gene set enrichment analysis (GSEA). Interestingly, top Gene Ontology (GO) Biological Process terms associated with

proteostasis, such as 'ribosome biogenesis', 'rRNA metabolic process', and 'rRNA processing',
were significantly downregulated (**Figure 1D, Supplementary Table S1D**). Other terms
associated with mitochondrial metabolism (like 'aerobic respiration' and 'electron transport chain')
and the cell cycle (like 'mitotic nuclear division' and 'cell cycle phase transition') were also
significantly downregulated. In contrast, top terms associated with the extracellular matrix, such
as 'homophilic cell adhesion via plasma membrane adhesion molecules', were significantly
upregulated. In parallel, top Reactome pathways associated with the cell cycle, such as 'cell cycle,
mitotic' and 'M phase', as well as pathways associated with proteostasis, such as 'translation',
were downregulated (**Figure 1E, Supplementary Table S1E**). Similar to the GO analysis,
extracellular matrix-related terms such as 'extracellular matrix organization' were significantly
upregulated. These results highlight recurrent correlations between *AluJb* expression and
alterations in aging-associated pathways related to proteostasis, mitochondrial function, the cell
cycle, and the extracellular environment, and raise the intriguing possibility that *AluJb* expression
itself may drive these phenotypes.

AluJb promotes widespread transcriptional and proteomic remodeling

Our analysis identified numerous pathways correlated with *AluJb* expression levels in
aging fibroblasts, though it was unclear whether *AluJb* was an upstream driver of changes in
these pathways or whether it was a simple bystander. To begin to answer this question and
characterize the effects of elevated *AluJb* expression on primary cell phenotypes, we placed the
consensus sequence under the control of the U6 RNA polymerase III promoter and transiently
transfected human IMR-90 fibroblasts (**Figure 2A**). After a ~24 hours recovery period following
electroporation, cells were re-seeded at equal densities and cultured in low serum media in
accordance with previously described guidelines for generating conditioned media from
senescent cells and quiescent control cells (Neri et al., 2021). We implemented this protocol
because (1) we hypothesized that *Alu* overexpression may induce senescence-associated
changes and (2) this protocol utilizes serum deprivation to induce quiescence in order to isolate
senescent versus non-senescent effects and eliminate non-proliferating vs proliferating effects.
After 72 hours, cells and conditioned media were collected for transcriptomic, proteomic, and
secretomic analysis (**Figure 2A, Supplementary Tables S2A-C**). Importantly, overexpression of
plasmid-specific *AluJb* was verified by reverse transcription (RT) followed by endpoint polymerase
chain reaction (PCR) (**Figure S1A**).

Interestingly, multidimensional scaling (MDS) analysis segregated the empty vector
control cells from the *AluJb*-overexpressing cells across the transcriptome (**Figure 2B**), cellular
proteome (**Figure 2C**), and secretome (**Figure 2D**). This suggests that *AluJb* overexpression
induces major changes across "-omics" layers. Consistent with this notion, *AluJb* overexpression
induced a significant (FDR < 0.05) upregulation of 107 genes and a downregulation of 102 genes
(**Figure 2E, Supplementary Table S2D**), a significant (Q < 5% and abs($\log_2$FC) > 0.20)
upregulation of 62 cellular proteins and a downregulation of 57 cellular proteins (**Figure 2F,
Supplementary Table S2E**), and a significant (Q < 5% and abs($\log_2$FC) > 0.58) upregulation of
871 secreted proteins and a downregulation of 8 secreted proteins (**Figure 2G, Supplementary
Table S2F**). Additionally, though the segregation was not as strong as with the gene expression
profiles, the repeat subfamily expression profiles also segregated empty vector and *AluJb*-
overexpressing cells by MDS analysis (**Figure S1B**), highlighting major shifts in the repeat
transcriptome itself following *AluJb* overexpression. In line with this notion, we observed a trend
where *AluJb*-overexpressing cells had more reads mapping to repeat subfamilies compared to
control cells (**Figure S1C**). Moreover, the differential expression analysis identified 104 repeat
subfamilies with significantly (FDR < 0.05) higher expression and 1 repeat subfamily with
significantly lower expression in the overexpression group (**Figure S1D, Supplementary Table
S2D**). These repeat subfamilies belonged to several repeat classes, including DNA transposons,
LINEs, LTRs, and SINEs. Thus, these results suggest that elevated *AluJb* expression can
promote the de-repression of other repeats from diverse repeat classes, potentially forming
positive feedback loops where newly upregulated repeats further promote the expression of
additional repeats.

Importantly, to contextualize our results within the broader *Alu* research literature, we
compared our findings to a previous study of IMR-90 fibroblasts stably overexpressing two *AluS*
retrotransposons (Cantarella et al., 2019) (**Figure S2A**). We observed that genes upregulated by
AluS were significantly enriched among genes significantly upregulated by *AluJb* (Fisher's exact
p-value = 3.03E-3), and genes downregulated by *AluS* were significantly enriched among genes
significantly downregulated by *AluJb* (Fisher's exact p-value = 1.52E-6; **Figure S2B**). These
results demonstrate a degree of consistency between *AluS*- and *AluJb*-regulated genes. As an
alternative approach, we also generated gene sets for *AluS* induced and *AluS* repressed genes
and carried out gene set enrichment analysis (GSEA) among *AluJb*-driven transcriptomic
changes (**Figure S2C, Supplementary Table S2G**). Surprisingly, while the set of *AluS* induced
genes was consistently upregulated by *AluJb*, the set of *AluS* repressed genes was inconsistently
upregulated by *AluJb*. These results suggest that differences in the *Alu* subfamily (*AluJb* vs *AluS*)

or differences in the overexpression duration (transient vs stable) may induce partially unique
cellular responses and phenotypic effects.

AluJb **overexpression elicits aging- and senescence-associated molecular alterations**

Transposon de-repression is often seen in aging and in cellular senescence, but it is
unclear whether aging and senescence follow transposon de-repression, or whether TE de-
repression follows aging and senescence. To test the former idea, we compared our multi-omics
measurements to published lists of senescence-induced or aging-induced gene changes (**Figure**
3A). Since our experimental approach was originally designed to capture senescence-associated
secretory phenotype (SASP) factors (Neri et al., 2021), we first compared our multi-omics results
to a list of core SASP factors (Basisty et al., 2020). Indeed, core SASP factors were enriched (p
= 2.19E-2) among significant, rather than non-significant, differentially expressed genes (**Figure**
3B). Additionally, there was a suggestive enrichment of core SASP factors among significant,
rather than non-significant, differentially abundant cellular or secreted proteins (**Figure 3C-3D**).
These results suggest that *AluJb* may drive differences in core SASP factors across the
transcriptome, cell proteome, and secretome.

For heightened sensitivity and to determine the directionality of any observed changes,
we carried out gene set enrichment analysis (GSEA) with several aging and senescence gene
sets. At the transcriptomic level, we observed that (1) genes downregulated with age in the
Genotype-Tissue Expression (GTEx) project (Jia et al., 2018), (2) genes downregulated with age
in human primary fibroblasts (Fleischer et al., 2018), and (3) repetitive elements upregulated with
age in human primary fibroblasts significantly (FDR < 0.05) changed with the same directionality
following *AluJb* overexpression (**Figure 3E, Supplementary Table S3A**). Other gene sets like
Senmayo (Saul et al., 2022) and the core SASP were also significantly repressed following
overexpression, while repeats that were downregulated in human aging primary fibroblasts were
significantly upregulated following overexpression. At the cellular proteomics level, core SASP
factors were significantly (FDR < 0.05) upregulated following *AluJb* overexpression (**Figure 3F,**
Supplementary Table S3B). We observed that genes downregulated with age in the GTEx
project were significantly upregulated at the protein level following overexpression, but the
directionality was inconsistent. Finally, at the secretomics level, core SASP factors were
significantly (FDR < 0.05) upregulated following *AluJb* overexpression (**Figure 3G,**
Supplementary Table S3C). These factors included insulin-like growth factor binding proteins
(like IGFBP4 and IGFBP5), matrix metalloproteinases (like MMP1 and MMP2), and tissue

inhibitors of metallopeptidase (like TIMP1). Though some of the effects vary in directionality, these results suggest that elevated *AluJb* expression can partially mirror molecular changes observed during cellular senescence and aging. Additionally, the significant upregulation of core SASP factors in the secretome highlights *AluJb* as a potential driver of inflammation and altered intercellular communication.

We next tested the inverse hypothesis that transposon-mediated effects would follow chronological aging (**Figure S3A**). Surprisingly, *AluJb*-induced genes were not significantly enriched among significant primary fibroblast aging genes, and downregulated *AluJb* genes were actually significantly depleted compared to their frequency among nonsignificant aging downregulated genes (**Figure S3B**). GSEA highlighted an inverted regulation of *AluJb*-induced genes with aging, where *AluJb* downregulated genes were upregulated with age and *AluJb* upregulated genes were downregulated with age (**Figure S3C, Supplementary Table S3D**). In contrast, many repetitive elements that were upregulated following *AluJb* overexpression were also upregulated in aged primary human fibroblasts (**Figure S3D-S3E, Supplementary Table S3D**). These results demonstrate that aging partially recapitulates the effects of *AluJb* and the upregulation of many endogenous repetitive elements, in particular. Taken together with the observation that *AluJb* is sufficient to induce aging- and senescence-associated changes, these results suggest the existence of a complex feedback mechanism whereby (1) *AluJb* can promote aging and senescence, (2) aging can promote heightened repetitive element expression, creating feedback loop pressure, and (3) aging simultaneously regulates *AluJb*-induced gene expression.

AluJb drives molecular changes in mitochondrial, proteostasis, cell cycle, and extracellular matrix pathways

To assign functions to molecular changes caused by elevated *AluJb* expression, we carried out gene set enrichment analysis (GSEA) in each individual "-omics" layer using functional gene set collections (**Figure 4A**). In the transcriptome and using the Gene Ontology (GO) Biological Process gene set collection, we identified an upregulation of extracellular matrix-related processes (*e.g.* "homophilic cell adhesion via plasma membrane adhesion molecules" and "cell junction organization"), as well as cell cycle-related processes (*e.g.* 'regulation of mitotic sister chromatid segregation'; **Figure 4B, Supplementary Table S4A**). We also observed a downregulation of terms related to mitochondrial metabolism (*e.g.* "aerobic respiration" and "generation of precursor metabolites and energy") and proteostasis (*e.g.* "cytoplasmic translation"). In the cellular proteome, the top upregulated processes were related to the cell cycle

(*e.g.* "cell cycle G2/M phase transition") and to protein phosphorylation (*e.g.* "regulation of

dephosphorylation"; **Figure 4C, Supplementary Table S4B**). Finally, in the secretome, the top

upregulated terms were related to responding to stimuli (*e.g.* "response to endogenous stimuli"

and "response to transforming growth factor beta") and the top downregulated terms were related

to aspects of proteostasis (*e.g.* "rRNA processing"; **Figure 4D, Supplementary Table S4C**).

GSEA with Reactome pathway gene sets (Milacic et al., 2023) mirror many of the results obtained

using the GO Biological Process terms. In the transcriptome, we again observed an upregulation

of extracellular matrix-related pathways (*e.g.* "extracellular matrix organization" and "integrin cell

surface interactions") and a downregulation of proteostasis pathways (*e.g.* "eukaryotic translation

elongation" and "eukaryotic translation termination") and mitochondrial metabolic pathways (*e.g.*

"aerobic respiration and respiratory electron transport"; **Figure 4E, Supplementary Table S4D**).

In this case, we could not detect significantly (FDR < 0.05) altered pathways in the cellular

proteome (**Figure 4F**). However, the secretome also exhibited an upregulation of extracellular

matrix-associated pathways, as well as a downregulation of pathways related to DNA repair or

epigenetic modifications (*e.g.* "base-excision repair, AP site formation" and "chromatin

modifications during the maternal to zygotic transition"; **Figure 4G, Supplementary Table S4E**).

These results demonstrate that *AluJb* can regulate functional pathways that are often differentially

regulated with age.

To ensure that these pathway-level changes were not unique to serum deprived cells and

were also observed in proliferating cells (where more of these pathways could be functionally

tested without the added stress of serum-deprivation), we carried out an additional transcriptomic

analysis of proliferating IMR-90 fibroblasts cultured in standard rich media (**Figure S4A**). Again,

we confirmed plasmid-specific *AluJb* overexpression by PCR (**Figure S4B**), observed a

segregation of control and overexpression samples by MDS analysis of gene (**Figure S4C**) and

repeat (**Figure S4D**) expression profiles, and observed a trending increasing in the percent of

reads mapping to repeat subfamilies following *AluJb* overexpression (**Figure S4E**). We observed

a significant (FDR < 0.05) increase in 3790 genes and a decrease in 987 genes, as well as an

increase in 201 repeat subfamilies (**Figure S4F, Supplementary Table S4F**). The altered repeat

subfamilies belonged to several repeat classes, including DNA transposons, LINEs, and LTRs.

GSEA analysis with GO Biological Process gene sets highlighted an upregulation of cell cycle

processes (*e.g.* "chromosome segregation" and "centriole assembly") and a repression of

mitochondrial metabolic processes (*e.g.* "aerobic respiration" and "oxidative phosphorylation")

and proteostasis processes (*e.g.* "protein folding") (**Figure S4G, Supplementary Table S4G**).

Likewise, GSEA with Reactome pathway gene sets highlighted a repression of proteostasis

pathways (*e.g.* "eukaryotic translation elongation", "peptide chain elongation", and "HSF1
activation") and mitochondrial metabolic pathways (**Figure S4H, Supplementary Table S4H**).
These results demonstrate that *AluJb* can also promote broad molecular alterations in rich media
conducive to cell proliferation.

Using the initial transcriptomic data, we next sought to characterize *AluJb*-induced
alterations across broad gene modules (**Figure 5A**). An enrichment analysis of transcription factor
(TF) regulons identified heat shock transcription factor 1 (HSF1) as one of the top TFs with
repressed targets (**Figure 5B, Supplementary Table S4I**). Since HSF1 plays a crucial role in the
heat shock response and therefore in maintaining proteostasis during stress (Pincus, 2020), these
results highlight potential master regulators of the previously noted *AluJb*-driven pathway
alterations. Indeed, PRRX1 has been identified as a master transcription factor in stromal
fibroblasts with functions related to extracellular remodeling (Lee et al., 2022), ETV5 regulates
fatty acid metabolism through peroxisome proliferator-activated receptor (PPAR) signaling (Mao
et al., 2021), and both KDM5A and CXXC1 play roles in epigenetic control (Blair et al., 2011;
Kiuchi et al., 2021). Additionally, a network analysis to construct a predicted protein-protein
interaction (PPI) network using significantly differentially expressed genes highlighted two major
clusters of corresponding proteins: one with proteins involved in mitochondrial function, such as
MT-ND2, MT-ND4, MT-ND5, and *MT-ND6*, and one with proteins involved in translation, such as
RPS25 and *RPL36AL* (**Figure 5C**). These results further highlight broad-scale *AluJb*-driven
alterations in molecular pathways involved with the extracellular environment, epigenetics,
metabolism, and proteostasis.

Multi-omic integration highlights alterations in extracellular, proteostasis, and metabolic
pathways
To further increase sensitivity and identify pathways alterations occurring in more than
one "-omics" analysis, we carried out multi-contrast gene set enrichment analysis (**Figure 6A**).
Indeed, an overlap analysis of individual significant genes/proteins across "-omics" analyses was
limited, and we identified four genes and corresponding proteins—*DCN, NES, POSTN*, and *DBI*—
that changed in all three "-omics" layers (**Figure 6B**, **Figure S5A-S5C**). This modest overlap could
result from multiple technical and biological reasons, including different detection sensitivities
across "-omics" layers and imperfect correlations between "-omics" layers. In these cases,
combinatorial analyses taking into account multiple "-omics" layers *a priori* (in the process of

enrichment analysis) instead of *a posteriori* (overlapping differential results in each independent
dataset) are more powerful to detect consistent functional changes elicited across layers.

Thus, we performed multi-contrast gene set enrichment analysis using a rank MANOVA
framework to identify pathways consistently regulated across our multi-omics profiling (**Figure 6**).
We first leveraged GO Biological Process terms, which revealed that the transcriptome was most
similar to the secretome, and that the cell proteome varied compared to the other two "-omics"
types (**Figure 6C, Supplementary Table S5A**). This analysis also identified extracellular matrix-
related terms, such as 'external encapsulating structure organization', 'cell adhesion', and 'cell
motility', that were upregulated across the transcriptome and secretome but varied in the cell
proteome (**Figure 6C-6D**). Similarly, proteostasis terms like 'cytoplasmic translation' and
'ribosomal small subunit biogenesis' were suppressed in the transcriptome and secretome but
varied in the cell proteome (**Figure 6C-6D**). The multi-contrast analysis with the Reactome
pathway gene sets also highlighted a stronger similarity between the transcriptome and
secretome compared to the cell proteome (**Figure 6E, Supplementary Table S5B**). Mirroring the
previous analysis, extracellular matrix terms like 'extracellular matrix organization' and
'degradation of the extracellular matrix' were upregulated across the three "-omics" analyses,
while proteostasis terms like 'cap-dependent translation initiation' and 'SRP-dependent
cotranslational protein targeting to membrane' were downregulated across all three "-omics"
layers (**Figure 6E-6F**). These results further emphasize widespread alterations that are
consistently observed in more than one "-omics" layer following *AluJb* overexpression.

***AluJb* overexpression leads to functional alterations, as predicted from multi-omics**
alterations

Our individual and integrated multi-omics analyses identified molecular changes
associated with several aging-regulated functional pathways, including mitochondrial metabolism,
the cell cycle, and proteostasis, among others. However, whether these molecular changes
translated to functional cellular changes remained unclear. To test the functional effects of *AluJb*
on cell physiology, we thus carried out several functional assays (**Figure 7A**).

First, we assessed mitochondrial respiration using a Seahorse Cell Mito Stress Test
(**Figure 7B**). This revealed a significant ($p < 0.05$) reduction in many oxygen consumption rate
(OCR)-related metrics, including basal respiration, maximal respiration, non-mitochondrial
respiration, ATP-linked respiration, proton leak, and spare capacity (**Figure 7B**, **Figure S6A-**

S6B). Though this assay is not specifically designed to evaluate resting glycolytic rate, parallel
measurements of extracellular acidification rate did not reveal any significant differences in resting
glycolytic rate (**Figure 7C**). These results demonstrate that mitochondrial respiration (but likely
not glycolytic potential) is substantially dampened following *AluJb* overexpression, consistent with
aging.

Next, we carried out a propidium iodide-based cell cycle assay (**Figure 7D, Figure S6C**).
Since cell proliferation is one of a limited number of phenotypes known to be disrupted by *Alu*
expression (Cantarella et al., 2019), we chose to re-analyze this phenotype since it (1) appeared
in our analyses and (2) could serve as a potential positive control. Though we did not detect
significant differences between control and *AluJb*-overexpressing cells in the G0/G1 and G2/M
phases, we did detect a significant ($p < 0.05$) accumulation of *AluJb*-overexpressing cells in the
S phase, consistent with a prior report (Cantarella et al., 2019). However, contrary to this report,
we interpret this accumulation in S-phase to represent likely replication stress rather than
increased proliferative potential (based on total cell numbers over the course of our experiment,
as well as the lack of a concomitant increase in G2/M cells). These results demonstrate a buildup
of cells in the S phase, which may be caused by replication stress or stalling.

Finally, since we detected alterations in proteostasis-related pathways, we carried out a
Proteostat Aggresome detection assay to identify differences in protein aggregate buildup (**Figure
7E, Figure S6D**). Interestingly, we observed a significantly ($p < 0.05$) lower median fluorescence
intensity in the *AluJb*-overexpressing cells compared to control cells. These results demonstrate
a reduced buildup of protein aggregates and further highlight alterations in proteostasis
machinery.

Taken together, our molecular multi-omics analyses combined with functional profiling
reveal *AluJb* retrotransposon-induced changes in several of the hallmarks of aging (**Figure 7F**)
(Kroemer et al., 2025). These include changes associated to (1) primary hallmarks like loss of
proteostasis, epigenetic alterations, and genomic instability, (2) antagonistic hallmarks like
mitochondrial dysfunction, and (3) integrative hallmarks like extracellular matrix changes, altered
intercellular communication, and cell cycle changes that can manifest as stem cell exhaustion.
Our results suggest that elevated *AluJb* retrotransposon expression is sufficient to drive mis-
regulation of aging-related pathways, and may thus directly contribute to aging phenotypes.

DISCUSSION

A new resource for studying the effects of increased transposon expression

In this study, we generated a multi-faceted resource for studying the effects of elevated *AluJb* transposon expression in "healthy" human IMR-90 fibroblasts. This resource encompasses a multi-omics characterization of the transcriptome, cell proteome, and secretome for human fibroblasts with and without *AluJb* overexpression. This resource expands the limited number of "-omics" resources where TE expression was directly modulated, including the previously mentioned transcriptomic study with stable *AluS* overexpression in IMR-90 fibroblasts (Cantarella et al., 2019), and a transcriptomic study with stably-integrated but inducible codon-optimized *LINE-1* expression in immortalized retinal pigment epithelial (RPE) cells (Ardeljan et al., 2020). Because RNA and protein levels do not always correlate (Vogel and Marcotte, 2012), our study addresses molecular blind-spots present in prior studies focusing on a single "-omics" layer. Importantly, because aging involves the deterioration of healthy organs, tissues, and cells, it will be important (1) to identify and characterize the regulatory mechanisms that fail with age in healthy organs, tissues, and cells, especially those that relate to transposon control, and (2) to characterize the effects of elevated transposon expression in healthy organs, tissues, and cells. In contrast to other studies utilizing cancer or immortalized cell lines to study transposons, our resource is primed for studying the causes and consequences of elevated transposon expression in "healthy", non-cancerous, and non-immortalized cells. By integrating this resource with existing and newly-generated "-omics" resources where transposon expression is experimentally manipulated, it will be possible to characterize (1) organ-, tissue-, and cell type-specific changes in response to transposon expression, as well as (2) common and unique responses to different transposon families, subfamilies, or loci. Ultimately, we anticipate that this resource will be a useful starting point for answering these questions, especially as they relate to senescence and aging.

Our study also provides molecular signatures for elevated *AluJb* expression that can be readily incorporated into ongoing senescence, aging, therapeutic, or other studies with an interest in transposon control. Like the aging and senescence gene sets used to determine whether aging or senescence may be regulated by *AluJb*, the *AluJb* gene sets and protein sets we present can be used to determine whether transposon activation may be regulated by aging, senescence, or any other treatment of interest. As elevated transposon activity is a feature of many aging-associated diseases like cancer (Di Ruocco et al., 2018; Iskow et al., 2010; Luca et al., 2015; Rodić et al., 2014) and Alzheimer's disease (Guo et al., 2018; Sun et al., 2018), our molecular

signatures can be used to simultaneously determine the effects of the disease and the effects of
candidate therapeutics on transposon activity. Thus, we believe this resource holds promising
potential for more thoroughly characterizing human diseases and the therapeutics used to treat
them.

Transposons as drivers of senescence and aging

This study presents several observations that are consistent with the hypothesis that *AluJb*
retrotransposons partially drive senescence and aging. First, we find that *AluJb* retrotransposons
are upregulated in human aging primary fibroblasts, and their expression is correlated with
alterations in pathways related to the hallmarks of aging (Kroemer et al., 2025), including
pathways involved in mitochondrial metabolism, proteostasis, the cell cycle, and the extracellular
matrix. Second, we find that *AluJb*-induced transcriptomic changes partially mirror transcriptomic
changes in human aging primary fibroblasts and in the GTEx project. Moreover, both the cell
proteome and secretome exhibited a significant upregulation of core SASP factors. Third, we find
that functional pathways responding to *AluJb* overexpression are also related to the hallmarks of
aging and include the pathways mentioned in the first point. Finally, we find that *AluJb*
overexpression promotes differences in cell functions related to the hallmarks of aging. Our
results add to the growing litany of studies demonstrating that *Alu* retrotransposons promote
features of aging.

Though the effects of *Alu* on cell function have not been broadly, unbiasedly, and
extensively studied with "-omics" approaches, several targeted studies have explored *Alu*'s
relationship to specific aging-regulated pathways, such as mitochondrial metabolism and the cell
cycle. *Alu*'s influence on mitochondrial function has been explored in the context of advanced
age-related macular degeneration. Specifically, in human cell culture and mouse models, *Alu*
RNA was sufficient to promote opening of the mitochondrial permeability transition pore, release
of mtDNA into the cytosol, and activation of inflammatory cGAS-STING signaling (Kerur et al.,
2017). Whether this mechanism is specific to advanced age-related macular degeneration or is
more broadly applicable to other aging contexts is an open question. Nonetheless, the
mitochondrial dysfunction observed in that study is consistent with the repression of mitochondrial
metabolism observed in this study.

With respect to cell cycle alterations, at least three studies have explored their relationship
to *Alu* RNA levels. First, *Alu* transcripts were found necessary for senescence, as knockdown of

Alu transcripts promoted exit of adult adipose-derived mesenchymal stem cells from senescence
(Wang et al., 2011). Second, consistent with this senescence-promoting model, introducing *Alu*
RNA into RPE cells from humans with advanced age-related macular degeneration led to the
upregulation of pro-inflammatory and senescence markers, including *IL-18, IL-1β, p16^{INK4a},* and
SPiDER-βGal staining (Yamada et al., 2020). Third, stable overexpression of two *AluS* elements
in IMR-90 human fibroblasts was shown to upregulate cell cycle genes and induce an
accumulation of cells in the S phase (Cantarella et al., 2019). Though the authors speculated that
the S phase accumulation reflects heightened cell proliferation, an alternative, more likely
hypothesis is that it represents replication stress or stalling. Indeed, similar to this study, we also
observe an accumulation of cells in the S phase without a concurrent accumulation in the G2/M
phase, supporting the notion of replication stalling. Moreover, though we don't detect a significant
enrichment of senescence gene sets in any "-omics" layers, we do observe a significant
upregulation of core SASP factors.

Taken together, our study, combined with previously published studies, highlight the
possibility that transcriptional upregulation of *Alu* transposons is sufficient to promote features of
cellular senescence or aging.

Limitations of the study

While we believe that physiologically-relevant principles about *Alu* biology can be readily
extracted from this study, we note potential further considerations. First, there are several viable
options to choose from concerning any specific transposon to modulate, even when restricting
the choice to a specific family, like *Alu*. We chose to focus on an *AluJb* element, instead of an
AluS or *AluY* element, because (1) we observed that *AluJb* increased with age in human primary
fibroblasts, making it a suitable candidate for studying its potential age-related effects and (2) we
hypothesized that mobilization of an *AluJ* element would be much more restricted compared to
an *AluS* or *AluY* element, potentially allowing us to focus on the effects of its transcriptional
upregulation with minimal or reduced effects from mobilization. Additionally, we chose to use a
consensus *AluJb* sequence instead of the sequence of a specific *AluJb* copy. We believe that the
former approach can provide more generalizable results across *Alu* copies, and the latter
approach would be better suited for identifying transposon locus-specific effects. Since we were
interested in broad and conserved effects, we opted for the consensus sequence option.

Secondly, there are several options concerning the gene expression manipulation
paradigm. We opted for a transient overexpression of *AluJb*, though stable *Alu* overexpression
lines have been previously generated (Cantarella et al., 2019). A comparison of the results from
these two approaches suggests that they at least partially mirror each other (**Figure S2**).
However, depending on whether one is interested in characterizing the effects of transient versus
sustained *AluJb* expression, one approach may be better suited for the research question at hand.
Although a stable overexpression approach may better model the sustained transposon
expression observed during aging, "healthy" cells may have time to respond to the overexpression
and employ compensatory regulatory mechanisms, such as DNA methylation, to restrict its
impact. In addition, genetic drift occurring during selection may add noise to the analysis. This
may or may not change the utility of the approach in modeling transposon-aging interactions. In
the future, overexpression approaches could be complemented by the incorporation of
knockdown approaches which can target endogenous *Alu* expression to provide additional
insights.

Finally, there are several options concerning the demographics underlying the samples
being considered for experimentation. In this proof-of-principle study, we utilized a well-
characterized female primary embryonic fibroblast cell line, IMR-90. As aging phenotypes,
including TE expression, are frequently sex-dimorphic (Sampathkumar et al., 2020), it would be
important to characterize both the common and sex-specific effects of *AluJb* overexpression,
especially as they relate to aging. Additionally, though we used IMR-90 embryonic fibroblasts
because of their frequent use as a model for studying senescence and aging, it would also be
informative to assess the effects of *Alu* overexpression in adult primary fibroblasts, which may
provide a more physiological environment to model the effects of elevated *Alu* expression with
age. Ultimately, we believe this study serves as a useful starting point – a proof-of-principle - for
the characterization of the relationship between transposon expression and aging.

RESOURCE AVAILABILITY

Lead contact

Further information and requests for resources and reagents should be directed to and will be fulfilled by the lead contact, Bérénice A. Benayoun (bbenayou@usc.edu).

Materials availability

The plasmids generated in this study, pUC19-U6 (ID: 240313) and pUC19-U6_AluJb (ID: 240314), are available through Addgene.

Data and code availability

- RNA-seq data have been deposited at the Sequence Read Archive (SRA) under BioProject PRJNA1008694.
- Raw data and complete mass spectrometry data sets have been uploaded to the Mass Spectrometry Interactive Virtual Environment (MassIVE) repository, developed by the Center for Computational Mass Spectrometry at the University of California San Diego, and can be downloaded using the following link: https://massive.ucsd.edu/ProteoSAFe/dataset.jsp?task=42e058c0f1244315aa9d3e61ad d4cdd3 (MassIVE ID number: MSV000097822; ProteomeXchange ID: PXD063739).
- Original DNA gel images, raw Agilent Seahorse data, and raw flow cytometry data have been deposited at Figshare at [DOI: 10.6084/m9.figshare.28928147].
- All scripts used to analyze the data in this manuscript are available on the Benayoun Lab GitHub at [https://github.com/BenayounLaboratory/AluJB_fibroblast_overexpression].
- Any additional information required to reanalyze the data reported in this paper is available from the lead contact upon request.

ACKNOWLEDGMENTS

This material is based upon work supported by the National Science Foundation Graduate Research Fellowship Program (NSF GRFP) under Grant No. DGE-1842487 (to J.I.B.), the National Institute on Aging (NIA) under Grant No. T32 AG052374 (to J.I.B.), the University of Southern California with a Provost Fellowship (to J.I.B.), and the National Institute of General Medical Sciences (NIGMS) under Grant No. R35 GM142395 (to B.A.B). This work was also made

possible by a pilot award under NIA grant P30 AG068345 (USC-Buck Institute Nathan Shock
Center of Excellence) and by the NIH-OD instrumentation grant S10 OD028654 (to B.S.) for the
Orbitrap Eclipse Tribrid mass spectrometry system.

We would like to thank Hemal Mehta at the USC Leonard Davis School of Gerontology
Seahorse Core for conducting the seahorse assays. We are saddened by the passing of Dr.
Judith Campisi and gratefully acknowledge her valuable contribution to this work.

Some artwork was taken from NIAID NIH BIOART Source (bioart.niaid.nih.gov) or from
Bioicons (bioicons.com).

AUTHOR CONTRIBUTIONS

Juan I. Bravo: Conceptualization, Data curation, Investigation, Formal analysis, Visualization,
Writing – original draft (co-lead), Writing – review & editing. **Eyael Tewelde:** Investigation, Formal
analysis, Writing – review & editing (co-lead). **Christina D. King:** Investigation, Formal analysis,
Writing – original draft, Writing – review & editing. **Joanna Bons:** Investigation, Formal analysis,
Writing – original draft, Writing – review & editing. **Samah Shah:** Investigation, Writing – review
& editing. **Jacob Rose:** Investigation, Writing – review & editing. **Judith
Campisi:** Conceptualization. **Birgit Schilling:** Conceptualization, Formal analysis, Writing –
original draft, Writing – review & editing, Supervision, Funding acquisition. **Bérénice A.
Benayoun:** Conceptualization, Data curation, Formal analysis, Visualization, Writing – original
draft (co-lead), Writing – review & editing (co-lead), Supervision, Funding acquisition.

DECLARATION OF INTERESTS

560   The authors declare that they have no competing interests. The content is solely the
561 responsibility of the authors and does not necessarily represent the official views of the National
562 Institutes of Health.

SUPPLEMENTAL INFORMATION

Document S1. Supplementary Figures S1–S6 and Supplementary Tables S1-S5

Figure 1. Aging upregulates repetitive elements, including *Alu* transposons, in primary human fibroblasts.

(A) A diagram illustrating the transcriptomic time course analysis carried out using a publicly-available mRNA-sequencing dataset (GSE113957) for N = 76 aging primary human fibroblasts. **(B)** Gene expression heatmap for significant (FDR < 0.05) differentially expressed repeat subfamilies across age. **(C)** Scatterplots for the library size-normalized counts across age for the total *AluJb* subfamily expression, the *AluJb* subfamily expression from intergenic loci within 5 kilobases from a gene, and the *AluJb* subfamily expression from loci overlapping gene exons. All three differential expression results were significant at an FDR < 0.05. Differential gene expression analysis across total endogenous *AluJb* expression was carried out, followed by gene set enrichment analysis, and the top 5 significant (FDR < 0.05) **(D)** GO Biological Process and **(E)** Reactome pathway gene sets were plotted. FDR: False Discovery Rate.

Figure 2. *AluJb* promotes widespread transcriptional and proteomic remodeling.

(A) A diagram illustrating how control and *AluJb* overexpressing IMR-90 fibroblast samples were prepared for multi-omic profiling. N = 5 replicates were independently transfected per group, and N = 4 replicates were analyzed by mRNA-sequencing, N = 5 replicates were analyzed by cellular proteomic profiling, and N = 4 replicates were analyzed by secretome profiling. Multidimensional scaling (MDS) analysis of the **(B)** genic transcriptome, **(C)** cellular proteome, and **(D)** secretome. Abundance heatmaps for significant **(E)** differentially expressed genes (FDR < 0.05), **(F)** differentially abundant cellular proteins (Q < 5% and abs($\log_2$FC) > 0.20), and **(G)** differentially secreted proteins (Q < 5% and abs($\log_2$FC) > 0.58). FDR: False Discovery Rate, Q: Q-value. See also Figure S1 and S2.

Figure 3. *AluJb* overexpression elicits aging- and senescence-associated molecular alterations.

(A) A diagram illustrating how *AluJb*-induced multi-omic changes and either senescence- or aging-induced features were compared. Mosaic plots showing the fraction of core SASP factors found among significant and non-significant *AluJb*-induced **(B)** mRNAs, **(C)** cellular proteins, and **(D)** secreted proteins. Statistical significance of frequency differences was assessed with Fisher's exact test, and p < 0.05 was considered significant. GSEA analysis with gene sets for

senescence- and aging-induced features in the *AluJb* **(E)** transcriptome, **(F)** cellular proteome, and **(G)** secretome. Gene sets with FDR < 0.05 were considered significant. SASP: Senescence-Associated Secretory Phenotype, FDR: False Discovery Rate, NES: Normalized Enrichment Score. See also Figure S3.

Figure 4. *AluJb* drives molecular changes in mitochondrial, proteostasis, cell cycle, and extracellular matrix pathways.

(A) A diagram illustrating how functional annotations were assigned to transcriptomic and proteomic changes with gene set enrichment analysis. The top 5 significant (FDR < 0.05) GO Biological Process gene sets in the **(B)** transcriptome, **(C)** cellular proteome, and **(D)** secretome were plotted. The top 5 significant (FDR < 0.05) Reactome pathway gene sets in the **(E)** transcriptome, **(F)** cellular proteome, and **(G)** secretome were also plotted. FDR: False Discovery Rate, NES: Normalized Enrichment Score. See also Figure S4.

Figure 5. *AluJb* overexpression leads to disruption of transcription factor regulons and predicted PPI networks.

(A) A diagram illustrating how the effects of *AluJb* on IMR-90 transcriptional networks was assessed. **(B)** Significantly (p < 0.05) enriched or depleted transcription factor regulons were identified with decoupleR, and the top 5 by magnitude were plotted. **(C)** Significant (FDR < 0.05) differentially expressed genes were used to construct a combined protein-protein interaction (PPI) and signaling network with NetworkAnalyst. The most populated subnetwork is shown. Blue nodes represent downregulated genes, and red nodes represent upregulated genes. FDR: False Discovery Rate.

Figure 6. Multi-omic integration highlights alterations in extracellular, proteostasis, and metabolic pathways.

(A) A diagram illustrating how transcriptome, proteome, and secretome changes were integrated via multi-contrast gene set enrichment analysis. **(B)** Venn diagram comparing individual genes and proteins that significantly changed in each "-omics" analysis. Highlighted are four genes and corresponding protein products—*DCN, NES, POSTN*, and *DBI*—that were altered in all three "-omics" layers. The top 25 multi-contrast gene set enrichment results using **(C)** GO Biological

Process and **(E)** Reactome pathway gene sets. Gene sets with an adjusted MANOVA p-value <

0.05 were considered significant. Violin plots for select **(D)** GO Biological Process and **(F)**

Reactome pathway gene sets related to recurring pathway themes are shown. See also Figure

S5.

Figure 7. *AluJb*-induced functional alterations mirror molecular alterations and are

consistent with disruption of aging hallmarks.

(A) A diagram illustrating how the functional effects of *AluJb* overexpression were assessed. **(B)**

A representative oxygen consumption rate time course from one experiment with N = 6 per group.

Points represent means at each timepoint, and error bars represent the standard error of the

mean. Two experiments, with a total of N = 12 per group, were used to calculate several OCR

sub-metrics, including basal OCR and maximal OCR. Statistical significance was assessed with

a Wilcoxon rank sum test, and $p < 0.05$ was considered significant. **(C)** A representative

extracellular acidification rate time course from one of the aforementioned experiments. Points

represent means at each timepoint, and error bars represent the standard error of the mean. Both

experiments were used to calculate the resting ECAR, and statistical significance was assessed

with a Wilcoxon rank sum test. **(D)** Representative flow cytometry histograms for propidium iodide-

stained control and *AluJb* overexpressing cells. Three experiments were combined, for a total of

N = 18 per group, and the relative number of cells in G0/G1, S, and G2/M phases in the control

and overexpression group were compared with a Wilcoxon rank sum test. $p < 0.05$ was

considered significant. **(E)** Representative flow cytometry histograms for Proteostat-stained

control and *AluJb* overexpressing cells. Four experiments were combined, for a total of N = 24

per group, and the relative median fluorescence intensities between the control and

overexpression groups were compared with a Wilcoxon rank sum test. $p < 0.05$ was considered

significant. **(F)** A diagram summarizing the findings from this study as they relate to the hallmarks

of aging. OCR: Oxygen Consumption Rate, ECAR: Extracellular Acidification Rate, MFI: Median

Fluorescence Intensity. See also Figure S6.

Figure 1

A Scheme for assessing age-related transcriptomic changes in fibroblasts

20 - 96 years old

Obtain transcriptomic data for aging human primary fibroblasts (GSE113957)

Gene expression time course analysis using DESeq2

B Significant (FDR 5%) differentially expressed repeat subfamilies across age

Gene expression z-score

Age
20s
30s
40s
50s
60s
70s
80s
90s

Repeat Class
DNA
LINE
LTR
Other
SINE

395 increase and 33 decrease

C AluJb subfamily expression across age

Total AluJb Expression
FDR = 1.02E-2

Intergenic (near genes) AluJb Expression
FDR = 2.03E-5

Exon-overlapping AluJb Expression
FDR = 7.52E-3

D GSEA across AluJb expression using GO Biological Process terms

Connective tissue development
Developmental growth
Homophilic cell adhesion via plasma membrane adhesion molecules
Chondrocyte differentiation
Epithelial cell proliferation
Ribosome biogenesis
Ribonucleoprotein complex biogenesis
rRNA metabolic process
rRNA processing
mRNA processing

NES
6
3
0
-3
-6

$-\log_{10}$(FDR)
10
20
30
40

E GSEA across AluJb expression using Reactome pathway gene sets

Extracellular matrix organization
O-glycosylation of TSR domain-containing proteins
Non-integrin membrane-ECM interactions
Defective B3GALTL causes PpS
Signaling by FLT3 fusion proteins
Translation
Cell Cycle, Mitotic
Processing of Capped Intron-Containing Pre-mRNA
M Phase
mRNA Splicing

NES
6
3
0
-3
-6

$-\log_{10}$(FDR)
10
20
30
40

Figure 2

A Scheme for assessing the molecular effects of AluJb overexpression

Extract plasmid DNA → Electroporation of IMR-90 fibroblasts → 24 hr. Recovery Standard Media → Re-seed fibroblasts at equal densities and begin experiment → 48 hrs. Low serum → 24 hrs. No serum or phenol-red → Carry out cellular transcriptomics/ proteomics and secretomics

Multidimensional scaling of transcriptomic and proteomic data

B Gene mRNA-seq

C Cellular Proteomics

D Secretomics

Empty, AluJb OE

Heatmaps of significantly altered genes and proteins

E Gene mRNA-seq
107 Up and 102 Down Genes
FDR < 5%

F Cellular Proteomics
62 Up and 57 Down Proteins
Q < 5% and abs(log₂FC) > 0.20

G Secretomics
871 Up and 8 Down Proteins
Q < 5% and abs(log₂FC) > 0.58

Gene expression z-score
2
1
0
−1
−2

Treatment
Empty
AluJb OE

Figure 3

A Scheme for assessing whether aging- and senescence-associated genes are impacted by Alu overexpression

Obtain differential gene/protein expression results for
AluJb overexpressing fibroblasts (Figure 2)

Mosaic plots and gene set enrichment analysis using clusterProfiler

Mosaic plots comparing core SASP factors (Basisty *et al.*, PLOS Biology) and Alu-induced changes

GSEA of aging- and senescence-associated genes in AluJb overexpressing fibroblasts

Figure 4

A Functional annotation of AluJb induced transcriptomic and proteomic changes

Differential gene/protein expression analysis → Rank genes/proteins using a summary statistic → Gene set enrichment analysis using clusterProfiler

GSEA using GO Biological Process terms

B Transcriptomics

Homophilic cell adhesion via plasma membrane adhesion molecules
Cell-cell adhesion via plasma-membrane adhesion molecules
Regulation of small GTPase-mediated signal transduction
Cell junction organization
Cell junction assembly
Cytoplasmic translation
Aerobic respiration
Cellular respiration
Energy derivation by oxidation of organic compounds
Generation of precursor metabolites and energy

C Cellular Proteomics

Regulation of phosphatase activity
Cell cycle G2/M phase transition
Protein dephosphorylation
Regulation of phosphoprotein phosphatase activity
Regulation of dephosphorylation
Tumor necrosis factor superfamily cytokine production

D Secretomics

Anatomical structure formation involved in morphogenesis
Response to transforming growth factor beta
Response to endogenous stimulus
Response to acid chemical
Cellular response to acid chemical
rRNA processing

GSEA using Reactome pathway gene sets

E

Extracellular matrix organization
RAC1 GTPase cycle
Laminin interactions
Integrin cell surface interactions
FASTK family proteins regulate processing and stability of mitochondrial RNAs
Eukaryotic Translation Elongation
Peptide chain elongation
Viral mRNA Translation
Eukaryotic Translation Termination
Selenocysteine synthesis

F

No significant pathways

G

Extracellular matrix organization
Degradation of the extracellular matrix
Integrin cell surface interactions
ECM proteoglycans
Collagen degradation
Activated PKN1 stimulates transcription of AR (androgen receptor) regulated genes KLK2 and KLK3
Assembly of the ORC complex at the origin of replication
Base−Excision Repair, AP Site Formation
Chromatin modifications during the maternal to zygotic transition (MZT)
Cleavage of the damaged purine

Figure 5

A Identification of AluJb altered gene modules

Genes/Repeats

Samples

Differential gene expression analysis

TF1
TF2
TF3
TF4

Transcription factor regulon analysis with decoupleR and gene network construction with NetworkAnalyst

B Top enriched TF regulons by decoupleR score

SNAI2
HOXB7
PRRX1
TWIST2
TRPS1
TTF1
ZBTB4
KDM5A
HSF1
ETV5
CXXC1
ZNF300

decoupleR score

−2 −1 0 1 2

C Protein-protein interaction and signaling network

NBR1
GDNF
MAPK3
F3
RAP1GDS1
SCN5A
NDUFA1
ND6
NDUFA4
STAT6
ND2
ND5
ND4
CDK5
PB28 dihydrochloride
MECP2
ATP6
RPS25
RPL36AL
POLR1A
WDR36

Figure 6

A Scheme for cross-integrating the multi-omic data

Load AluJb overexpression summary differential gene/protein expression results (Figure 2)

Multi-contrast gene set enrichment analysis with mitch

B Venn diagram for individual significant genes/proteins across -omic analyses

DCN
NES
POSTN
DBI

C Mitch results for top GO Biological Process terms

D Violin plots for the distribution of GO Biological Process term members

E Mitch results for top Reactome pathway gene sets

F Violin plots for the distribution of Reactome gene set members

Figure 7

A Scheme for assessing the effects of AluJb overexpression on cell function

Extract plasmid DNA — Electroporation of IMR-90 fibroblasts — Re-seed fibroblasts at equal densities and begin experiment — Functional assays

Cell Mito Stress Test

PI Cell Cycle
ProteoStat Aggresome

B Oxygen consumption rate (OCR) time course and sub-metrics

C Extracellular acidification rate (ECAR) time course

D Propidium iodide-based cell cycle phase proportions

E Comparison of Proteostat aggresome MFI

F Relationship between *AluJb* and the Hallmarks of Aging

Primary Hallmarks
Cause of damage

Antagonistic Hallmarks
Responses to damage

Transcriptome Evidence
Proteome Evidence
Secretome Evidence

Experimental Validation

Integrative Hallmarks
Manifest the aging phenotype

REFERENCES

Ardeljan, D., Steranka, J.P., Liu, C., Li, Z., Taylor, M.S., Taylor, M.S., Payer, L.M., Gorbounov, M., Sarnecki, J.S., Deshpande, V., *et al.* (2020). Cell fitness screens reveal a conflict between LINE-1 retrotransposition and DNA replication. Nat Struct Mol Biol *27*, 168-178.

Avelar, R.A., Ortega, J.G., Tacutu, R., Tyler, E.J., Bennett, D., Binetti, P., Budovsky, A., Chatsirisupachai, K., Johnson, E., Murray, A., *et al.* (2020). A multidimensional systems biology analysis of cellular senescence in aging and disease. Genome Biology *21*, 91.

Badia-i-Mompel, P., Vélez Santiago, J., Braunger, J., Geiss, C., Dimitrov, D., Müller-Dott, S., Taus, P., Dugourd, A., Holland, C.H., Ramirez Flores, R.O., *et al.* (2022). decoupleR: ensemble of computational methods to infer biological activities from omics data. Bioinformatics Advances *2*.

Bao, W., Kojima, K.K., and Kohany, O. (2015). Repbase Update, a database of repetitive elements in eukaryotic genomes. Mobile DNA *6*, 11.

Basisty, N., Kale, A., Jeon, O.H., Kuehnemann, C., Payne, T., Rao, C., Holtz, A., Shah, S., Sharma, V., Ferrucci, L., *et al.* (2020). A proteomic atlas of senescence-associated secretomes for aging biomarker development. PLOS Biology *18*, e3000599.

Benayoun, B.A., Pollina, E., Singh, P.P., Mahmoudi, S., Harel, I., Casey, K., Dulken, B., Kundaje, A., and Brunet, A. (2018). Remodeling of epigenome and transcriptome landscapes with aging in mice reveals widespread induction of inflammatory responses. bioRxiv, 336172.

Bennett, E.A., Keller, H., Mills, R.E., Schmidt, S., Moran, J.V., Weichenrieder, O., and Devine, S.E. (2008). Active Alu retrotransposons in the human genome. Genome research *18*, 1875-1883.

Blair, L.P., Cao, J., Zou, M.R., Sayegh, J., and Yan, Q. (2011). Epigenetic Regulation by Lysine Demethylase 5 (KDM5) Enzymes in Cancer. Cancers (Basel) *3*, 1383-1404.

Bravo, J.I., Mizrahi, C.R., Kim, S., Zhang, L., Suh, Y., and Benayoun, B.A. (2024). An eQTL-based approach reveals candidate regulators of LINE-1 RNA levels in lymphoblastoid cells. PLOS Genetics *20*, e1011311.

Bravo, J.I., Nozownik, S., Danthi, P.S., and Benayoun, B.A. (2020). Transposable elements, circular RNAs and mitochondrial transcription in age-related genomic regulation. Development *147*.

Bruderer, R., Bernhardt, O.M., Gandhi, T., Xuan, Y., Sondermann, J., Schmidt, M., Gomez-Varela, D., and Reiter, L. (2017). Optimization of Experimental Parameters in Data-Independent Mass Spectrometry Significantly Increases Depth and Reproducibility of Results. Molecular & cellular proteomics : MCP *16*, 2296-2309.

Bujisic, B., Lee, H.-G., Xu, L., Weissbein, U., Rivera, C., Topisirovic, I., and Lee, J.T. (2025). 7SL
RNA and signal recognition particle orchestrate a global cellular response to acute thermal stress.
Nature Communications *16*, 1630.

Burger, T. (2018). Gentle Introduction to the Statistical Foundations of False Discovery Rate in
Quantitative Proteomics. Journal of Proteome Research *17*, 12-22.

Cantarella, S., Carnevali, D., Morselli, M., Conti, A., Pellegrini, M., Montanini, B., and Dieci, G.
(2019). Alu RNA Modulates the Expression of Cell Cycle Genes in Human Fibroblasts. Int J Mol
Sci *20*.

Chen, H., Zheng, X., Xiao, D., and Zheng, Y. (2016). Age-associated de-repression of
retrotransposons in the Drosophila fat body, its potential cause and consequence. Aging Cell *15*,
542-552.

Chen, S., Zhou, Y., Chen, Y., and Gu, J. (2018). fastp: an ultra-fast all-in-one FASTQ
preprocessor. Bioinformatics *34*, i884-i890.

Collins, B.C., Hunter, C.L., Liu, Y., Schilling, B., Rosenberger, G., Bader, S.L., Chan, D.W.,
Gibson, B.W., Gingras, A.-C., Held, J.M.*, et al.* (2017). Multi-laboratory assessment of
reproducibility, qualitative and quantitative performance of SWATH-mass spectrometry. Nature
communications *8*, 291-291.

De Cecco, M., Criscione, S.W., Peckham, E.J., Hillenmeyer, S., Hamm, E.A., Manivannan, J.,
Peterson, A.L., Kreiling, J.A., Neretti, N., and Sedivy, J.M. (2013a). Genomes of replicatively
senescent cells undergo global epigenetic changes leading to gene silencing and activation of
transposable elements. Aging Cell *12*, 247-256.

De Cecco, M., Criscione, S.W., Peterson, A.L., Neretti, N., Sedivy, J.M., and Kreiling, J.A.
(2013b). Transposable elements become active and mobile in the genomes of aging mammalian
somatic tissues. Aging (Albany NY) *5*, 867-883.

De Cecco, M., Ito, T., Petrashen, A.P., Elias, A.E., Skvir, N.J., Criscione, S.W., Caligiana, A.,
Brocculi, G., Adney, E.M., Boeke, J.D.*, et al.* (2019). L1 drives IFN in senescent cells and
promotes age-associated inflammation. Nature *566*, 73-78.

Dennis, S., Sheth, U., Feldman, J.L., English, K.A., and Priess, J.R. (2012). C. elegans Germ
Cells Show Temperature and Age-Dependent Expression of Cer1, a Gypsy/Ty3-Related
Retrotransposon. PLOS Pathogens *8*, e1002591.

Dewannieux, M., Esnault, C., and Heidmann, T. (2003). LINE-mediated retrotransposition of
marked Alu sequences. Nature Genetics *35*, 41-48.

Di Ruocco, F., Basso, V., Rivoire, M., Mehlen, P., Ambati, J., De Falco, S., and Tarallo, V. (2018).
Alu RNA accumulation induces epithelial-to-mesenchymal transition by modulating miR-566 and
is associated with cancer progression. Oncogene *37*, 627-637.

Dobin, A., Davis, C.A., Schlesinger, F., Drenkow, J., Zaleski, C., Jha, S., Batut, P., Chaisson, M.,
and Gingeras, T.R. (2012). STAR: ultrafast universal RNA-seq aligner. Bioinformatics *29*, 15-21.

Escher, C., Reiter, L., MacLean, B., Ossola, R., Herzog, F., Chilton, J., MacCoss, M.J., and
Rinner, O. (2012). Using iRT, a normalized retention time for more targeted measurement of
peptides. Proteomics *12*, 1111-1121.

Fleischer, J.G., Schulte, R., Tsai, H.H., Tyagi, S., Ibarra, A., Shokhirev, M.N., Huang, L., Hetzer,
M.W., and Navlakha, S. (2018). Predicting age from the transcriptome of human dermal
fibroblasts. Genome Biology *19*, 221.

Frankish, A., Diekhans, M., Ferreira, A.-M., Johnson, R., Jungreis, I., Loveland, J., Mudge, J.M.,
Sisu, C., Wright, J., Armstrong, J.*, et al.* (2018). GENCODE reference annotation for the human
and mouse genomes. Nucleic Acids Research *47*, D766-D773.

Gao, Z., Herrera-Carrillo, E., and Berkhout, B. (2018). Delineation of the Exact Transcription
Termination Signal for Type 3 Polymerase III. Molecular Therapy - Nucleic Acids *10*, 36-44.

Gillet, L.C., Navarro, P., Tate, S., Röst, H., Selevsek, N., Reiter, L., Bonner, R., and Aebersold,
R. (2012). Targeted data extraction of the MS/MS spectra generated by data-independent
acquisition: a new concept for consistent and accurate proteome analysis. Molecular & cellular
proteomics : MCP *11*, O111.016717-O016111.016717.

Guo, C., Jeong, H.-H., Hsieh, Y.-C., Klein, H.-U., Bennett, D.A., De Jager, P.L., Liu, Z., and
Shulman, J.M. (2018). Tau Activates Transposable Elements in Alzheimer's Disease.
Cell Reports *23*, 2874-2880.

Iskow, R.C., McCabe, M.T., Mills, R.E., Torene, S., Pittard, W.S., Neuwald, A.F., Van Meir, E.G.,
Vertino, P.M., and Devine, S.E. (2010). Natural Mutagenesis of Human Genomes by Endogenous
Retrotransposons. Cell *141*, 1253-1261.

Jia, K., Cui, C., Gao, Y., Zhou, Y., and Cui, Q. (2018). An analysis of aging-related genes derived
from the Genotype-Tissue Expression project (GTEx). Cell Death Discovery *4*, 91.

Jin, Y., Tam, O.H., Paniagua, E., and Hammell, M. (2015). TEtranscripts: a package for including
transposable elements in differential expression analysis of RNA-seq datasets. Bioinformatics *31*,
3593-3599.

Kaspi, A., and Ziemann, M. (2020). mitch: multi-contrast pathway enrichment for multi-omics and
single-cell profiling data. BMC Genomics *21*, 447.

Kerur, N., Fukuda, S., Banerjee, D., Kim, Y., Fu, D., Apicella, I., Varshney, A., Yasuma, R., Fowler,
B.J., Baghdasaryan, E.*, et al.* (2017). cGAS drives noncanonical-inflammasome activation in age-
related macular degeneration. Nature Medicine *24*, 50.

Kidwell, M.G. (2002). Transposable elements and the evolution of genome size in eukaryotes.
Genetica *115*, 49-63.

Kiuchi, M., Onodera, A., Kokubo, K., Ichikawa, T., Morimoto, Y., Kawakami, E., Takayama, N.,
Eto, K., Koseki, H., Hirahara, K.*, et al.* (2021). The Cxxc1 subunit of the Trithorax complex directs
epigenetic licensing of CD4+ T cell differentiation. J Exp Med *218*.

Kroemer, G., Maier, A.B., Cuervo, A.M., Gladyshev, V.N., Ferrucci, L., Gorbunova, V., Kennedy,
B.K., Rando, T.A., Seluanov, A., Sierra, F.*, et al.* (2025). From geroscience to precision
geromedicine: Understanding and managing aging. Cell *188*, 2043-2062.

Lander, E.S., Linton, L.M., Birren, B., Nusbaum, C., Zody, M.C., Baldwin, J., Devon, K., Dewar,
K., Doyle, M., FitzHugh, W.*, et al.* (2001). Initial sequencing and analysis of the human genome.
Nature *409*, 860-921.

LaRocca, T.J., Cavalier, A.N., and Wahl, D. (2020). Repetitive elements as a transcriptomic
marker of aging: Evidence in multiple datasets and models. Aging Cell *19*, e13167.

Lee, K.-W., Yeo, S.-Y., Gong, J.-R., Koo, O.-J., Sohn, I., Lee, W.Y., Kim, H.C., Yun, S.H., Cho,
Y.B., Choi, M.-A.*, et al.* (2022). PRRX1 is a master transcription factor of stromal fibroblasts for
myofibroblastic lineage progression. Nature Communications *13*, 2793.

Li, W., Prazak, L., Chatterjee, N., Grüninger, S., Krug, L., Theodorou, D., and Dubnau, J. (2013).
Activation of transposable elements during aging and neuronal decline in Drosophila. Nature
neuroscience *16*, 529.

Liberzon, A., Birger, C., Thorvaldsdóttir, H., Ghandi, M., Mesirov, J.P., and Tamayo, P. (2015).
The Molecular Signatures Database (MSigDB) hallmark gene set collection. Cell Syst *1*, 417-425.

Love, M.I., Huber, W., and Anders, S. (2014). Moderated estimation of fold change and dispersion
for RNA-seq data with DESeq2. Genome Biology *15*, 550.

Luca, C.D., Guadagni, F., Sinibaldi-Vallebona, P., Sentinelli, S., Gallucci, M., Hoffmann, A.,
Schumann, G.G., Spadafora, C., and Sciamanna, I. (2015). Enhanced expression of LINE-1-
encoded ORF2 protein in early stages of colon and prostate transformation. Oncotarget *7*.

Mao, Z., Feng, M., Li, Z., Zhou, M., Xu, L., Pan, K., Wang, S., Su, W., and Zhang, W. (2021).
ETV5 Regulates Hepatic Fatty Acid Metabolism Through PPAR Signaling Pathway. Diabetes *70*,
214-226.

Milacic, M., Beavers, D., Conley, P., Gong, C., Gillespie, M., Griss, J., Haw, R., Jassal, B.,
Matthews, L., May, B.*, et al.* (2023). The Reactome Pathway Knowledgebase 2024. Nucleic Acids
Research *52*, D672-D678.

Müller-Dott, S., Tsirvouli, E., Vazquez, M., Ramirez Flores, Ricardo O., Badia-i-Mompel, P.,
Fallegger, R., Türei, D., Lægreid, A., and Saez-Rodriguez, J. (2023). Expanding the coverage of
regulons from high-confidence prior knowledge for accurate estimation of transcription factor
activities. Nucleic Acids Research *51*, 10934-10949.

Neri, F., Basisty, N., Desprez, P.-Y., Campisi, J., and Schilling, B. (2021). Quantitative Proteomic
Analysis of the Senescence-Associated Secretory Phenotype by Data-Independent Acquisition.
Current Protocols *1*, e32.

Nyathi, Y., Wilkinson, B.M., and Pool, M.R. (2013). Co-translational targeting and translocation of
proteins to the endoplasmic reticulum. Biochimica et Biophysica Acta (BBA) - Molecular Cell
Research *1833*, 2392-2402.

Pabis, K., Barardo, D., Sirbu, O., Selvarajoo, K., Gruber, J., and Kennedy, B.K. (2024). A
concerted increase in readthrough and intron retention drives transposon expression during aging
and senescence. eLife *12*, RP87811.

Pincus, D. (2020). Regulation of Hsf1 and the Heat Shock Response. Adv Exp Med Biol *1243*,
41-50.

Ritchie, M.E., Phipson, B., Wu, D., Hu, Y., Law, C.W., Shi, W., and Smyth, G.K. (2015). limma
powers differential expression analyses for RNA-sequencing and microarray studies. Nucleic
Acids Research *43*, e47-e47.

Rodić, N., Sharma, R., Sharma, R., Zampella, J., Dai, L., Taylor, M.S., Hruban, R.H., Iacobuzio-
Donahue, C.A., Maitra, A., Torbenson, M.S.*, et al.* (2014). Long Interspersed Element-1 Protein
Expression Is a Hallmark of Many Human Cancers. The American Journal of Pathology *184*,
1280-1286.

Rubin, C.M., Houck, C.M., Deininger, P.L., Friedmann, T., and Schmid, C.W. (1980). Partial
nucleotide sequence of the 300-nucleotide interspersed repeated human DNA sequences. Nature
284, 372-374.

Sampathkumar, N.K., Bravo, J.I., Chen, Y., Danthi, P.S., Donahue, E.K., Lai, R.W., Lu, R.,
Randall, L.T., Vinson, N., and Benayoun, B.A. (2020). Widespread sex dimorphism in aging and
age-related diseases. Hum Genet *139*, 333-356.

Saul, D., Kosinsky, R.L., Atkinson, E.J., Doolittle, M.L., Zhang, X., LeBrasseur, N.K., Pignolo,
R.J., Robbins, P.D., Niedernhofer, L.J., Ikeno, Y.*, et al.* (2022). A new gene set identifies

senescent cells and predicts senescence-associated pathways across tissues. Nature
Communications *13*, 4827.

Subramanian, A., Tamayo, P., Mootha, V.K., Mukherjee, S., Ebert, B.L., Gillette, M.A., Paulovich,
A., Pomeroy, S.L., Golub, T.R., Lander, E.S*., et al.* (2005). Gene set enrichment analysis: A
knowledge-based approach for interpreting genome-wide expression profiles. Proceedings of the
National Academy of Sciences *102*, 15545-15550.

Sun, W., Samimi, H., Gamez, M., Zare, H., and Frost, B. (2018). Pathogenic tau-induced piRNA
depletion promotes neuronal death through transposable element dysregulation in
neurodegenerative tauopathies. Nature neuroscience *21*, 1038-1048.

Ullu, E., and Tschudi, C. (1984). Alu sequences are processed 7SL RNA genes. Nature *312*, 171-
172.

Venter, J.C., Adams, M.D., Myers, E.W., Li, P.W., Mural, R.J., Sutton, G.G., Smith, H.O., Yandell,
M., Evans, C.A., Holt, R.A*., et al.* (2001). The Sequence of the Human Genome. Science *291*,
1304-1351.

Vogel, C., and Marcotte, E.M. (2012). Insights into the regulation of protein abundance from
proteomic and transcriptomic analyses. Nature Reviews Genetics *13*, 227-232.

Wallace, N., Wagstaff, B.J., Deininger, P.L., and Roy-Engel, A.M. (2008). LINE-1 ORF1 protein
enhances Alu SINE retrotransposition. Gene *419*, 1-6.

Walter, P., and Blobel, G. (1982). Signal recognition particle contains a 7S RNA essential for
protein translocation across the endoplasmic reticulum. Nature *299*, 691-698.

Wang, J., Geesman, G.J., Hostikka, S.L., Atallah, M., Blackwell, B., Lee, E., Cook, P.J., Pasaniuc,
B., Shariat, G., Halperin, E*., et al.* (2011). Inhibition of activated pericentromeric SINE/Alu repeat
transcription in senescent human adult stem cells reinstates self-renewal. Cell Cycle *10*, 3016-
3030.

Wild, K., Weichenrieder, O., Strub, K., Sinning, I., and Cusack, S. (2002). Towards the structure
of the mammalian signal recognition particle. Current Opinion in Structural Biology *12*, 72-81.

Wood, J.G., Jones, B.C., Jiang, N., Chang, C., Hosier, S., Wickremesinghe, P., Garcia, M.,
Hartnett, D.A., Burhenn, L., Neretti, N*., et al.* (2016). Chromatin-modifying genetic interventions
suppress age-associated transposable element activation and extend life span in
Drosophila. Proceedings of the National Academy of Sciences *113*, 11277-11282.

Wu, T., Hu, E., Xu, S., Chen, M., Guo, P., Dai, Z., Feng, T., Zhou, L., Tang, W., Zhan, L*., et al.*
(2021). clusterProfiler 4.0: A universal enrichment tool for interpreting omics data. The Innovation
2, 100141.

Xia, J., Benner, M.J., and Hancock, R.E.W. (2014). NetworkAnalyst - integrative approaches for

protein–protein interaction network analysis and visual exploration. Nucleic Acids Research *42*,

W167-W174.

Xia, J., Gill, E.E., and Hancock, R.E.W. (2015). NetworkAnalyst for statistical, visual and network-

based meta-analysis of gene expression data. Nature Protocols *10*, 823-844.

Yamada, K., Kaneko, H., Shimizu, H., Suzumura, A., Namba, R., Takayama, K., Ito, S., Sugimoto,

M., and Terasaki, H. (2020). Lamivudine Inhibits Alu RNA-induced Retinal Pigment Epithelium

Degeneration via Anti-inflammatory and Anti-senescence Activities. Translational Vision Science

& Technology *9*, 1-1.

Zhou, G., Soufan, O., Ewald, J., Hancock, R.E.W., Basu, N., and Xia, J. (2019). NetworkAnalyst

3.0: a visual analytics platform for comprehensive gene expression profiling and meta-analysis.

Nucleic Acids Research *47*, W234-W241.

STAR★METHODS

KEY RESOURCES TABLE

REAGENT OR RESOURCE	SOURCE	IDENTIFIER
Bacterial and virus strains		
NEB Turbo Competent *E. coli*	New England Biolabs	C2984H
Chemicals, peptides, and recombinant proteins		
Propidium Iodide	Alfa Aesar	J66584
PureLink RNase A	Invitrogen	12091021
Triton X-100	MP	194854
Critical commercial assays		
Seahorse XF Cell Mito Stress Test Kit	Agilent	103015-100
Seahorse XF Pro M Cell Culture Microplate	Agilent	103774-100
Seahorse XF Base Medium	Agilent	102353-100
PROTEOSTAT Aggresome Detection Kit	Enzo	ENZ-51035-K100
Deposited data		
GRCh38 GENCODE release 44 annotations	(Frankish et al., 2018)	
Aging human primary fibroblast mRNA-seq	(Fleischer et al., 2018)	GSE113957
IMR-90 *AluJb* overexpression mRNA-seq	This study	PRJNA1008694

IMR-90 *AluJb* overexpression MS data	This study	MassIVE ID: MSV000097822; ProteomeXchange ID: PXD063739
IMR-90 *AluJb* overexpression functional data	This study	Figshare DOI: 10.6084/m9.figshare.28928147
IMR-90 *AluS* stable overexpression gene set	(Cantarella et al., 2019)	
Gene Ontology (GO) Biological Process gene sets v2024.1.Hs	Molecular Signature Database	
Reactome v92 pathway gene sets	Reactome	
Core SASP factors gene set	(Basisty et al., 2020)	
SenMayo gene set	(Saul et al., 2022)	
CellAge build 3 gene sets	(Avelar et al., 2020)	
GTEx aging-associated genes	(Jia et al., 2018)	
Experimental models: Cell lines		
IMR-90 (received at Passage 4 with PDL 9.74)	Coriell Institute	I90-83; RRID: CVCL_0347
Oligonucleotides		
TAAGCA_HindIII_U6_For 5'-TAAGCAAAGCTTgagggcctatttcccatgattcct-3'	This study	

TAAGCA_EcoRI_U6_R 5'-TAAGCAGAATTCgtcctttccacaagatatataaag-3'	This study	
AluJB_exten_U6_R 5'-ccgcgcccggcCgtcctttccacaagatatataaag-3'	This study	
U6_exten_AluJB_F 5'-ctttatatatcttgtggaaaggacGgccgggcgcgg-3'	This study	
TAAGCA_EcoRI_5T_AluJB_R 5'-TAAGCAGAATTCaaaaatgagacagggtctcgctctgt-3'	This study	
AluJb_qPCR4 F 5'-ACAAAAATTAGCCGGGCGTG-3' AluJb_qPCR4 R 5'-CAGGGTTTTCCCAGTCACGA-3'	This study	
Recombinant DNA		
pLKO.1 cloning vector	Addgene	RRID: Addgene_10878
pUC19 cloning vector	New England Biolabs	N3041S
pUC57_AluJb	This study	
pUC19-U6	This study	RRID: Addgene_240313

pUC19-U6_AluJb	This study	RRID: Addgene_240314
Software and algorithms		
R v4.3.3	R Foundation	
fastp v0.20.1	(Chen et al., 2018)	https://github.com/ OpenGene/fastp
fastqc v0.11.9	Simon Andrews	https://github.com/ s-andrews/FastQC
STAR v2.7.3a	(Dobin et al., 2012)	https://github.com/ alexdobin/STAR
TEtranscripts v2.1.4	(Jin et al., 2015)	https://github.com/ mhammell- laboratory/TEtrans cripts
TElocal v1.1.1	(Jin et al., 2015)	https://github.com/ mhammell- laboratory/TElocal
DESeq2 v1.42.1	(Love et al., 2014)	
Limma v3.58.1	(Ritchie et al., 2015).	
clusterProfiler v4.10.1	(Wu et al., 2021)	
mitch v1.14.0	(Kaspi and Ziemann, 2020)	https://github.com/ markziemann/mitc h
decoupleR v2.8.0	(Badia-i-Mompel et al., 2022)	

Other		
AccuPrime *Pfx* DNA polymerase	Invitrogen	12344024
Nucleospin Gel and PCR Cleanup Kit	Macherey-Nagel	740609.50
Quick Ligation Kit	NEB	M2200S
Minimum essential medium with Earle's salts without L-glutamine	Corning	15-010-CV
Fetal bovine serum	Sigma-Aldrich	F0926-500ML
Non-essential amino acids	Quality Biological	116-078-721
Penicillin-Streptomycin-Glutamine	Corning	30-009-CI
Dulbecco's phosphate-buffered saline	Corning	21-031-CV
0.25% trypsin	HyClone	95053-258
Minimum essential medium with Earle's salts without L-glutamine or phenol red	Corning	17-305-CV
Target2 0.45 μm polyvinylidene fluoride syringe filters	Thermo Scientific	F2500-5
0.05% trypsin	Corning	25-052-CI
Nucleobond Xtra Midi Plus EF kit	Macherey-Nagel	740422.50
Neon Transfection System 100 μL Kit	Invitrogen	MPK10096
Direct-zol RNA Miniprep kit	Zymo Research	R2052
Maxima H Minus cDNA Synthesis Master Mix with dsDNase	Thermo Scientific	M1682
MyTaq HS Red Mix	Meridian Bioscience	BIO-25048

 EXPERIMENTAL MODEL AND STUDY PARTICIPANT DETAILS

881 Cell lines and cell culture conditions

IMR-90 (Coriell cat. I90-83, RRID: CVCL_0347) human female embryonic fibroblast cells
were purchased from the Coriell Institute. Cells were maintained in Minimum Essential Medium
(MEM) containing Earle's salts (Corning cat. 15-010-CV), 15% fetal bovine serum (FBS, Sigma-
Aldrich cat. F0926-500ML), 1X non-essential amino acids (NEAA, Quality Biological cat. 116-078-
721), and 1X Penicillin-Streptomycin-Glutamine (Corning cat. 30-009-CI). Cells were cultured in
a humidified incubator at 37°C and 5% CO_2, subculturing cells 1:6 once they reached ~90%
confluency. All cells used were maintained below passage 30 and routinely tested for
mycoplasma contamination using the PlasmoTest Mycoplasma Detection Kit (InvivoGen). The
identity and purity of cells used in this study were verified using ATCC's Human Cell STR Profiling
Service (ATCC 135-XV).

METHOD DETAILS

894 Plasmid Construction

The empty pLKO.1 cloning vector, which contains the U6 promoter, was a gift from David
Root (Addgene plasmid #10878; http://n2t.net/addgene:10878; RRID: Addgene_10878). The
empty pUC19 cloning vector was purchased from New England Biolabs (NEB; cat. N3041S).

The *AluJb* overexpression construct was generated by overlap extension polymerase
chain reaction (PCR). To begin, the *AluJb* consensus sequence was obtained from Repbase (Bao
et al., 2015) and submitted to Genewiz for gene synthesis, yielding pUC57_AluJb. Next, the U6
promoter was amplified from pLKO.1 using primers TAAGCA_HindIII_U6_For and
AluJB_exten_U6_R, and *AluJb* was amplified from pUC57_AluJb using primers
U6_exten_AluJB_F and TAAGCA_EcoRI_5T_AluJB_R. Importantly, the *AluJb* amplification
primers introduced a stretch of 5 thymidine residues in the *AluJb* 3' terminal region to act as a
minimal RNA polymerase III termination signal (Gao et al., 2018). A first round of PCRs was
carried out using AccuPrime *Pfx* DNA polymerase (Invitrogen cat. 12344024) in a Biorad C1000
Touch Thermal Cycler with these steps: initial denaturation (95°C, 2 minutes) and 35 cycles of
denaturation (95°C, 15 seconds), annealing (55°C, 30 seconds), and extension (68°C, 60
seconds). The PCR products were run on an agarose gel, the amplicons of the expected size
were excised, and the DNA was purified using the Nucleospin Gel and PCR Cleanup Kit
(Macherey-Nagel item 740609.50). After, equimolar amounts of the U6 amplicon and the *AluJb*

amplicon were mixed together with *Pfx* DNA polymerase, in order to fuse the U6 promoter with

AluJb through a second round of PCRs (initial denaturation at 98°C for 30 seconds and 7 cycles

of denaturation at 98°C for 10 second, annealing at 72°C for 30 second, and extension at 72°C

for 15 seconds). An aliquot of the resulting PCR products was used as a template for a third round

of PCRs to amplify the final 541 base pair U6_AluJb fusion product using primers

TAAGCA_HindIII_U6_For and TAAGCA_EcoRI_5T_AluJB_R. This third set of PCRs was run

under the same conditions as the first round but only for 25 cycles and using an annealing

temperature of 60°C. Again, PCR products were run on an agarose gel and purified as before.

Then, the pUC19 backbone and purified U6_AluJb amplicon were both digested with HindIII-HF

and EcoRI-HF, the desired digestion products were purified from an agarose gel, and the

backbone and insert were ligated together using the Quick Ligation Kit (NEB cat. M2200S),

generating pUC19-U6_AluJb. NEB Turbo competent *Escherichia coli* (*E. coli*) (cat. C2984H) were

transformed with the ligation product using the manufacturer recommended high efficiency

transformation protocol. The final U6_AluJb fusion on the pUC19 backbone was sequence

verified using Sanger sequencing. For a control plasmid, we introduced only the U6 promoter onto

the pUC19 backbone (pUC19-U6) following the protocol outlined above with these modifications:

(i) the U6 promoter was amplified with primers TAAGCA_HindIII_U6_For and

TAAGCA_EcoRI_U6_R during the first PCRs and then gel-purified, and (ii) the second and third

PCRs were skipped since the promoter was not fused with any other amplicon. The U6 promoter

insert on the pUC19 backbone was also sequence verified using Sanger sequencing.

Transfections and sample collections for 'omics' analyses

E. coli were cultured in LB Broth (Thermo Fisher Scientific) supplemented with 50 μg/mL

carbenicillin to an optical density 600 (OD_{600}) of 2 – 4. Plasmid extractions were carried out using

the Nucleobond Xtra Midi Plus EF kit (Macherey-Nagel item no. 740422.50) following

manufacturer recommendations. Plasmids were aliquoted and stored at -20°C until the time of

transfection.

On the day of transfection, we washed IMR-90 fibroblasts twice with Dulbecco's

phosphate-buffered saline (DPBS, Corning cat. 21-031-CV), detached cells using 0.25% trypsin

(HyClone cat. 95053-258), neutralized the trypsin using a two-fold higher volume of media, spun

cells down (500xG, 5 minutes), resuspended cells in fresh media, and counted cells by trypan

blue staining using a Countess II FL automated cell counter (Thermo Fisher) or a CellDrop

Automated Cell Counter (DeNovix). The number of cells necessary for the experiment were then
aliquoted, spun down, and washed once with DPBS. Fibroblasts were transfected by
electroporation using the Neon Transfection System (Invitrogen) with the following parameters:
Buffer R for cell resuspension, 1500 V, 30 ms, and 1 pulse. Per reaction, we maintained a plasmid
mass : cell number ratio of 2.5 μg : 2*10^6 cells. We independently transfected 1.0 – 1.2 * 10^7
fibroblasts per 100 mm tissue culture-treated petri dish (GenClone cat. 25-202), preparing 1 – 2
dishes to be used for each biological replicate downstream. Immediately after transfection, cells
were cultured in Penicillin-Streptomycin-free media and allowed to recover from the
electroporation for ~24 hours. Since cell viability following electroporation exhibited plate-to-plate
variability, surviving cells were then detached by trypsinization, counted, and re-seeded at equal
densities across biological replicates and experimental conditions. We subsequently defined this
time point as "0 hours".

For paired transcriptomic and proteomic analyses, fibroblasts were prepared following
previously described guidelines for generating conditioned media from senescent cells and
quiescent control cells (Neri et al., 2021). We implemented this protocol because (i) we
hypothesized that *Alu* overexpression may induce senescence-associated changes, based on the
published literature, and (ii) this protocol utilizes serum deprivation to restrict proliferation in order
to isolate senescent versus non-senescent effects by eliminating non-proliferating vs proliferating
effects. More specifically, fibroblasts were independently re-seeded at a density of 6 * 10^6 cells
per 150 mm tissue culture-treated dish (Corning cat. 430599), with 5 biological replicates per
experimental group. Cells were cultured in 60 mL of 0.2% FBS media, which was replaced after
24 hours. At 48 hours, the media was removed, cells were washed twice with DPBS, and cells
were fed with 60 mL of FBS-free and phenol red-free MEM media (Corning cat. 17-305-CV)
containing Penicillin-Streptomycin-Glutamine and non-essential amino acids. At 72 hours,
supernatants were collected in conicals, conicals were spun down (4000xG, 5 minutes, 4°C) to
pellet cell debris, and supernatants were processed through Target2 0.45 μm polyvinylidene
fluoride (PVDF) syringe filters (Thermo Scientific cat. F2500-5) to remove any remaining cellular
debris. Filtered conditioned media was snap frozen in liquid nitrogen and stored at -80°C. Cells
were washed with DPBS and detached with 0.05% trypsin (Corning cat. 25-052-CI), trypsin was
neutralized with FBS-containing media, and cells were spun down. Cells were washed once with
FBS-free and phenol red-free media, spun down, and resuspended again in that same media.
Cell viability was assessed by trypan blue staining, ensuring that cell viability > 90% for all
samples, and each sample was aliquoted into two tubes, saving 40% of the cells for proteomic

analysis and 60% for transcriptomic analysis. Cells were spun down, the supernatants were
discarded, and the cell pellets were snap frozen in liquid nitrogen and stored at -80°C. Cellular
pellets for transcriptomic analysis were later lysed in TRIzol Reagent (Invitrogen) for downstream
total RNA isolation (see below).

To ensure that major *Alu*-induced pathway changes replicated in proliferating cells, we
prepared additional transcriptomic samples for IMR-90 fibroblasts overexpressing *AluJb* in
standard, serum-containing maintenance media. More specifically, fibroblasts were
independently transfected as before. Following recovery from the electroporation, fibroblasts were
independently re-seeded at a density of $2 - 3 * 10^6$ fibroblasts per 100 mm dish containing
maintenance media, with 4 biological replicates per experimental group. After 24 hours, cells were
lysed in TRIzol Reagent (Invitrogen) for downstream total RNA isolation (see below).

RNA extractions and mRNA sequencing

RNA was extracted using the Direct-zol RNA Miniprep kit (Zymo Research cat. R2052) following
manufacturer recommendations. To confirm *AluJb* overexpression, complementary DNA (cDNA)
was generated for each RNA sample using the Maxima H Minus cDNA Synthesis Master Mix with
dsDNase (Thermo Scientific cat. M1682), following manufacturer instructions and including
reverse transcriptase negative (RT-) controls. We verified plasmid-specific *AluJb* overexpression
by endpoint PCR using MyTaq HS Red Mix (Meridian Bioscience cat. BIO-25048) with primers
AluJb_qPCR4 forward/reverse and these PCR settings: initial denaturation (95°C, 1 minute) and
35 cycles of denaturation (95°C, 15 seconds), annealing (60°C, 15 seconds), and extension
(72°C, 10 seconds). We note that the primers used here were designed to specifically amplify the
AluJb copy on the overexpression plasmid by targeting the *AluJb* 3'end and the downstream
plasmid backbone sequence.

The integrity of RNA samples was evaluated using an Agilent High Sensitivity RNA
ScreenTape assay (Agilent Technologies). Of the 5 biological replicates per group in the paired
transcriptome/proteome experiment, the 4 samples with the highest eRIN scores, ranging
between 6.2 and 8.8, were selected for sequencing. In the follow-up experiment with standard
serum-containing media, all samples had an eRIN score > 9. We submitted total RNA samples to
Novogene (Sacramento, California) for unstranded mRNA library preparation and sequencing on
the NovaSeq 6000 platform as paired-end 150 bp reads. The raw FASTQ reads have been
deposited to SRA under BioProject PRJNA1008694.

1009

Protein digestion and desalting

Frozen cellular pellets and frozen conditioned media were shipped to the USC-Buck
Institute Nathan Shock Center Cellular Senescence and Beyond Core (CSBC) for proteomic
analysis. Conditioned media (30 mL per sample) from either empty vector (N=4) or *Alu*
overexpression (N=4) IMR-90 cultures were concentrated using 3 kDa molecular cut-off filters
(Millipore Sigma, Burlington, MA) and protein concentrations were determined using Bicinchoninic
Acid (BCA) assay (Thermo Fisher Scientific, Waltham, MA). Cell pellets from either empty vector
(N=5) or *Alu* overexpression (N=5) IMR-90 cultures were solubilized in 100 µL of 0.5% sodium
dodecyl sulfate (SDS) in 100 mM Triethylamonium bicarbonate (TEAB) with 1X protease inhibitor
cocktail (PIC). Protein concentrations were determined using BCA assay.

Samples originating from cell pellets (~100 µg) were brought to the same overall volume
of 100 µL with water, while secretome samples (~100 µg) were prepared directly. All samples
were reduced using 20 mM dithiothreitol in 50 mM TEAB at 50°C for 10 minutes, cooled to room
temperature (RT) and held at RT for 10 minutes, and alkylated using 40 mM iodoacetamide in 50
mM TEAB at RT in the dark for 30 minutes. Samples were acidified with 12% phosphoric acid to
obtain a final concentration of 1.2% phosphoric acid. S-Trap buffer consisting of 90% methanol in
100 mM TEAB at pH ~7.1 was added and samples were loaded onto S-Trap mini spin columns
(Protifi). The entire sample volume was spun through the S-Trap mini spin columns at 4,000 x g
and RT, binding the proteins to the micro spin columns. Subsequently, S-Trap micro spin columns
were washed twice with S-Trap buffer at 4,000 x g and RT and placed into clean elution tubes.
Samples were incubated for one-hour at 47°C with sequencing grade trypsin (Promega, San Luis
Obispo, CA) dissolved in 50 mM TEAB at a 1:25 (w/w) enzyme:protein ratio. An additional aliquot
of trypsin dissolved in 50 mM TEAB was added and samples were digested overnight at 37°C.

Peptides were sequentially eluted from mini S-Trap spin columns with 50 mM TEAB, 0.5%
formic acid (FA) in water, and 50% acetonitrile (ACN) in 0.5% FA. After centrifugal evaporation,
samples were resuspended in 0.2% FA in water and desalted with Oasis 10-mg Sorbent
Cartridges (Waters, Milford, MA). The desalted elutions were then subjected to an additional
round of centrifugal evaporation and re-suspended in 0.1% FA in water at a final concentration of
1 µg/µL. Eight microliters of each sample were diluted with 2% ACN in 0.1% FA to obtain a
concentration of 400 ng/µL. One microliter of indexed Retention Time Standard (iRT, Biognosys,
Schlieren, Switzerland) was added to each sample, thus bringing up the total volume to 20 µL
(Escher et al., 2012).

Mass spectrometric analysis (secretome)

Reverse-phase high-performance liquid chromatography (HPLC)-MS/MS analyses were performed on a Dionex UltiMate 3000 system coupled online to an Orbitrap Exploris 480 mass spectrometer (Thermo Fisher Scientific, Bremen, Germany). The solvent system consisted of 2% ACN, 0.1% FA in water (solvent A) and 80% ACN, 0.1% FA in ACN (solvent B). Digested peptides (800 ng) were loaded onto an Acclaim PepMap 100 C_{18} trap column (0.1 x 20 mm, 5 µm particle size; Thermo Fisher Scientific) over 5 minutes at 5 µL/min with 100% solvent A. Peptides were eluted on an Acclaim PepMap 100 C_{18} analytical column (75 µm x 50 cm, 3 µm particle size; Thermo Fisher Scientific) at 300 nL/min using the following gradient: linear from 2.5% to 24.5% of solvent B in 125 min, linear from 24.5% to 39.2% of solvent B in 40 min, up to 98% of solvent B in 1 min, and back to 2.5% of solvent B in 1 min. The column was re-equilibrated for 30 min with 2.5% of solvent B, and the total gradient length was 210 min. Each sample was acquired in data-independent acquisition (DIA) mode (Bruderer et al., 2017; Collins et al., 2017; Gillet et al., 2012). Full MS spectra were collected at 120,000 resolution (Automatic Gain Control (AGC) target: 3e6 ions, maximum injection time: 60 ms, 350-1,650 *m/z*), and MS2 spectra at 30,000 resolution (AGC target: 3e6 ions, maximum injection time: Auto, Normalized Collision Energy (NCE): 30, fixed first mass 200 *m/z*). The isolation scheme consisted of 26 variable windows covering the 350-1,650 *m/z* range with an overlap of 1 *m/z* (see **Supplementary Table S2A**) (Bruderer et al., 2017).

Mass spectrometric analysis (intracellular protein)

LC-MS/MS analyses were performed on a Dionex UltiMate 3000 system coupled to an Orbitrap Eclipse Tribrid mass spectrometer (both from Thermo Fisher Scientific, San Jose, CA). The solvent system consisted of 2% ACN, 0.1% FA in water (solvent A) and 98% ACN, 0.1% FA in water (solvent B). Proteolytic peptides (600 ng) were loaded onto an Acclaim PepMap 100 C_{18} trap column (0.1 x 20 mm, 5-µm particle size; Thermo Fisher Scientific) for 5 min at 5 µL/min with 100% solvent A. Peptides were eluted on an Acclaim PepMap 100 C_{18} analytical column (75 µm x 50 cm, 3 µm particle size; Thermo Fisher Scientific) at 300 nL/min using the following gradient of solvent B: 2% for 5 min, linear from 2% to 20% in 125 min, linear from 20% to 32% in 40 min, up to 80% in 1 min, 80% for 9 min, and down to 2% in 1 min. The column was equilibrated with 2% of solvent B for 29 min, with a total gradient length of 210 min. All samples were acquired in DIA mode. Full MS spectra were collected at 120,000 resolution (AGC target: 3e6 ions, maximum

1075 injection time: 60 ms, 350-1,650 m/z), and MS2 spectra at 30,000 resolution (AGC target: 3e6

1076 ions, maximum injection time: Auto, NCE: 27, fixed first mass 200 m/z). The isolation scheme

1077 consisted of 26 variable windows covering the 350-1,650 m/z range with an overlap of 1 *m/z* (see

1078 **Supplementary Table S2A**) (Bruderer et al., 2017).

1079

QUANTIFICATION AND STATISTICAL ANALYSIS

RNA-seq read trimming, mapping, and quantification

Fastq files were first trimmed using fastp v0.20.1 (Chen et al., 2018) to (i) remove adapter

sequences, (ii) hard trim the first 15 base pairs of each read to remove biased sequence

composition, (iii) remove low quality bases, and (iv) remove reads shorter than 36 base pairs.

Read quality for each sample was then inspected using fastqc v0.11.9. Next, the GRCh38 primary

human genome assembly and comprehensive gene annotation were obtained from GENCODE

release 44 (Frankish et al., 2018). We modified the reference genome to include the sequence

for the *AluJb* overexpression plasmid as an additional contig. The trimmed reads were aligned to

this modified reference genome using STAR v2.7.3a (Dobin et al., 2012) with the following

parameters: outFilterMultimapNmax 100, winAnchorMultimapNmax 100, and

outFilterMismatchNoverLmax 0.04. Finally, the TEcount function in the TEtranscripts v2.1.4 (Jin

et al., 2015) package was employed to obtain gene and repeat subfamily counts, using the

GENCODE annotations to define gene boundaries and a repeat GTF file provided on the Hammell

lab website (downloaded on September 14 2023 from

https://labshare.cshl.edu/shares/mhammelllab/www-

data/TEtranscripts/TE_GTF/GRCh38_GENCODE_rmsk_TE.gtf.gz) to define repeat element

boundaries.

1098

Differential gene expression analyses

Gene and repeat subfamily count files were loaded into R v4.3.3. To filter lowly expressed

genes in each analysis, a counts-per-million (cpm) threshold corresponding to 10 reads in the

median-length library was defined. Genes and repeat subfamilies were kept for analysis if they

were expressed at levels surpassing this cpm threshold in at least as many samples as the

smallest group. DESeq2 v1.42.1 (Love et al., 2014) was used to identify significant (FDR < 0.05)

differentially expressed genes and repeat subfamilies between groups. To visualize sample

grouping patterns from the expression data, we carried out multidimensional scaling (MDS)

analysis using a distance metric between samples based on Spearman's rank correlation value

(1-Rho), which was then provided to the 'cmdscale' R function.

1109

Re-analysis of publicly available transcriptomic data

We leveraged publicly available mRNA-sequencing data for 133 aging human primary

fibroblast samples (Fleischer et al., 2018) to characterize the effects of aging on the repetitive

element transcriptome. Though others have conducted similar analyses (LaRocca et al., 2020;

Pabis et al., 2024), we applied additional sample processing and filtering criteria to remove batch

effects and isolate aging effects. First, we only kept samples from adults at least 20 years old to

avoid the confounding effects of human development occurring prior to adulthood (leaving 107

samples). We also only kept samples from people who specified 'Caucasian' for their ethnicity

(leaving 95 samples), since this was the most well-represented group, and only kept fibroblast

samples extracted from skin on the arm (leaving 82 samples), to avoid potential confounding

effects from extraction site. Fastq files for the remaining samples were trimmed, mapped, and

quantified as described above, with three modifications: (i) since raw reads were of two different

lengths, the longer reads were hard trimmed with fastp v0.20.1 (Chen et al., 2018) at the 3' end

to ensure that read lengths were equal across all samples, (ii) reads were mapped to the

unmodified human reference genome, and (iii) individual repeat locus counts, in addition to the

repeat subfamily counts, were generated using the TElocal v1.1.1 package and a repeat file

provided on the Hammell lab website (downloaded on October 31 2023

from https://labshare.cshl.edu/shares/mhammelllab/www-data/TElocal/prebuilt_indices/).

Individual repeat locus counts were then aggregated by subfamily and the following genomic

context categories as previously described (Bravo et al., 2024): intronic, exon-overlapping,

intergenic and near a gene (within 5 kilobases), or intergenic and distal from a gene (farther than

5 kilobases).

With the generated counts files, we then checked for potential sample mislabeling or

cross-contamination by checking the expression of the sex-specific markers *XIST* and *DDX3Y*.

Six potential outliers using the 1.5*IQR (interquartile range) rule were omitted from downstream

analyses. This yielded 76 samples that were utilized for differential gene expression analysis

across age, which was carried out as listed above with these alterations: (i) a gene was

considered expressed if it met the cpm threshold in at least 20% of samples and (ii) batch effects

corresponding to biological sex and sequencing instrument were regressed out from the raw read

counts using the 'removeBatchEffect' function in the R package Limma v3.58.1 (Ritchie et al.,
2015).

1141

DIA-MS Data Processing and Statistical Analysis

DIA data was processed in Spectronaut (versions 14.10.201222.47784 and
15.1.210713.50606) using directDIA. Data extraction parameters were set as dynamic and non-
linear iRT calibration with precision iRT was selected. Data was searched against the *Homo*
Sapiens reference proteome with 20,380 entries (UniProtKB-SwissProt), accessed on
01/29/2021. Trypsin/P was set as the digestion enzyme and two missed cleavages were allowed.
Cysteine carbamidomethylation was set as a fixed modification while methionine oxidation and
protein N-terminus acetylation were set as dynamic modifications. Identification was performed
using 1% precursor and protein q-value. Quantification was based on the peak areas of extracted
ion chromatograms (XICs) of 3 – 6 MS2 fragment ions, specifically b- and y-ions, with q-value
sparse data filtering and iRT profiling applied (**Supplementary Table S2F**). Local normalization
was applied for intracellular protein analysis (i.e., cell pellets), but not for secretome analysis.
Differential protein expression analysis comparing 1) *Alu* overexpression to empty vector was
performed using a paired t-test, and p-values were corrected for multiple testing, using the Storey
method (Burger, 2018). Specifically, group wise testing corrections were applied to obtain q-
values. For intracellular protein analysis, protein groups with at least two unique peptides, q-value
< 0.05, and absolute $\log_2$(fold-change) > 0.2 were called as significantly-altered (**Supplementary**
Table S2E). For secretome analysis, protein groups with at least two unique peptides, q-value <
0.05, and absolute $\log_2$(fold-change) > 0.58 were called as significantly-altered (**Supplementary**
Table S2F).

1162

Functional enrichment and network analyses

We used the Gene Set Enrichment Analysis (GSEA) paradigm as implemented in the R
package clusterProfiler v4.10.1 (Wu et al., 2021). Multi-contrast pathway enrichment was also
carried out across "-omics" layers using the mitch v1.14.0 R package (Kaspi and Ziemann, 2020).
Gene Ontology (GO) gene sets were obtained from the Molecular Signature Database release
2024.1.Hs (Liberzon et al., 2015; Subramanian et al., 2005). Reactome v92 pathway gene sets
were obtained directly from the Reactome website (Milacic et al., 2023). We also obtained several
aging- and senescence-associated gene sets, including core senescence-associated secretory

phenotype (SASP) factors (Basisty et al., 2020), SenMayo (Saul et al., 2022), CellAge build 3 (Avelar et al., 2020), aging-related genes derived from the Genotype-Tissue Expression project (Jia et al., 2018), and differentially expressed genes/repeats identified in our analysis of the human aging fibroblast data (Fleischer et al., 2018). Finally, we obtained previously published lists of genes upregulated and downregulated by stable overexpression of *AluSq2* or *AluSx* transposons in IMR-90 fibroblasts (Cantarella et al., 2019). For simplicity, the union of upregulated genes and the union of downregulated genes across both conditions were defined as *AluS* upregulated and downregulated genes, respectively.

For gene set enrichment analysis of transcriptomic changes, the DESeq2 v1.42.1 Wald-statistic was used to generate a ranked list of genes and repeats. For gene set enrichment analysis of proteomic and secretomic changes, the product of the $\log_2$(fold change) and $-\log_{10}$(Q-value) was used to generate a ranked list of proteins, which were then mapped to their corresponding gene symbol. All gene sets with an FDR < 0.05 were considered significant. For plots with a single analysis, the top 5 downregulated and top 5 upregulated gene sets were plotted, at most. For plots with multiple analyses, shared gene sets with consistent expression patterns across individual analyses were first identified. Then, the p-values for shared gene sets were combined using Fisher's method, and this meta-analysis p-value was used to rank shared gene sets. Finally, the top 5 upregulated gene sets and the top 5 downregulated gene sets were plotted, at most. If there were less than 5 gene sets in either group, those were replaced with gene sets exhibiting the opposite regulation, in order to plot 10 shared gene sets whenever possible. For multi-contrast pathway enrichment analysis with mitch, gene sets with an adjusted MANOVA (Multivariate Analysis of Variance) p-value < 0.05 were considered significant. For mosaic plots comparing the abundances of gene set members in differentially versus non-differentially expressed genes/proteins, statistical significance was assessed using Fisher's method, and comparisons with p < 0.05 were considered significantly enriched.

For the transcriptional data, predicted transcription factor activity was inferred using the decoupleR v2.8.0 package (Badia-i-Mompel et al., 2022). The 'fgsea' algorithm was run on the list of genes, and their accompanying Wald statistic, using the CollecTRI curated collection of transcription factors and their targets (Müller-Dott et al., 2023). All regulons with a p < 0.05 were considered significantly differentially impacted, and the top 5 upregulated regulons and the top 5 downregulated regulons by magnitude were plotted. In addition, a gene network was constructed with NetworkAnalyst (Xia et al., 2014; Xia et al., 2015; Zhou et al., 2019) on May 15, 2025. All differentially expressed genes (FDR < 0.05) were ordered by their Wald statistic and submitted to

1204 NetworkAnalyst as a gene list. A network was then constructed by taking the union of a generic

1205 PPI (first order network using the STRING interactome database, 900 confidence score cutoff,

1206 and requiring experimental evidence) and a signaling network (using the SIGNOR 2.0 database).

1207 The most populated subnetwork, subnetwork 1, was then visualized on the platform.

1208

1209 **Functional Assays**

1210   For functional assays, $2\text{-}4*10^6$ IMR-90 fibroblasts were transfected by electroporation as

1211 previously described and allowed to recover for ~24 hours on 6-well plates. Six independent

1212 transfections per group served as biological replicates in each experiment.

1213

Metabolic profiling using the Agilent Seahorse platform

To assess respiratory capacity, cells were detached, and 90,000 cells per well were

seeded on a Seahorse XF Pro M Cell Culture Microplate (Agilent Part No. 103774-100) containing

maintenance media. For each independent transfection, three technical replicate wells were

prepared and cultured for 24 hours. Then, cells were washed and cultured in unbuffered Seahorse

XF base media (Agilent cat. 102353-100) containing 5.5 mM of glucose, and the Seahorse XF

Cell Mito Stress Test (part no. 103015-100) was carried out by the USC Leonard Davis School of

Gerontology Seahorse Core. Afterwards, the media was removed, cells were lysed by freezing at

$-80°C$ overnight, 100 μL of water were added, the plate was placed in a $37°C$ incubator for 1 hour,

and cells were frozen at $-80°C$ for another hour. After thawing, a 200 $\mu g/mL$ working solution of

Hoechst 33342 in Tris-NaCl-EDTA (TNE) buffer was prepared, and 100 μL were added per well.

Fluorescence was measured using an excitation wavelength of 346 nm and an emission

wavelength of 460 nm, in order to normalize for cell number differences across wells. This

experiment was repeated twice which yielded n = 12 independent transfection samples per group,

the values were normalized to the median of the control group in each experiment, the values

across experiments were combined, and statistical significance was reached if a Wilcoxon test

yielded $p < 0.05$.

1231

Cell cycle stage profiling using propidium iodide staining

Cell cycle status was determined by propidium iodide (PI) staining. After the recovery

period, cells were detached, and ~500,000 - 600,000 cells per well were seeded on 6-well plates

containing maintenance media. After 24 hours, cells were detached, cells were spun down

(300xG, 5 minutes), cells were washed once in DPBS, cells were fixed by drop-wise adding pre-

chilled 70% ethanol, and fixed cells were stored at -20°C for a minimum of 12 hours. Then, cells

were spun down (500xG, 5 minutes, 4°C), cells were washed once with ice-cold DPBS, cells were

resuspended in labeling buffer, and cells were stained for 30 minutes in the dark. Staining buffer

was prepared in DPBS with the following final concentrations: 50 μg/mL propidium iodide (Alfa

Aesar cat. J66584), 100 μg/mL PureLink RNase A (Invitrogen cat. 12091021), and 0.05% Triton

X-100 (MP cat. 194854). This experiment was repeated three times which yielded n = 18

independent transfection samples per group, the values were normalized to the median of the

control group in each experiment, the values across experiments were combined, and statistical

significance was reached if a Wilcoxon test yielded $p < 0.05$.

1246

Protein aggregation assessment using proteostat staining

The relative amounts of protein aggregates were determined using the PROTEOSTAT

Aggresome Detection Kit (Enzo cat. No. ENZ-51035-K100). After the recovery period, cells were

detached, and ~500,000 - 600,000 cells per well were seeded on 6-well plates containing

maintenance media. After 24 hours, the assay was carried out, preparing staining solution by

adding Proteostat dye and Hoechst 33342 at a dilution of 1/10,000 and 1/1,000, respectively. This

experiment was repeated four times which yielded n = 24 independent transfection samples per

group, the values were normalized to the median of the control group in each experiment, the

values across experiments were combined, and statistical significance was reached if a Wilcoxon

test yielded $p < 0.05$.

Flow cytometry for Proteostat and cell cycle assays was carried out on a MACSQuant

Analyzer 10 (Miltenyi Biotec, 130-096-343). Flow cytometry data was analyzed in Flowlogic

Solution 1.0.

1260

1261   **Other software versions**

1262   Analyses were conducted using R version 4.3.3 and code was re-run independently on R version

1263   4.3.3 to check for reproducibility. Flow cytometry results were analyzed using Flowlogic Solution

1264   1.0.

1265