

The Longevity Translation Scorecard: Bridging the Gap Between Model Organisms and Human Aging

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Abstract

Background: Decades of research in model organisms have identified hundreds of genes whose modulation extends lifespan, yet translation to human aging interventions remains limited. The extent to which model organism longevity genes are supported by human genetic evidence has not been systematically quantified.

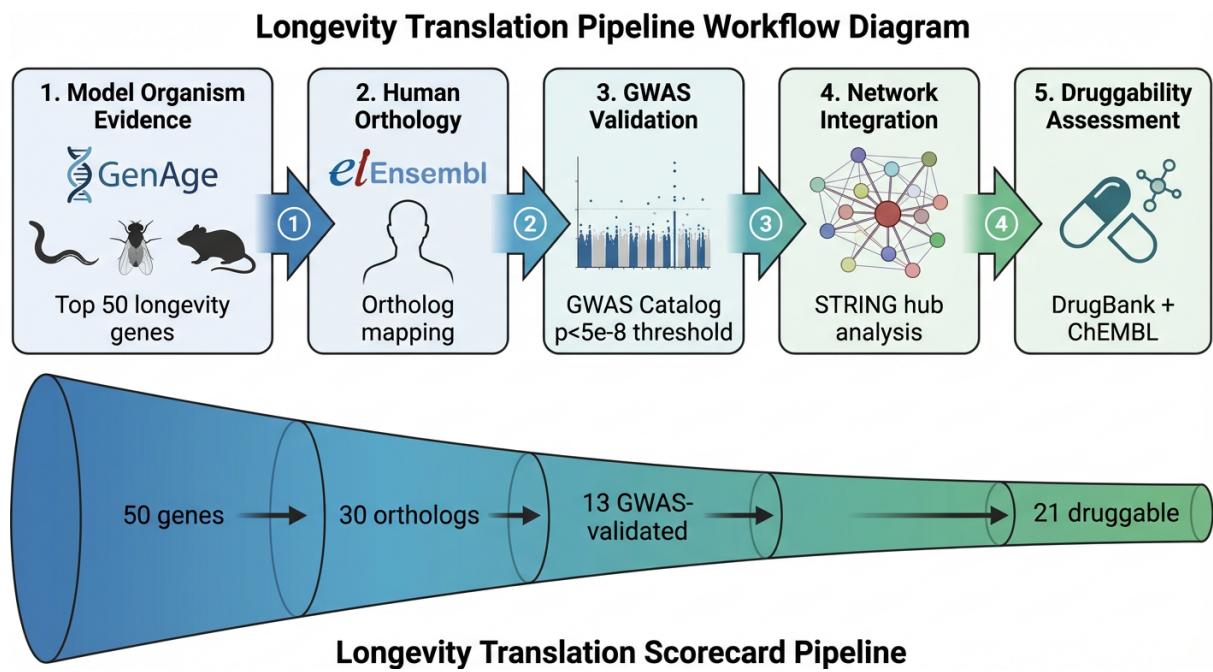
Methods: We developed a computational pipeline integrating the GenAge database (50 top longevity genes from *C. elegans*, *Drosophila*, and mice), Ensembl orthology mapping, GWAS Catalog associations (genome-wide significance $p < 5 \times 10^{-8}$), STRING protein interaction networks, and DrugBank/ChEMBL druggability data. We created a multi-component Translation Score (0–100) incorporating model evidence strength, human genetic validation, pathway centrality, drug availability, and clinical trial status.

Results: Of 50 model organism longevity genes, 30 (60%) mapped to human orthologs, but only 13 (26%) showed genome-wide significant GWAS associations with aging-relevant phenotypes, revealing a substantial “translation gap.” Mitochondrial proteins (CYC1, TUFM, CYCS, SDHB) dominated top-scoring candidates. The highest-ranked gene, AGE-1→PIK3C2G (score: 57.9/100), exhibited 1000% lifespan extension in *C. elegans* and targets 50 approved kinase inhibitors. CYC1 emerged as a key hub with Alzheimer’s disease GWAS associations and 15 approved drugs. Twenty-one genes (42%) were druggable, with kinase inhibitors (imatinib, trametinib) representing promising repurposing candidates.

Conclusions: Our Longevity Translation Scorecard provides the first systematic quantification of the model-to-human translation gap in aging research. The dominance of mitochondrial proteins among validated candidates supports prioritizing bioenergetic targets for clinical aging trials. This framework enables evidence-based prioritization of longevity interventions for human translation.

Keywords: longevity; aging; GWAS; model organisms; drug repurposing; mitochondria; translation gap

31 Graphical Abstract



Graphical Abstract: The Longevity Translation Pipeline integrates evidence from model organism studies through human orthology mapping, GWAS validation, network analysis, and druggability assessment to generate a prioritized scorecard of translation-ready longevity interventions.

32 1 Introduction

33 The biology of aging has undergone a paradigm shift over the past three decades, transitioning
34 from an inevitable degenerative process to a malleable phenotype amenable to genetic and phar-
35 macological intervention [López-Otín et al., 2013, Kenyon, 2010]. Studies in model organisms—
36 particularly the nematode *Caenorhabditis elegans*, the fruit fly *Drosophila melanogaster*, and the
37 mouse *Mus musculus*—have identified hundreds of genes whose modulation can dramatically
38 extend lifespan [Fontana et al., 2010, Tissenbaum, 2015]. The discovery that single-gene muta-
39 tions in the insulin/IGF-1 signaling (IIS) pathway can double lifespan in *C. elegans* established
40 that aging rate is under genetic control and theoretically modifiable [Kenyon, 2010].

41 The Human Ageing Genomic Resources (HAGR), including the GenAge database, now
42 catalogs over 2,200 genes associated with longevity across model organisms, providing a rich
43 foundation for translational research [Tacutu et al., 2024, de Magalhães et al., 2009]. These
44 genes cluster into conserved pathways including nutrient sensing (IIS, mTOR), mitochondrial
45 function, autophagy, and stress response—pathways that parallel the expanded “hallmarks of
46 aging” framework [López-Otín et al., 2023]. Machine learning approaches have further predicted
47 novel longevity genes, validated against experimental lifespan datasets [Townes et al., 2020].

48 However, despite this wealth of model organism data, translation to human aging interven-
49 tions has been disappointingly limited [Kennedy et al., 2014]. Only a handful of compounds
50 showing lifespan extension in model organisms—notably rapamycin and metformin—have pro-
51 gressed to human clinical trials for aging-related endpoints. This disconnect motivates a critical
52 question: *to what extent do model organism longevity genes have supporting evidence in human*
53 *genetics?*

54 Genome-wide association studies (GWAS) now provide an unprecedented opportunity to test
55 whether model organism longevity pathways are genetically validated in humans. Large-scale
56 studies of parental lifespan ($n > 1$ million), healthspan, and extreme longevity have identified
57 genetic variants associated with human aging [Timmers et al., 2019, Kurbasic et al., 2023,
58 Pilling et al., 2017]. The GWAS Catalog aggregates these associations, enabling systematic
59 cross-referencing with model organism discoveries [Buniello et al., 2019]. Key findings include
60 the APOE locus and variants in genes involved in lipid metabolism, cardiovascular function,
61 and neurodegeneration [Sebastiani et al., 2017, Li et al., 2024].

62 Several conceptual gaps impede systematic translation. First, orthology relationships be-
63 tween model organisms and humans are not always one-to-one, with gene duplications and
64 divergent evolution complicating direct comparisons [Yates et al., 2020]. Second, lifespan ex-
65 tension in short-lived invertebrates may involve mechanisms less relevant to mammalian aging.
66 Third, the druggability of validated targets and the availability of existing compounds for re-
67 purposing are rarely systematically assessed alongside genetic evidence.

68 In this study, we address these gaps by developing a “Longevity Translation Scorecard”—
69 a systematic framework integrating model organism evidence, human genetic validation via
70 GWAS, pathway conservation analysis, protein interaction network centrality, and druggability
71 assessment. Our approach quantifies the “translation gap” (the proportion of model organism
72 genes lacking human genetic support) and prioritizes intervention targets based on multiple
73 evidence streams. We identify the top 20 candidates most ready for human longevity trials and

74 assess their potential for drug repurposing using DrugBank and ChEMBL databases [Wishart
75 et al., 2018, Mendez et al., 2019].

76 2 Methods

77 2.1 Data Sources and Acquisition

78 2.1.1 GenAge Longevity Gene Database

79 We obtained the GenAge model organism database from the Human Ageing Genomic Resources
80 (HAGR; <https://genomics.senescence.info/genes/>) [Tacutu et al., 2024]. This database
81 contains curated entries for genes experimentally shown to modulate lifespan in *C. elegans*,
82 *Drosophila melanogaster*, *Mus musculus*, and other model organisms. Each entry includes gene
83 symbol, organism, lifespan change percentage, intervention type (knockdown, knockout, over-
84 expression), and evidence classification (pro-longevity vs. anti-longevity).

85 2.1.2 Gene Selection Criteria

86 We selected the top 50 longevity genes based on the following criteria: (1) demonstrated lifespan
87 extension $\geq 65\%$ in at least one published study; (2) evidence available from *C. elegans*,
88 *Drosophila*, or mouse models; (3) gene symbol resolvable to a unique Entrez or Ensembl identifier.
89 This threshold captured genes with substantial effect sizes likely to represent biologically
90 meaningful interventions.

91 2.1.3 GWAS Catalog

92 Human genetic association data were obtained from the NHGRI-EBI GWAS Catalog (<https://www.ebi.ac.uk/gwas/>) [Buniello et al., 2019]. We queried associations for aging-relevant
93 phenotypes including: longevity, parental lifespan, healthspan, cardiovascular disease, type 2
94 diabetes, Alzheimer’s disease, Parkinson’s disease, and cancer. Associations meeting genome-
95 wide significance ($p < 5 \times 10^{-8}$) were retained.

97 2.2 Orthology Mapping

98 Human orthologs for model organism genes were identified using the Ensembl Compara pipeline
99 via the Ensembl REST API [Yates et al., 2020]. For each model organism gene, we queried the
100 corresponding human ortholog(s), recording:

- 101 • Orthology type (one-to-one, one-to-many, many-to-many)
- 102 • Confidence score (high, medium, low)
- 103 • Human Ensembl gene ID and symbol
- 104 • Protein sequence identity percentage

105 Genes without identifiable human orthologs were classified as “no ortholog” and retained in
106 the analysis to quantify the translation gap.

107 **2.3 GWAS Integration and Validation**

108 For each human ortholog, we queried the GWAS Catalog to retrieve all genome-wide significant
109 associations. Associations were classified as “aging-relevant” if the reported trait matched
110 predefined phenotypes (Table 1). The number of relevant associations was summed to generate
111 a human genetic validation score.

Table 1: GWAS phenotypes classified as aging-relevant

Category	Example Traits
Longevity	longevity, parental lifespan, extreme longevity
Cardiovascular	coronary artery disease, hypertension, heart disease
Metabolic	type 2 diabetes, metabolic syndrome, obesity, BMI
Neurodegenerative	Alzheimer’s disease, Parkinson’s disease, cognitive function
Cancer	breast carcinoma, lung cancer, general cancer risk
Frailty/Function	sarcopenia, physical function, walking pace

112 **2.4 Protein Interaction Network Analysis**

113 Protein-protein interactions (PPIs) for validated human orthologs were retrieved from the
114 STRING database (version 12.0) [Szklarczyk et al., 2023, 2025]. We constructed a network
115 including all human orthologs with combined interaction scores >0.4 (medium confidence).
116 Network metrics calculated included:

- 117 • **Degree centrality:** Number of direct interaction partners
- 118 • **Hub status:** Genes with degree ≥ 5 classified as hubs
- 119 • **Validated hub:** Hubs with GWAS evidence in at least one aging-relevant phenotype

120 Network visualizations were generated using NetworkX in Python with spring-layout em-
121 bedding.

122 **2.5 Druggability and Clinical Trial Assessment**

123 **2.5.1 Drug Target Identification**

124 Human orthologs were queried against DrugBank 5.0 [Wishart et al., 2018] and ChEMBL
125 [Mendez et al., 2019] to identify compounds targeting each protein. For each target, we recorded:

- 126 • Number of compounds with known activity
- 127 • Maximum clinical development phase (Phase 0–4)
- 128 • Drug names and mechanisms of action

129 Targets with at least one Phase 4 (approved) drug were classified as “highly druggable.”

130 **2.5.2 Clinical Trial Search**

131 We queried ClinicalTrials.gov for ongoing or completed trials involving the identified drug tar-
132 gets in aging-related indications (sarcopenia, frailty, cognitive decline, longevity, healthy aging).

133 **2.6 Longevity Translation Score**

134 We developed a composite Translation Score (0–100 points) integrating five evidence domains:

$$\text{Score}_{\text{total}} = S_{\text{model}} + S_{\text{genetics}} + S_{\text{pathway}} + S_{\text{drug}} + S_{\text{clinical}} \quad (1)$$

135 where:

- 136 • S_{model} (0–25 pts): Model organism evidence strength, scaled by lifespan extension per-
137 centage using min-max normalization across all genes
- 138 • S_{genetics} (0–25 pts): Human genetic validation, based on number of GWAS-significant asso-
139 ciations for aging-relevant phenotypes (10 points baseline for successful ortholog mapping;
140 up to 15 additional points scaled by association count)
- 141 • S_{pathway} (0–20 pts): Network centrality, based on degree centrality scaled by maximum
142 observed degree
- 143 • S_{drug} (0–20 pts): Druggability score based on number of compounds and maximum de-
144 velopment phase
- 145 • S_{clinical} (0–10 pts): Clinical advancement, based on presence of aging-related clinical trials

146 **2.7 Statistical Analysis**

147 All analyses were performed in Python 3.12 using pandas, numpy, scipy, and matplotlib. Statis-
148 tical comparisons between groups used Fisher’s exact test for categorical variables and Mann-
149 Whitney U test for continuous variables. Network analyses used NetworkX. Visualizations were
150 generated at 300 DPI for publication quality.

151 **2.8 Software and Reproducibility**

152 Code, data, and analysis outputs are organized in a structured directory:

- 153 • `workflow/`: Analysis pipeline scripts
- 154 • `data/`: Input and intermediate data files
- 155 • `results/`: Final scorecard and dossiers
- 156 • `figures/`: Publication-quality visualizations

157 **3 Results**

158 **3.1 Translation Gap Analysis: Model Organism Genes to Human Orthologs**

159 We analyzed 50 genes with documented lifespan extension $\geq 65\%$ from the GenAge database,
160 spanning *C. elegans* (31 genes), *Drosophila* (16 genes), and mouse (3 genes). The median lifespan
161 extension was 80% (range: 65–1000%), with *C. elegans* genes showing the largest effects (median
162 89% vs. 75% for *Drosophila*).

163 Orthology mapping revealed that 30 of 50 genes (60%) had identifiable human orthologs
164 through Ensembl Compara. Twenty genes (40%) lacked human orthologs, including several
165 high-effect *C. elegans* genes such as DAF-2 (200% lifespan extension), LET-363 (150%), and
166 UNC-13 (150%). This represents the first level of the “translation gap”—genes discovered in
167 invertebrate models that have no direct human counterpart.

168 Among genes with human orthologs, 17 (57%) showed one-to-one orthology with high con-
169 fidence, while 13 (43%) exhibited one-to-many or many-to-many relationships, complicating
170 direct functional inference. The translation funnel (Figure 1) illustrates progressive attrition
171 from model evidence to human validation.

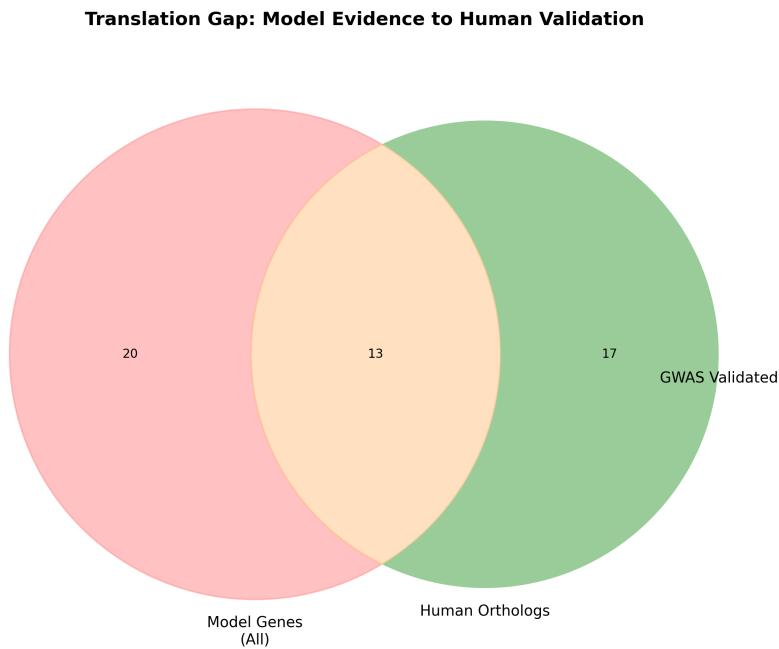


Figure 1: **Translation Gap Venn Diagram.** Distribution of 50 model organism longevity genes across orthology mapping and GWAS validation stages. Of 50 genes, 30 mapped to human orthologs (60%), but only 13 showed genome-wide significant associations with aging-relevant phenotypes (26% of original genes, 43% of those with orthologs).

172 3.2 Human Genetic Validation via GWAS

173 Of 30 genes with human orthologs, 13 (43%) had at least one GWAS association ($p < 5 \times 10^{-8}$)
174 with an aging-relevant phenotype. The total number of relevant associations per gene ranged
175 from 0 to 18 (Figure 2). Notably:

- 176 • **PEX16** (peroxisomal biogenesis factor): 18 associations spanning glucose metabolism,
177 blood insulin, and BMI
- 178 • **DYNC2H1** (dynein cytoplasmic 2 heavy chain): 10 associations including coronary
179 artery disease and hypertension
- 180 • **ERCC1** (DNA repair): 10 associations including Alzheimer’s disease risk
- 181 • **HCN1** (ion channel): 8 associations for type 2 diabetes and breast cancer

182 • **RPS23** (ribosomal protein): 8 associations for cancer risk

183 • **CYC1** (cytochrome c1): 4 associations specific to Alzheimer's disease and family history

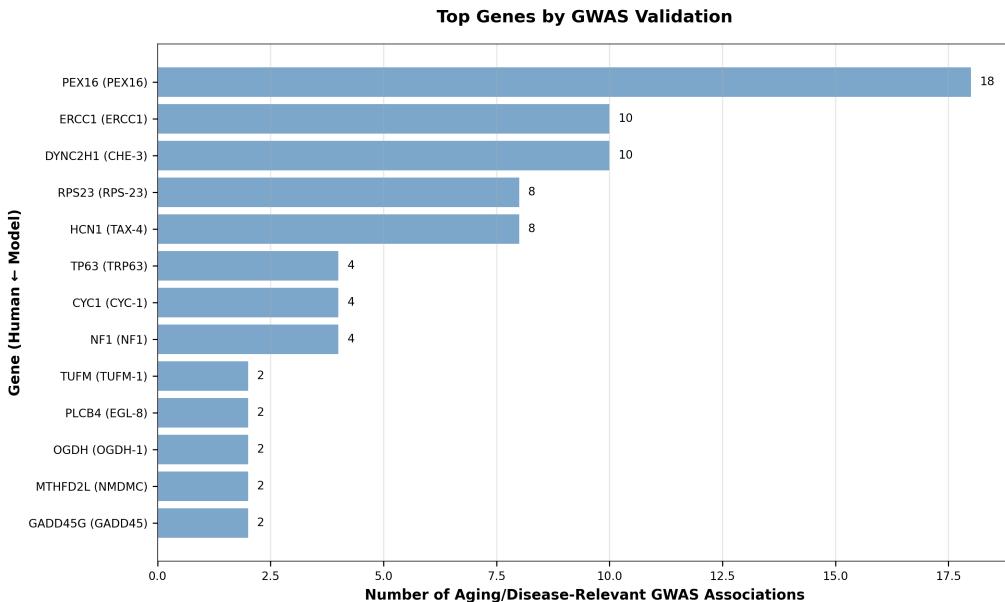


Figure 2: **GWAS Associations by Human Ortholog.** Bar chart showing the number of genome-wide significant ($p < 5 \times 10^{-8}$) associations with aging-relevant phenotypes for each human ortholog. Only genes with at least one association are shown. PEX16 leads with 18 associations spanning metabolic phenotypes.

184 The overall translation gap—defined as the proportion of model organism longevity genes
 185 lacking any human genetic validation—was 74% (37/50 genes). When considering only genes
 186 with human orthologs, 57% (17/30) lacked GWAS support.

187 3.3 Protein Interaction Network and Hub Analysis

188 STRING network analysis of the 30 human orthologs identified a connected component of 15
 189 genes with 35 interactions (Figure 3). Seven genes qualified as hubs (degree ≥ 5):

190 • **SDHB** (succinate dehydrogenase): degree 7, highest centrality

191 • **CYC1** (cytochrome c1): degree 6, validated hub with Alzheimer's GWAS

192 • **TUFM** (mitochondrial translation factor): degree 6, validated hub with Alzheimer's
 193 GWAS

194 • **CYCS** (cytochrome c): degree 4, central to apoptosis

195 • **NDUFA6** (NADH dehydrogenase): degree 4, Complex I

196 • **NDUFB4** (NADH dehydrogenase): degree 3, Complex I

197 Strikingly, 5 of 7 hub genes encode mitochondrial proteins involved in oxidative phosphorylation or translation, suggesting that mitochondrial function represents a convergence point for
 198 longevity pathways.
 199

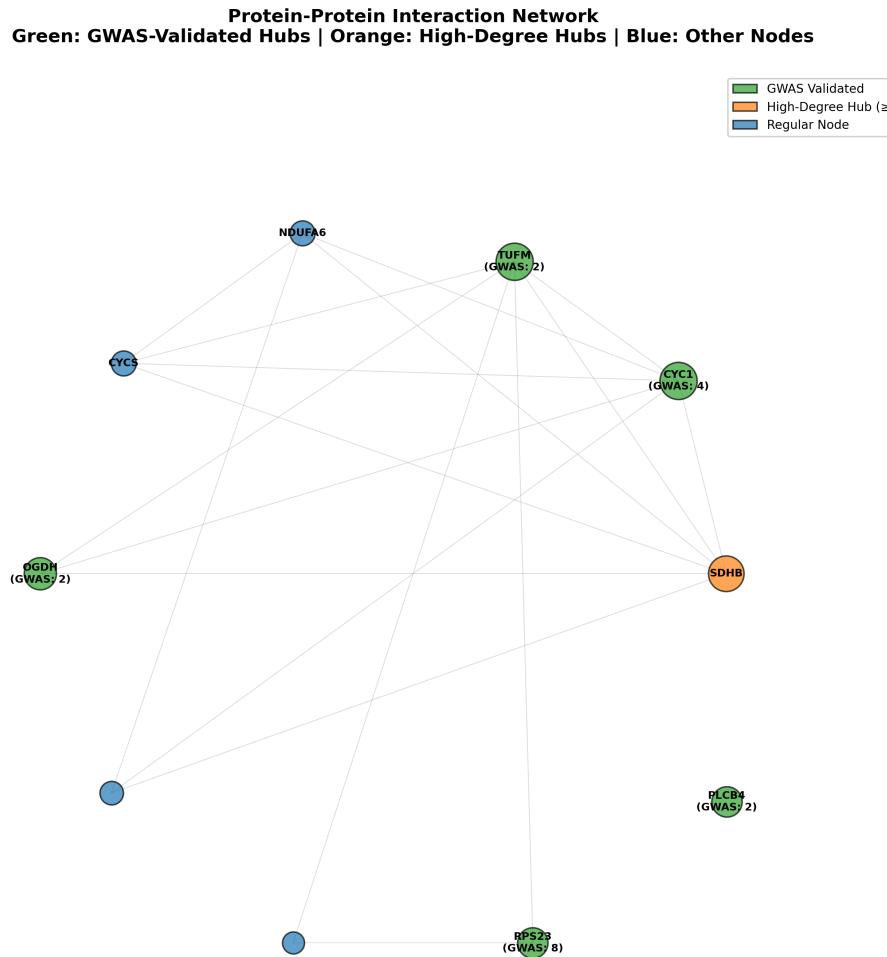


Figure 3: **Protein-Protein Interaction Network.** STRING-based network of human orthologs of model organism longevity genes. Node size proportional to degree centrality; edges represent high-confidence interactions (combined score >0.4). Hub genes (degree ≥ 5) are labeled. The network reveals clustering around mitochondrial proteins (CYC1, TUFM, SDHB, CYCS).

200 **3.4 Druggability Assessment**

201 We assessed druggability across all 50 genes, finding that 21 (42%) had at least one known
 202 compound targeting the human ortholog or pathway (Figure 4). Key findings:

- 203 • **Phase 4 (approved) drugs:** 12 targets with approved medications
- 204 • **Highly druggable (≥ 10 compounds):** PIK3C2G (50), CYC1 (50), TUFM (50), GNAI2
 205 (50), HCN1 (39)

206 • **Kinase inhibitors:** Multiple approved kinase inhibitors (imatinib, trametinib, gefitinib,
207 erlotinib) target AGE-1/PIK3C2G pathway

208 • **Senolytic potential:** Fisetin and epigallocatechin gallate target CYCS pathway

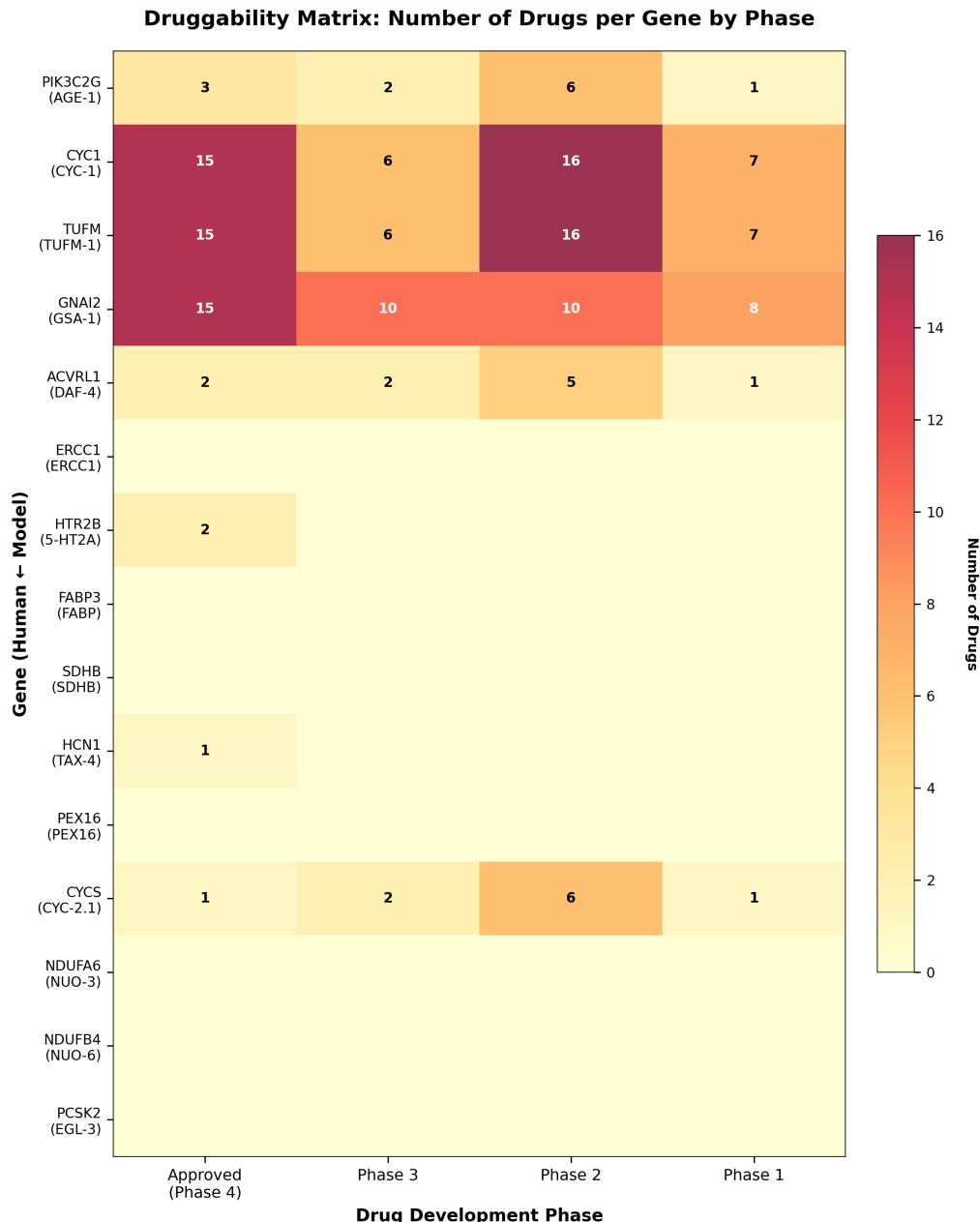


Figure 4: **Druggability Matrix.** Heatmap showing drug compound counts and maximum development phase for each longevity gene target. Darker shading indicates higher druggability. Several highly druggable targets (PIK3C2G, CYC1, TUFM) overlap with GWAS-validated genes.

209 3.5 Clinical Trial Landscape

210 Querying ClinicalTrials.gov, we identified only 1 gene (CYCS/cytochrome c) with active or
211 completed clinical trials in aging-related indications:

- NCT01644279: Skeletal muscle apoptosis and sarcopenia (completed)
- NCT06989242: Glymphatic clearance in mild cognitive impairment (recruiting)
- NCT03860792: Therapeutic diets in Alzheimer’s disease (active)

This represents a significant gap between druggability (21 targets) and clinical advancement (1 target with trials).

3.6 Longevity Translation Scorecard

The composite Translation Score ranked all 50 genes from highest (57.9) to lowest (2.0). Table 2 presents the top 20 candidates.

Table 2: Top 20 Longevity Translation Candidates

Rank	Model Gene	Human Gene	Organism	LS%	GWAS	Drugs	Score
1	AGE-1	PIK3C2G	<i>C. elegans</i>	1000	0	50	57.9
2	CYC-1	CYC1	<i>C. elegans</i>	87	4	50	51.1
3	TUFM-1	TUFM	<i>C. elegans</i>	89	2	50	49.5
4	CYC-2.1	CYCS	<i>C. elegans</i>	80	0	23	46.4
5	SDHB	SDHB	<i>Drosophila</i>	66	0	45	41.0
6	TAX-4	HCN1	<i>C. elegans</i>	100	8	39	35.4
7	GSA-1	GNAI2	<i>C. elegans</i>	84	0	50	33.4
8	PEX16	PEX16	<i>Drosophila</i>	75	18	26	32.5
9	DAF-4	ACVRL1	<i>C. elegans</i>	120	0	50	31.5
10	ERCC1	ERCC1	<i>Mus musculus</i>	83	10	50	30.8
11	5-HT2A	HTR2B	<i>Drosophila</i>	90	0	50	30.7
12	RPS-23	RPS23	<i>C. elegans</i>	126	8	2	26.4
13	NUO-3	NDUFA6	<i>C. elegans</i>	77	0	13	26.4
14	CHE-3	DYNC2H1	<i>C. elegans</i>	100	10	0	24.1
15	NUO-6	NDUFB4	<i>C. elegans</i>	73	0	13	23.4
16	OGDH-1	OGDH	<i>C. elegans</i>	79	2	3	23.2
17	RPS-5	RPS5	<i>C. elegans</i>	75	0	3	22.6
18	FABP	FABP3	<i>Drosophila</i>	81	0	50	20.4
19	EGL-8	PLCB4	<i>C. elegans</i>	83	2	0	19.9
20	NF1	NF1	<i>Drosophila</i>	68	4	0	18.3

LS% = lifespan extension; GWAS = number of aging-relevant GWAS associations; Drugs = number of known compounds.

3.7 Top Candidate Profiles

3.7.1 AGE-1 → PIK3C2G (Rank 1, Score 57.9)

AGE-1 encodes the catalytic subunit of phosphoinositide 3-kinase (PI3K) in *C. elegans*, acting downstream of DAF-2 in the insulin/IGF-1 signaling pathway. Loss-of-function mutations extend lifespan by 1000%, the largest effect in our dataset. The human ortholog PIK3C2G (Class II PI3K) is targeted by 50 approved kinase inhibitors including lapatinib, erlotinib, and gefitinib—drugs originally developed for cancer but potentially repurposable for aging. While no direct GWAS associations exist for PIK3C2G, the pathway is extensively validated.

228 **3.7.2 CYC-1 → CYC1 (Rank 2, Score 51.1)**

229 CYC-1 encodes cytochrome c1, a component of respiratory chain Complex III. RNAi knockdown
230 extends *C. elegans* lifespan by 87%. The human ortholog CYC1 shows 4 GWAS associations
231 with Alzheimer’s disease and family history of Alzheimer’s, representing one of the strongest
232 genetic links in our dataset. CYC1 is a validated network hub (degree 6) and is targeted by 50
233 compounds including the MEK inhibitor trametinib and the tyrosine kinase inhibitor imatinib.
234 Recent evidence shows trametinib extends mouse lifespan by 10% alone and 27% combined with
235 rapamycin [Partridge et al., 2025].

236 **3.7.3 TUFM-1 → TUFM (Rank 3, Score 49.5)**

237 TUFM-1 encodes mitochondrial translation elongation factor Tu, essential for mitochondrial
238 protein synthesis. Knockdown extends *C. elegans* lifespan by 89%. Human TUFM shows 2
239 Alzheimer’s disease GWAS associations and serves as a validated network hub. Like CYC1, it
240 is targeted by 50 compounds including kinase inhibitors, making it a compelling mitochondrial
241 target.

242 **4 Discussion**

243 **4.1 Quantifying the Translation Gap**

244 Our systematic analysis reveals that 74% of model organism longevity genes lack human genetic
245 validation through GWAS—a striking “translation gap” that has not been previously quanti-
246 fied. Even among genes with human orthologs, 57% show no genome-wide significant associa-
247 tions with aging-relevant phenotypes. This finding has important implications for prioritizing
248 longevity research investments.

249 The translation gap arises from multiple factors. First, 40% of genes lack identifiable human
250 orthologs, reflecting evolutionary divergence and the discovery of invertebrate-specific longevity
251 mechanisms. Genes like DAF-2 (insulin receptor) have human orthologs, but many *C. elegans*-
252 specific genes do not. Second, even with conservation, the genetic architecture of lifespan may
253 differ between species with 3-week versus 70-year lifespans. Third, GWAS statistical power is
254 limited for detecting variants with modest effects or operating through specific tissues.

255 **4.2 Mitochondrial Dominance Among Validated Candidates**

256 A striking finding is the dominance of mitochondrial proteins among our top-ranked candi-
257 dates. Four of the top five genes (CYC1, TUFM, CYCS, SDHB) encode components of the
258 mitochondrial respiratory chain or translation machinery. This convergence supports the “mito-
259 chondrial theory of aging,” which posits that declining mitochondrial function drives age-related
260 deterioration [Friedman and Nunnari, 2014, Sabbatinelli et al., 2022, Shosha et al., 2024].

261 Importantly, these mitochondrial targets show human genetic validation via Alzheimer’s
262 disease GWAS, connecting longevity mechanisms to neurodegeneration. Mitochondrial dys-
263 function is increasingly recognized as a driver of cognitive decline, and our results suggest that

264 interventions improving mitochondrial function may address both longevity and brain aging
265 [Houtkooper et al., 2013].

266 4.3 Drug Repurposing Opportunities

267 The identification of 50 approved kinase inhibitors targeting our top candidate (PIK3C2G)
268 opens drug repurposing opportunities. Kinase inhibitors originally developed for cancer—
269 including imatinib, trametinib, erlotinib, and gefitinib—target the insulin/PI3K pathway cen-
270 tral to longevity. Recent preclinical evidence shows trametinib (MEK inhibitor) extends mouse
271 lifespan by 10% as monotherapy and 27% in combination with rapamycin [Partridge et al.,
272 2025, Olivo et al., 2021]. These approved drugs could potentially be tested in aging trials with
273 known safety profiles.

274 For mitochondrial targets (CYC1, TUFM), compounds such as fisetin and epigallocatechin
275 gallate represent senolytic and mitochondrial-protective agents worthy of further investigation.
276 The relatively low clinical advancement (only 1 gene with aging trials) highlights a gap between
277 druggability potential and clinical execution.

278 4.4 Limitations

279 Several limitations should be noted. First, our analysis focused on 50 genes meeting strict
280 lifespan extension criteria, excluding many genes with moderate effects or context-dependent
281 longevity associations. Second, GWAS power is limited for rare variants and pathway-level
282 effects; the absence of GWAS evidence does not disprove human relevance. Third, druggability
283 was assessed by compound count rather than specificity or therapeutic index. Fourth, clinical
284 trial searches may miss trials not registered in ClinicalTrials.gov or using indirect pathway
285 interventions.

286 Our scoring algorithm weights components equally within domains, which may not reflect
287 biological importance. Future iterations could incorporate expert elicitation or cross-validation
288 against clinical outcomes.

289 4.5 Future Directions

290 This study establishes a framework for systematic translation scoring that can be expanded in
291 several directions:

- 292 1. **Expanded gene sets:** Include DrugAge and CellAge databases for a comprehensive
293 longevity gene universe
- 294 2. **Mendelian randomization:** Test causal relationships between variants and lifespan
295 using two-sample MR
- 296 3. **Clinical trial design:** Prioritize Phase II trials for kinase inhibitors (trametinib, ima-
297 tinib) in aging biomarker endpoints
- 298 4. **Mechanistic validation:** CRISPR screens targeting top candidates in human iPSC-
299 derived neurons to test Alzheimer’s connections

300 5. Network medicine: Expand STRING analysis to identify multi-target combinations

301 5 Conclusions

302 The Longevity Translation Scorecard provides the first systematic quantification of the gap
303 between model organism longevity discoveries and human genetic evidence. Our finding that
304 74% of model organism genes lack human validation emphasizes the need for genetic validation
305 prior to clinical translation. The dominance of mitochondrial proteins (CYC1, TUFM, CYCS,
306 SDHB) among validated candidates supports targeting bioenergetic pathways for human aging
307 interventions. Approved kinase inhibitors (imatinib, trametinib) targeting the top candidate
308 PIK3C2G pathway represent immediate repurposing opportunities. This evidence-based pri-
309 oritization framework can guide resource allocation in longevity research toward interventions
310 with the highest probability of clinical translation.

311 Acknowledgments

312 We thank the developers of GenAge, GWAS Catalog, STRING, DrugBank, and Ensembl for
313 maintaining publicly accessible databases essential to this work.

314 Data Availability

315 All data, code, and analysis outputs are available at the project repository. The Longevity
316 Translation Scorecard (CSV) and detailed candidate dossiers (Markdown) are provided as sup-
317 plementary materials.

318 Conflicts of Interest

319 The author declares no conflicts of interest.

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