Grb10a knockdown in *Danio rerio* during early life alters growth and cardiometabolic function associated with a remodelled transcriptome

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Abstract

Embryonic growth trajectory is a risk factor for chronic metabolic and cardiovascular disorders and influences birth weight along with early post-natal weight gain in humans. Grb10 is a negative regulator of the main pathways driving embryonic growth and knock-out in mammals increases insulin sensitivity and growth trajectory. This study investigates in *Danio rerio* the long-term cardiometabolic consequences and associated transcriptomic profiles of morpholino induced early life disruption of *grb10a* expression. The associated transient knockdown of *grb10a* increased embryonic growth (+7 %) and metabolic rate (+25 %), while decreasing heart rate (-50 %) in early life. Juvenile growth and respiratory rate were also elevated (+30 % and 7-fold increase respectively). This was associated with permanent remodelling of the transcriptional landscape and the dysregulation of multiple growth-related pathways. This study indicates that zebrafish are a suitable model for life-long investigation of the link between early growth and later life disease risk.

Introduction

In humans, small and large for gestational age (SGA, LGA) status, caused by embryonic growth aberration, are early risk factors for chronic metabolic and cardiovascular disorders, such as type II diabetes (TIID), obesity, cardiac dysfunction, and hypertension (1–3). As these disorders are an ever-increasing concern, efforts must be made to identify early risk factors and develop novel therapeutics for prevention and treatment. While this correlation is widely replicated in human populations, targeted in-vivo studies to elucidate this phenomenon and the pathways involved are lacking. The zebrafish is an ideal model organism for longitudinal study owing to its rapid generation time and is also highly suitable for developmental studies as embryos are easily accessible and transparent.

Embryonic growth is driven by the insulin/insulin like growth factor (Ins/IGF) signaling pathway (4). Circulating insulin and IGF levels indicate the caloric and nutrient condition of the extrauterine environment and developmental rate positively correlate with Ins/IGF serum levels. Glucose metabolism, glycogen and protein synthesis, as well as proliferation are promoted if the environment is considered favourable (5). Developmental plasticity enables phenotypic alterations to occur in response to fluctuations in the external environment to ensure survival. This is important for healthy development, though phenotypic responses for immediate survival may come at the expense of elevated disease risk in later life. While dysfunction of the Ins/IGF pathway correlates with growth restriction and dysfunctional energy homeostasis (6), SGA and LGA individuals rarely present with mutations in the core pathway, suggesting other factors must be involved in subsequent pathway deregulation.

Growth factor receptor bound protein 10 (GRB10) is a negative regulator of the Insulin/IGF signaling pathway. Inhibition by GRB10 downregulates the growth response, promoting a switch from glucose to fat metabolism and halting cell cycle progression (7–9). GRB10 expression limits placental growth and efficiency (10) and correlates with small body size (11). In humans, genome wide association studies show *GRB10* is strongly associated with TIID (12), and *GRB10* copy number variation is associated with Silver Russell Syndrome (13), a rare growth disorder typically characterised by intrauterine growth restriction, SGA status, hypoglycemia, poor muscle development, and fat deposition. The role of GRB10 in the regulation of human growth is notably associated with response to recombinant human

growth hormone in children with growth hormone deficiency (14,15). The interaction between the environment and the control of *GRB10* expression has also been investigated, and growth response was shown to be modulated by genotype in association with day length (16). As metabolic and cardiac disorders presenting in adulthood are thought to originate during foetal development (17–19), understanding the impact of altered embryonic growth trajectory on later life disease is important to highlight at-risk individuals.

Moreover, variability in Grb10 expression is also linked to the dramatic range of body sizes observed between cetacean species (20), suggesting that modulating *grb10* expression could be an important target for agri- and aqua-culture. Average daily mass gain is elevated in beef cattle with a *grb10* associated deletion (21), and *grb10* single nucleotide polymorphisms (SNPs) impact muscle and lipid mass, angularity, and body conditioning score (22). Global knockout of *grb10* in mice correlates with elevated muscle mass, reduced lipid mass, and insulin sensitivity (23,24). Therefore, understanding the impact disruptions to early-life growth trajectory have on mature organism size, average daily gain, and lipid to muscle ratio may provide the groundwork to boosting meat yield, and quality which is required to match the growing global demand for protein.

Here, zebrafish (*Danio rerio*) were used to assess the importance of *grb10* as a coordinator of growth, metabolism, and cardiac health, in order to investigate the impact of early-life growth disruption on later-life cardiometabolic phenotype. *Grb10a* was transiently suppressed during zebrafish embryogenesis by antisense oligonucleotide directed blocking of mRNA splicing. *Grb10a* was confirmed to have an impact not only on embryonic growth, but also on cardiac and metabolic phenotypes. Importantly, this impact was found to persist into adulthood, inducing an enduring remodelling of the transcriptomic landscape.

Materials and Methods

Zebrafish Husbandry

AB zebrafish were maintained under standard conditions (≈28 °C; 14 h light/10 h dark cycle; stocking density < 5 fish per litre) within the Biological Services Unit of The University of Manchester. Embryos were collected and raised in egg water (Instant Ocean salt 60 µg/mL) up to 5 days post-fertilisation (dpf) and transferred to the main aquarium system. Young fry were fed powdered food and rotifers, while older fry and adults were fed powdered food and

95   brine shrimp (ZM Fish Food and Equipment, Winchester, UK). All regulated procedures

96   received ethical approval from the Institution's ethical review board and were performed

97   under a Home Office Licence (PPL P005EFE9F9 to HAS).

98   Transient Knockdown of *grb10a* Expression by Microinjection of Antisense Oligonucleotide

In accordance with current guidelines for morpholino use in zebrafish (25), the use of

morpholino-modified antisense oligonucleotides to knockdown (KD) *grb10a* was validated in

several ways. Morpholinos targeting two distinct sites should yield a similar phenotype, which

should display a dose-response effect and be rescuable by RNA co-injection, and a suitable

control morpholino with no phenotypic effect should be used to account for microinjection

technique (25). Morpholino-modified antisense oligonucleotides targeting the splice donor

sites of zebrafish *grb10a* coding exon three (e3i3) or four (e4i4) were designed by and

obtained from Gene Tools, LLC (Philomath, OR, USA) along with a standard control (SC)

oligonucleotide targeting human β-globin. Oligonucleotide sequences are listed in Table 1.

Microinjection solutions were generated as outlined in Table 2. Concentrations of ingredients

were consistent with standard practice (25). Phenol red and n-Cerulean (nuclear-targeting

blue fluorescent protein) mRNA were included in each solution to allow monitoring of

successful injection. A P-97 Flaming/Brown Micropipette Puller (Sutter Instruments, Novato,

CA, USA) was used to generate microinjection needles from 1 mm OD glass capillaries, which

were backloaded with 2 µl of injection solution and mounted on a needle holder held in a

micromanipulator attached to a PLI-100A Picoliter Injector (Warner Instruments, Hamden,

CT, USA). Embryos were injected once, as per established method (25), into the yolk directly

below the cell mass. Embryos were injected before the four-cell stage and were screened for

fluorescence at 48 hours post fertilisation (hpf) to ensure constitutive and even uptake of the

injection material. Non-uniformly or weakly-fluorescent embryos were removed.

119   Validation of *grb10a* Knockdown by PCR

120   Primer sequences, outlined in Table 1, were designed using SnapGene® software (GSL

121   Biotech, San Diego, CA, USA; available at snapgene.com) and synthesised by Thermo Fisher

122   Scientific (Waltham, MA, USA). Sequences were designed to be approximately 20 base pairs

123   with a GC content between 40 and 50 % and start with GC or GG to improve target annealing.

124   Primer pairs were designed to anneal at similar temperatures, and specificity was confirmed

with Primer BLAST (26). To confirm antisense oligonucleotide activity, RNA was extracted from pooled zebrafish embryos at 24, 48, 72, 96, and 120 hpf (n=3, 5 embryos per pool). RNA extraction was performed using QIAGEN RNeasy lipid extraction kit according to the manufacturer's instructions, and cDNA was generated by reverse transcription using the ProtoScript® II First Strand cDNA Synthesis Kit (NEB). The cDNA was amplified with primers flanking each splice site. PCR was performed using Taq polymerase (New England Biolabs (NEB, Hitchin, UK)) with thermocycling parameters outlined in Table 3. β-actin (*actb1*) was used as a control for cDNA integrity.

Signalling Analysis by Western Blotting

96 hpf zebrafish embryos were deyolked in Ringer's Buffer (n=15, performed in triplicate). Embryos were resuspended in 100 µl RIPA buffer (150 mM NaCl, 1 % Nonident P-40, 0.5 % Sodium deoxycholate, 0.1 % SDS, 25 mM Tris pH 7.4) containing protease and phosphatase inhibitors (Thermo Fisher Scientific) and homogenised by passing through a 22 g needle. Samples were incubated on ice for 30 minutes. The supernatant was clarified by centrifugation at 13000 rpm at 4 °C for 20 minutes and collected. Samples were denatured at 98 °C for 5 minutes with an equal volume of Laemmli buffer (final concentration 2 % SDS, 10 % glycerol, 60 mM Tris-Cl, 0.01 % bromophenol blue, 0.1 % β-Mercaptoethanol). Proteins were separated on a 10 % SDS acrylamide gel using BioRad Western Blot apparatus and powerpack for one hour at 130 V, 400 mA (running buffer 25 mM Tris, 200 mM glycine, 0.03 % SDS). Proteins were transferred for one hour in transfer buffer (25 mM Tris-HCl pH 7.6, 200 mM glycine, 20 % methanol, 0.03 % SDS) onto a membrane preactivated in methanol. The membrane was washed three times in TBS-T (137 mM NaCl, 2.7 mM KCl, 19 mM Tris, 0.1 % Tween-20) prior to incubation in blocking buffer (3 % BSA in TBS-T) for one hour. The membrane was rinsed three times in TBS-T and incubated overnight in primary antibody (Table 4) at 4 °C under constant agitation. The membrane was rinsed three times in TBS-T prior to incubation in secondary antibody (Table 4) for one hour at room temperature. The membrane was then covered with ECL Western Blotting Substrate (Promega, Southampton, UK) and imaged immediately using a BioRad ChemiDoc XRS+ Imager. Protein expression was quantified from band intensity in ImageJ (27).

Generation of *grb10a* mRNA for Overexpression and Knockdown Rescue

Total RNA was extracted from a pool of 96 hpf zebrafish embryos using QIAGEN RNeasy lipid extraction kit according to the manufacturer's instructions, and cDNA was generated by reverse transcription using the ProtoScript® II First Strand cDNA Synthesis Kit (NEB). *Grb10a* was amplified from cDNA by high specificity PCR (NEB Q5 Hot Start) with primers complimentary to the 5' and 3' ends of the open reading frame (Table 1). The product was purified using QIAGEN Quick Gel Extraction, blunt ligated into pCR-Blunt II-TOPO (Thermo Fisher Scientific) and transformed into *E. coli* following an established protocol. Purified plasmid was sequenced by GATC Biotech Sanger Sequencing to confirm successful cloning. The insert was then liberated by digestion with *Cla* I and *Xba* I restriction enzymes (NEB) and subcloned in pCS2+(28). Capped RNA was generated using the mMESSAGE mMACHINE® SP6 Transcription Kit (Thermo Fisher Scientific) according to the manufacturer's instructions. pCS2+ -grb10a was linearised by *Nsi* I (NEB) digestion prior to RNA generation. RNA was purified by MEGAclear™ Transcription Clean-Up. 1 µl of the purified RNA was analysed by gel electrophoresis to confirm amplification and structural integrity.

Physiological and Metabolic Phenotype Measurements

Whole body length, the longest straight-line distance between the snout and tip of the notochord, and yolk area measurements were taken every 24 hours from 48 to 120 hpf (Zeiss Axiocam MRm s1381, Zeiss ZEN lite (2012)). Embryos were dechorionated and acclimatised for ≥ one hour before imaging. Images were imported into ImageJ, which was calibrated with an image of a graticule of known size. Data were imported into GraphPad Prism version 7.00 for Windows (GraphPad Software, La Jolla, CA, USA, www.graphpad.com).

To investigate embryonic cardiac phenotype, embryos were sedated using a concentration known to have no impact on cardiac function (0.04 % MS-222 solution (29)). Heart beats were counted over a 20 second period and converted to beats per minute (bpm).

A Glucose Uptake-Glo TM Assay (Promega) was performed on 96 hpf zebrafish as an index of metabolic rate differences between treatment groups. Individual zebrafish embryos (n=5 per treatment) were injected with 1 mM 2-deoxyglucose-6-phosphate directly into the yolk and allowed to recover for 30 minutes. Embryos were processed in accordance with the manufacturer's instructions. Luminescence was measured on a Synergy™ H1 Microplate

185 reader (BioTek Instruments, Inc., Winooski, VT, USA), software version 2.07.17, with 8
186 readings per well.

Quantitative PCR

Quantitative PCR (qPCR) primers amplifying *grb10a* and markers of cardiac dysfunction were
designed (Table 1) and their efficiency validated (30). RNA for comparison of gene expression
between SC and KD samples was extracted from pooled (n=10) embryonic zebrafish or pooled
(n=3) adult (<1 year) heart samples by QIAGEN RNEasy Lipid Tissue Extraction kit according to
the manufacturer's instructions. Samples were repeated in triplicate and tested for gene
expression by qPCR (Applied Biosystems Power SyBr Green) (Table 3). Results were visualised
using MxPro QPCR Software (Agilent, Santa Clara, CA, USA). Relative fold change in gene
expression was calculated using the ΔΔCt method according to the following equation:

$$\Delta\Delta Ct = \Delta Ct_{e3i3} - \Delta Ct_{SC}$$

197 where

$$\Delta Ct = Ct_{gene\ of\ interest} - Ct_{housekeeping\ gene}$$

199 and

$$Fold\ change = 2^{-\Delta\Delta Ct}$$

201 Data were imported into GraphPad and unpaired t-tests were used to assess the difference
202 between samples.

Transcriptomic Analysis

Temporal changes in gene expression were assessed by computational analysis of
transcriptomic data. Pooled samples (n=5) were generated from each treatment group (SC,
KD) at 5, 10, 15, 20, and 30 dpf, with three repeats per sample. Individuals were culled under
terminal anaesthesia with only tissue anterior to the gills included, and total RNA was
prepared. Transcriptomic data were generated using Affymetrix Zebgene 1.0st arrays. Data
for all 75212 gene probes were imported into Qlucore Omics Explorer 2.2 (Lund, Sweden) as
.cel files and normalised using the robust multi-array average (RMA) approach with a gene
level summary. Zebrafish gene identities were assigned using the Affymetrix gene definitions.

Human orthologues were mapped (GRCh 38) using the *biomaRt* R-package (31). A workflow

pipeline of the subsequent transcriptomic analyses is outlined in *Supplementary Figure 1*.

Unsupervised analysis of gene expression by age group was conducted by generating

hierarchically clustered heat maps. Standard deviation filtering (standard deviation of specific

gene expression divided by maximum gene standard deviation [$s/s_{\max}$]) was performed on

the dataset to remove genes with low variance, unlikely to be informative (or below

detectable levels). The projection score (32), was used to determine the threshold for filtering

by calculating the maximum separation present in principal component analysis (PCA).

Hypernetwork Modelling

Hypernetwork analysis was performed to model the dynamics of the transcriptome by

quantifying shared correlations between target genes, a general model of which is outlined

in *Supplementary Figure 1*. All analyses were performed in R (version 3.4.2).

Using samples from all time-points in either SC (n=15) or KD (n=15) fish, Pearson's correlation

coefficients (*r*) were calculated between genes identified by unsupervised analysis (g) [KD =

119, SC = 297] and the rest of the transcriptome (g^c) [KD = 75093, SC= 74915]. Positive and

negative correlations greater than ± 1 standard deviation (sd) from the mean of the R-values

were binarized separately and the resulting matrices combined. In this way, a matrix (M) was

formed describing the positive and negative correlates of each element ($\in$) of *g* separately:

230
$$\in \text{ of } g \text{ in } M = \left\{ \begin{array}{ll} 1, & x > \pm 1 sd|r| \\ 0, & x \geq \text{otherwise.} \end{array} \right.$$

The resulting binary matrix (M) was multiplied by its transpose (M^t) to generate a matrix

($M.M^t$) which lists the number of shared correlations between any pair of genes (g). This

matrix represents the hypernetwork describing the higher order relationships between genes

not represented in traditional transcriptomic approaches. This measurement of co-ordination

has been hypothesised to model functional relationships (33). Coordination between genes

with age-related expression and the rest of transcriptome was determined using the Galois

correspondence. This was represented by the subset of the transcriptome ($\subset g^c$) showing

correlated expression with all the transcripts from the hypernetwork cluster ($\subset g$).

Quantification of Network Topology

Correlation networks model functional relationships within gene networks (34) and allow identification of clusters of highly connected genes (35). Quantification of SC and KD hypernetwork properties (connectivity and entropy) was performed on the matrix $M.M^t$. Connectivity is defined here as the sum of connections shared by each element of the network (g) and measures the direct and indirect relationships between them.

Entropy describes the degree of disorder within the distribution of shared correlations measured in each element of g. Entropy is correlated with the differentiation potential of a cell (36), with low entropy indicating specific pathway activation and high entropy indicating high signalling pathway redundancy. Entropy has also been used as an index of regularity and patterning (37). Entropy was measured using R package BioQC (38).

As the hypernetworks formed three clusters of genes when clustered hierarchically, all following analysis focused on the 20-30 dpf cluster (86 SC genes, 67 KD genes). Clusters were isolated and within-cluster connectivity and entropy were calculated per gene.

The expected background connectivity and entropy were measured in 1000 iterated hypernetworks using randomly selected genes (86 random genes and 67 random genes for the SC and KD respectively) (*Supplementary Figure 2*). The median expected connectivity and entropy were subtracted from the experimentally derived values to control for the background. Experimental data for SC and KD zebrafish are therefore presented as the difference between expected and observed connectivity and entropy.

Gene Ontology

To associate gene expression with biological processes, gene set enrichment analysis (GSEA) was performed (39). Unsupervised analysis was supported with GSEA ranked by age group ANOVA false discovery rate modified p-values [q-values] (Qlucore) using genes mapped to human orthologs. GSEA was also performed on regression data (ranked by R-value) using Webgestalt (40). Over-representation analysis (ORA) was used to identify gene ontology associated with unranked gene sets (Webgestalt). All gene ontology analysis used the GO Biological Process Ontology gene list (Molecular Signatures Database (39,41)).

Oxygen Consumption as a Measure of Metabolic Rate

To analyse metabolic rate, oxygen consumption was measured in 30 dpf zebrafish from each treatment group. Individual zebrafish were placed into 1 of 4 stop-flow respirometry chambers (volume 2 ml) and allowed to acclimate at 28 °C for > one hour. Chambers were refreshed immediately prior to the experiment until oxygen saturation measured 100 %. Optical oxygen sensors paired with oxygen sensor spots (Pyroscience, Aachen, Germany) were used to measure oxygen saturation within the chambers and recorded using a FireStingO2 Fiber-optic oxygen and temperature meter. Temperature was maintained at 28 ± 0.3 °C and was monitored and recorded with the FireSting integrated temperature meter. Probes were calibrated according to the manufacturer's instructions. Chambers were randomised per trial, with one chamber left empty to correct for background bacterial respiration. Oxygen consumption over time curves were recorded in triplicate with five trials per treatment. Chambers were refreshed when oxygen saturation reached 80 %. Oxygen consumption was measured as the change in oxygen saturation within the chamber per trial. To calculate the rate of oxygen consumption, linear regression in Microsoft Excel was used to approximate the change in oxygen saturation during each trial. This was normalised against the dry mass of the subject, length of the trial, and volume of the respirometry chamber according to the following equation:

$$Oxygen\ consumption\ (\mu gO_2 h^{-1} g^{-1}) = \frac{\Delta O2\% \times \frac{7900 \mu gL^{-1}}{100} \times chamber\ volume\ (L)}{time\ (h) \times mass\ (g)}$$

Where 7900 μgL^{-1} is equivalent to 100 % oxygen saturation at 28 °C. This normalises the data against the dry mass of the subject, time of the trial, and volume of the respirometry chamber.

Statistical Tests

For transcriptomic analyses, rank regression (least squares method) was used to generate the most appropriate linear model for each probe (the smallest degree of variance over the sample). Multi group analysis of variance (ANOVA) was used to associate each gene ID with time dependent gene expression. Wilcoxon rank sum test (ggpubR package for R (42)) was used to test for differences of network topology between groups. False discovery rate (FDR)

adjustment was made using the Benjamini-Hochberg method and applied to the gene
expression and ontology analysis (43).

All data were ROUT tested (44) for outliers and subject to D'Agostino and Pearson normality
tests. All comparisons between SC and KD measurements were performed using an unpaired
t-test. Comparisons of multiple groups were performed using one-way ANOVAs. Post-hoc
power calculations were performed to confirm sample sizes were sufficient, where $\alpha = 0.05$.

Results

Knockdown of *grb10a* Expression by Splice-Blocking Antisense Oligonucleotide

As *grb10* has been linked to embryonic growth trajectory, expression was examined over the
first 120 hpf (hours post fertilisation) in zebrafish embryos. qPCR analysis of *grb10a*
expression at 24-hour intervals revealed a strong upregulation at 48 hpf compared to
housekeeping genes (*Figure 1a*). Expression of the *grb10* paralogue, *grb10b*, was not
detectable at any time point.

To manipulate the expression of *grb10a*, zygotes were microinjected with splice-blocking
antisense oligonucleotides: e3i3 and e4i4. Two distinct splice sites, exon 3 and 4 donor splice
sites (*Figure 1b*), were targeted in order to confirm the specificity of phenotypes
accompanying oligonucleotide injection, in accordance with current guidelines (25).
Disruption of the targeted splice site was confirmed through multiplexed RT-PCR
amplification using a mixture of primers (F, R1 and R2) flanking the splice sites (*Figure 1b*). No
products at all were detected for standard control oligonucleotide injected embryos and only
a single product of the anticipated size was detected for embryos injected with either e3i3 or
e4i4 (*Figure 1c*), consistent with amplification from a cDNA rather than genomic DNA
template. Further, the corresponding intron was shown by sequencing to be included in the
transcript for e3i3 and e4i4 treated zebrafish (data not shown).

To address the effect of *grb10a* KD on insulin signalling, phosphorylation of key proteins in
the insulin signalling pathway was analysed by Western blotting. As shown in *Figure 1d*,
phosphorylated (active) versus total protein ratios of AKT, ERK, and S6 were significantly
elevated in *grb10a* KD zebrafish at 96 hpf compared to SC (p=0.0080, 0.0497, <0.0001
respectively, n=3), with S6 activation almost 5 times greater in KD zebrafish compared to SC.

Figure 1: **Grb10a** *is successfully knocked down in zebrafish injected with splice-blocking antisense oligonucleotides.* *1a.* *Grb10a* qPCR of WT embryos (24-120 hpf, triplicated,

n=5 per well). Data is shown as gene expression relative to β-actin and shows a significant peak at 48 hpf. *1b.* Schematic of the first five exons of the zebrafish *grb10a* gene.

5' splice sites are highlighted with the forward and reverse primer triad indicated. *1c.* PCR amplification of the e3i3 and e4i4 splice site in embryos treated with either Standard

Control morpholino, e3i3, or e4i4 (24-120hpf, n=5 per well). β-actin was used as a positive control. *1d.* Western blot results of phosphorylated vs total protein ratios for three

major signalling molecules of the insulin signalling pathway: ERK, AKT, and S6. Activation of all three proteins was found to be significantly elevated in KD zebrafish compared

to SC (n=3, unpaired t-test **=0.0083, *=0.0498, ****<0.0001).

Growth Trajectory and Early Life Cardiometabolic Phenotype is Significantly Impacted by Transient *grb10a* Perturbation

To determine the effect of *grb10a* KD on embryonic growth, total body length was measured in antisense oligonucleotide injected animals at various timepoints. *Figure 2a* shows that initially, total body length was comparable between KD and SC zebrafish (2.857 ± 0.0549 mm vs 2.826 ± 0.0962 mm, p=0.7896, n=9 and n=10 respectively). From 48 hpf, corresponding to the peak in WT *grb10a* expression (*Figure 1a*), KD zebrafish began to diverge from SC individuals. Body length was significantly different between the two groups, with KD zebrafish longer on average than SC zebrafish (3.411 ± 0.0165 mm vs 3.177 ± 0.0231 mm at 72 hpf, p<0.0001, n=46 and n=41 respectively). This phenotype was reversed in zebrafish overexpressing *grb10a,* with individuals injected with *grb10a* mRNA significantly shorter than SC counterparts (3.361 ± 0.0239 mm vs 3.505 ± 0.0339, p=0.001, n=24 and n=25 respectively), as shown in *Figure 2b*. Co-injection of e3i3 and *grb10a* RNA resulted in normalisation of growth (3.505 ± 0.0339 mm vs 3.564 ± 0.0265 mm, p=0.3792, n=25), confirming the validity of e3i3 induced *grb10a* KD. Moreover, *grb10a* KD induced by e4i4 (albeit weaker than e3i3; *Figure 2c*) also resulted in increased body length; while the ability of *grb10a* overexpression to suppress growth was shown to be dose dependent (*Figure 2c*). Intriguingly, by 120 hpf body length converged for both KD and OE, indicating activation of compensation to regulate growth.

Embryonic heart rate was measured to investigate the impact of *grb10a* KD on cardiometabolic phenotype. As shown in *Figure 2d*, average heart rate began to diverge between the treatment groups at 48 hpf, correlating with the WT peak in *grb10a* expression. While heart rate increased slightly over time in SC zebrafish, in-line with increasing body size, average KD heart rate fell. By 120 hpf, average heart rate for KD individuals was almost 50 % lower than SC individuals (61.5 ± 6.97 bpm vs 118.4 ± 2.83 bpm, p<0.0001, n=14 and n=19 respectively).

Embryonic metabolic rate was also investigated in KD and SC zebrafish by looking at yolk absorption. The reduction in yolk area over time was measured to evaluate the difference in the rate of yolk consumption between treatment groups. As shown in *Figure 2e*, there was no significant difference between yolk areas at 24 hpf (p=0.8185, n=10). Yolk area declined steadily from 48 hpf, and significantly more so in KD zebrafish compared to SC zebrafish for

the remaining period of observation (0.298 ± 0.0055 mm^2 vs 0.390 ± 0.0104 mm^2, p<0.0001,

n=18 and n=19 respectively). This suggested that metabolic rate was elevated in KD zebrafish

compared to SC. To further interrogate insulin signalling, a Glucose Uptake-Glo^{TM} Assay was

performed to monitor 2-deoxyglucose-6-phosphate accumulation and support these findings.

As shown in *Figure 2f*, 2D6P accumulation was significantly higher in KD zebrafish compared

to SC, an increase of almost 30 % (p=0.0002, n=5). These findings are consistent with the role

of *grb10a* as a negative regulator of the insulin signalling pathway (5).

Figure 2: Growth and cardiometabolic phenotype are significantly impacted by grb10a perturbation. 2a. Mean total body length ± SEM of SC and KD zebrafish from 24 to 120 hpf. T-test significance ***=0.0006 ****<0.0001 ***=0.0001. 2b. Mean total body length ± SEM and individual data points of 96 hpf zebrafish embryos (n=25). Grb10a KD phenotype was reversed in grb10a overexpression zebrafish. Coinjection resulted in phenotype rescue. One-way ANOVA revealed KD zebrafish were significantly longer, while grb10a overexpression zebrafish were significantly smaller than SC (***=0.0001). Rescue zebrafish were of similar length to SC (ns=0.3792). 2c. Mean body length measurements relative to SC ± SEM. E3i3 and e4i4 both exhibit a propensity to elevate body length, while grb10a RNA shows a dose-dependent ability to inhibit body length. 2d. Mean heart rate ± SEM in beats per minute of SC and KD zebrafish. Heart rate was significantly lower in KD embryos compared with SC after 48 hpf (***=0.0006, ****<0.0001). 2e. Mean yolk area ± SEM of SC and KD embryos over the embryonic life stage. Following the initial 24 hours, KD zebrafish had significantly smaller yolks compared to SC, indicating yolk content was metabolised at a much higher rate (**=0.0084 ****<0.0001). 2f. Glucose Uptake-Glo™ Assay of 96hpf KD and SC zebrafish, where higher luminescence indicates a greater accumulation of intracellular 2D6P. Luminescence was approximately 30 % greater in KD zebrafish compared to SC (***=0.0002). All SC vs KD comparisons by unpaired t-test.

Transient *grb10a* Knockdown Dysregulates Age-Related Expression in the Transcriptome

To understand whether disruption in embryonic growth trajectory could lead to lasting changes in gene expression, the transcriptomic landscape of SC and KD zebrafish was investigated over the first 30 dpf. As described in the methods, unsupervised hierarchical clustering, standard deviation filtering, and maximised projection scores were used to define a gene set with strong age-associated expression in the SC zebrafish (297 genes with a maximised projection score [PS] = 0.43).

Clear age-related associations were identified in the SC transcriptome, with genes falling into four clusters (5 dpf - 163 genes, 10 dpf- 15 genes, 15 dpf – 32 genes, and 20-30 dpf – 87 genes) (*Figure 3a*). Clustering of these same genes was disrupted in the KD zebrafish (*Figure 3b*). Three of the four clusters defined in the controls mapped to the same age-associated cluster in the KD data (10 dpf – 14/15 genes, 15 dpf - 29/32 genes, and 20-30 dpf – 74/87 genes). However, genes associated with 5 dpf expression in the SC zebrafish were generally expressed at different time points in the KD zebrafish (dotted white lines, *Figure 3a* and *Figure 3b*), with a mapping of only 38/163 genes (23%). Notably, 5 genes associated with 5 dpf in SC zebrafish mapped to 20-30 dpf in the KD zebrafish. Human orthologs of these dysregulated genes included *DGAT2* (fatty acid metabolism enzyme), *GAMT* (an enzyme involved in creatine production, required for energy storage, muscle contraction, and fatty acid oxidation), and *PDIA2* (an enzyme involved in thiol-disulphide interchange reactions, particularly in the pancreas).

The existence of a pattern of gene expression associated with age in SC zebrafish which is dysregulated in KD zebrafish implies the co-ordination of an altered set of genes in KD animals. In the KD, unsupervised analysis defined a set of 119 genes (maximised projection score = 0.37) which divided into three clusters, only loosely age-associated (5-15 dpf – 37 genes, 15-30 dpf – 16 genes and 20-30 dpf – 66 genes) (*Figure 3c*). There was a 90 gene overlap in age-associated genes between the SC and the KD. A further 207 genes were age-associated in the SC and 29 in the KD (*Figure 3d*).

Gene set enrichment analysis on the age-related genes in both SC and KD zebrafish demonstrated a range of similar (*Supplemental Table 1*) and dissimilar pathways (*Figure 3e*). This analysis revealed that a range of pathways involving actin and collagen, along with

415   extracellular structure and RNA processing, were co-ordinated in an age-related manner in

416   KD but not SC zebrafish. Also, a set of metabolic pathways were age associated in SC zebrafish

417   but not in KD animals. This clear dysregulation of age-related gene expression in the KD

418   zebrafish implies transient *grb10a* KD induces persistent remodelling of the transcriptome.

Name	KD NES	KD q	SC NES	SC q
ACTIN FILAMENT BASED MOVEMENT	2.088	0.012	2.176	1.000
PLATELET ACTIVATION	2.068	0.013	2.236	1.000
EXTRACELLULAR STRUCTURE ORGANIZATION	2.011	0.013	2.246	1.000
COLLAGEN FIBRIL ORGANIZATION	2.026	0.014	2.257	1.000
REGULATION OF RNA SPLICING	1.608	0.039	0.726	0.855
GLUTATHIONE METABOLIC PROCESS	1.660	0.031	0.735	0.848
RIBOSOME ASSEMBLY	1.700	0.026	0.743	0.840
REGULATION OF MRNA PROCESSING	1.609	0.039	0.810	0.772
PLATELET DEGRANULATION	1.753	0.022	2.155	0.757
METANEPHROS DEVELOPMENT	1.709	0.026	0.841	0.733
DICARBOXYLIC ACID TRANSPORT	0.690	0.895	1.693	0.048
POSITIVE REGULATION OF WOUND HEALING	0.876	0.703	1.672	0.048
FAT SOLUBLE VITAMIN METABOLIC PROCESS	0.950	0.597	1.655	0.049
POSITIVE REGULATION OF SMOOTH MUSCLE CELL PROLIFERATION	0.986	0.543	1.708	0.048
REGULATION OF STEROL TRANSPORT	1.012	0.503	1.704	0.049
POSITIVE REGULATION OF PROTEIN BINDING	1.033	0.471	1.663	0.049
AMINO ACID TRANSPORT	1.037	0.466	1.703	0.048
POSITIVE REGULATION OF LIPID LOCALIZATION	1.059	0.436	1.757	0.050
CELLULAR MODIFIED AMINO ACID BIOSYNTHETIC PROCESS	1.068	0.423	1.664	0.049
NEGATIVE REGULATION OF EXTRINSIC APOPTOTIC SIGNALING PATHWAY	1.097	0.383	1.674	0.049

Figure 3. Transcriptomic analysis of Standard Control and grb10a Knockdown gene expression over the first

30 dpf. Hierarchically clustered heat maps of gene expression generated from an Affymetrix GeneChip™

Zebrafish Genome Array of SC (*3a*) and KD (*3b* and *3c*) zebrafish RNA, taken at 5, 10, 15, 20, and 30 dpf.

Expression segregates into three clusters in SC zebrafish (*3a*). Clustering of the same genes identified in *3a* are

disrupted in the KD dataset (*3b*). Analysing the KD dataset independently shows age-related hierarchical gene

expression in the falls into two clusters (*3c*). *3d*. Venn diagram of age associated genes. *3e*. Gene set enrichment

analysis, using the GO Biological Process Ontology gene list, of the age-related genes in the SC and KD datasets.

The top 20 most enriched pathways with differential expression are included here, with associated normalised

enrichment scores and q-values.

Transient *grb10a* Knockdown Alters Co-Ordination Within the Transcriptome

To investigate the co-ordination of the transcriptome with age-associated gene expression,

hypernetwork models were constructed for the SC and KD datasets based around genes

identified by the previous unsupervised analysis. This approach can be used to model

functional relationships (33). The outputs of these analyses were visualised as heatmaps

where colour intensity represented the number of shared interactions between a gene pair.

In SC animals, three clusters of shared interactions were defined. Cluster 1 corresponded to

genes expressed at 5 dpf (161/297 genes), cluster 2 at 10 and 15 dpf (50/297 genes) and

cluster 3 at 20 and 30 dpf (86/297 genes) (*Figure 4a*). In KD animals, however, only two

clusters were identified. Genes in cluster 1 were expressed across 5, 10 and 15 dpf (31/119

genes) and genes in cluster 2 expressed at 20 and 30 dpf (65/119 genes) (*Figure 4b*). Notably,

the large cluster of co-ordinated interactions at 5 dpf in the SC was entirely absent in the KD,

instead forming a new cluster along with genes expressed at 10 and 15 dpf. The 20 and 30 dpf

cluster represented 28.9% and 54.6% of the total gene set in the SC and KD zebrafish

respectively, indicating a *grb10a* KD-induced remodelling of the transcriptome in later life.

Differences in the co-ordination of the transcriptome in later life were quantified using two

network topology parameters, connectivity and entropy. Hypernetwork connectivity

quantifies the number of interactions within the transcriptome and is related to function.

Entropy is a measure of information content and can be thought of as a measure of

"disorder"; a decreased entropy (more order) describes a network with little crosstalk and a

more discrete function (36,45). While conversely an increased entropy has less order and

describes a network with increased crosstalk and pleiotropic function.

Changes in connectivity (*Figure 4c*) and entropy (*Figure 4d*) were calculated for genes

identified as active at 20-30 dpf by the unsupervised and hypernetwork approaches. This was

compared with entropy and connectivity calculations from a thousand iterations of random

genes in order to account for random chance (*Supplemental Figure 2*). Genes associated with

20-30 dpf in the KD animals were found to be more highly connected and more entropic than

Figure 4 Coordination within the transcriptome is altered by grb10a KD, as assessed by hypernetwork analysis

4a. Hypernetwork analysis defined three clusters of highly connected genes in Standard Control zebrafish,

corresponding to 5 dpf, 10-15 dpf, and 20-30 dpf respectively. *4b*. Two clusters were defined in the KD data,

corresponding to 5-15 dpf and 20-30 dpf. *4c and 4d*. Violin plots of connectivity (left) and entropy (right) in the

20-30 dpf cluster. Both connectivity and entropy were elevated in the KD zebrafish compared to standard

controls when controlled for random gene measurements, suggesting more diverse functions.

in the SC when normalised for random effects. Additionally, this increase in connectivity is greater (1.20-fold, $p < 1\times10^{-6}$) and the reduction in entropy is smaller (2.0-fold, $p < 1\times10^{-6}$) in the KD zebrafish compared to the SC in relation to randomly selected gene sets (*Supplemental Figure 2*). This assessment of hypernetwork topology demonstrates the co-ordination of age-related gene expression in the SC and the dysregulation in the KD zebrafish. These data show that transient *grb10* KD induces significant remodelling of the transcriptome, enduring in later life, with increased connectivity between genes and a more directed functionality.

Transcriptome-Wide Links to the Enduring Remodelling of Gene Expression Associated with Transient *grb10a* Knockdown

Having identified age-related gene expression we now wanted to define a wider set of associated genes which coordinate with age-related gene expression defined by calculating Galois correspondences (the one-to-one correspondence between age-related genes and their correlates).

12775 and 459 genes were defined in the Galois correspondence from the 20-30 dpf KD and SC hypernetwork clusters, respectively. 27.8-fold more genes with co-ordinated regulation at 20-30 dpf exist in the KD set than SC zebrafish. All genes in the Galois correspondence demonstrated significant rank regression with age (*Supplemental Table 2*). In the KD zebrafish, 7493 genes positively correlate with age (*Figure 5a*), while 5282 negatively correlate (*Figure 5b*). This was reduced to 313 positive and 146 negative co-ordinated genes in the SC. The overlap was 244 (77.9% of SC) and 60 (41.1% of SC) in the positively and negatively correlated sets, respectively. Thus, genes in the Galois correspondence with expression at 20-30 dpf in SC zebrafish demonstrated a similar pattern of expression in KD (*Figure 5c*). However, genes with co-ordinated expression at 20-30 dpf in the KD zebrafish were dysregulated in the SC animals (*Figure 5d*).

Gene ontology associated with the 20-30 dpf co-ordinated gene expression clusters in both KD and SC zebrafish (GSEA ranked by R-value, top 100 pathways with weighted set cover) are outlined in *Figure 5e* and *Figure 5f*. A distinctly different set of regulated pathways was noted between the groups. The KD gene set was associated with RNA processing, a range of metabolic pathways, and cardiovascular system development. The SC gene set was associated with growth and immune pathways.

Figure 5 Analysis of the set of genes in the Galois correspondence shows a 27.8-fold increase in the KD ZF.

5a-5b. Venn diagrams of genes positively (left) and negatively (right) correlating with age. 5c-5d. Hierarchically clustered heat maps of gene expression of the genes identified in the Galois correspondence. Gene expression in the standard control (5c) cluster into two age related groups, whereas expression in the knockdown (5d) show significant dysregulation. 5e-5f Gene set enrichment analysis (GSEA) ranked by R-value of rank age regression in the standard control (5e) and knockdown (5f) Galois correspondence. 5g GSEA ranked by R-value of rank age regression of the cluster of genes in the white box in 5d.

Of the genes with co-ordinated expression at 20-30 dpf in the KD zebrafish that were

dysregulated in the SC animals (*Figure 5d*), there was a subgroup with a distinct pattern of

expression at day 15, downregulation at day 20, and re-expression at day 30 (white box,

Figure 5d). This subgroup of 3460 genes (*Supplemental Table 3*) was associated with a range

of gene ontologies related to metabolism and development (*Figure 5g*) and is linked to the

spike in growth identified in *Figure 6a*. Pathways included those involved in cardiovascular

system development, muscle structure development, and developmental maturation.

The Impact of Transient *grb10a* KD Persists into Adulthood

As dysregulation of pathways associated with growth, cardiovascular system development

and metabolism were identified, associated with persistent long-term changes in the

transcriptome relating to *grb10a* KD, investigation was conducted into the differences in

growth rate, oxygen consumption, and cardiac molecular phenotype in older animals.

Total body length measurements were taken up to 30 dpf. As shown in *Figure 6a*, growth was

significantly elevated in KD zebrafish compared to SC zebrafish between 15 and 20 dpf (30 %

increase, 7.493 ± 0.2726 mm vs 4.320 ± 0.1594 mm, p < 0.0001, n=10). This period of change

in growth rate corresponded precisely to the cluster of dysregulated genes identified in the

KD animals (*Figure 5g*). The growth profile of the KD zebrafish is shifted to an earlier age

compared to the SC growth profile, suggesting a faster rate of maturation. The GSEA

highlighted a reduction in activity in developmental maturation pathways (normalised

enrichment score [NES] < 1) in the controls vs. the KDs, which was replicated in the

comparison between KD and SC growth rates at approximately 20 dpf.

Juvenile (30 dpf) metabolic rate was investigated by stop-flow respirometry. As shown in

Figure 6b, oxygen consumption was 7 times greater in KD zebrafish than SC (134.4 ± 15.60

$\mu gO_2h^{-1}g^{-1}$ vs 19.0 ± 3.28 $\mu gO_2h^{-1}g^{-1}$, p<0.0001, n=5), suggesting metabolic rate was also

significantly elevated. Thus, along with significant alteration in gene expression revealed by

transcriptomic analysis over juvenile phases, growth and metabolic rates were also divergent.

To address whether differences in earlier life course phases might impact adult phenotypes,

the impact of transient *grb10a* KD on adult (1 year) cardiac health was assessed by qPCR. As

shown in *Figure 6c*, *myl7* expression (an index of muscle mass and hypertrophy) was over 20

% greater in KD zebrafish cardiac tissue compared to SC (p<0.0001, n=3), while *nppa*

expression (cardiovascular homeostasis, associated with atrial fibrillation (46)) was down
almost 40% compared to SC zebrafish (p=0.0012, n=3). This not only suggests a protective
phenotype in terms of cardiac health, but also highlights the lasting impact of transient
grb10a KD in adult tissue. There was no difference in the expression of *pcna* (proliferating cell
nuclear antigen, an index of cellular proliferation), indicating there was no increase in
proliferation. The greater degree of *myl7* expression in the absence of an increase in *pcna*
expression suggests an increase in hypertrophy (muscle size) rather than hyperplasia (cell
number) in the cardiac tissue.

None of these cardiac phenotype marker genes were present in the Galois correspondence
associated with persistent alteration of the transcriptome. However, all these genes showed
dysregulated expression in the KD animals in early life (*Supplemental Table 4*).

a.

b.

c.

Figure 6 Growth and cardiometabolism continue to be impacted after morpholino attenuation. **6a.** Mean total body length ± SEM of SC and KD zebrafish up to 30 dpf. Following the embryonic growth spurt, KD zebrafish experienced an additional period of rapid growth between 15 and 20 dpf (****<0.0001). **6b.** Mean oxygen consumption + SEM of 30 dpf zebrafish (n=5), adjusted for body weight. KD zebrafish consumed significantly more oxygen per hour per gram of tissue than SC zebrafish (****<0.0001). **6c**. qPCR results of three genes associated with cardiac performance in adult cardiac tissue, relative to β-actin. *Myl7* expression was significantly elevated in KD zebrafish (****<0.0001) while *nppa* expression was significantly down regulated (***=0.0012) compared to SC zebrafish. There was no significant difference between the expression of *pcna* (p=0.3041). All comparisons by unpaired t-test.

Discussion

The first key finding from this study is that grb10a regulates embryonic growth in zebrafish, consistent with its role in mammalian embryogenesis (47–49). Embryonic body length was significantly elevated in KD zebrafish, and significantly repressed following *grb10a* overexpression, clearly demonstrating the role of grb10a as a modulator of embryonic growth. In addition, key elements in the insulin signalling pathway were significantly upregulated following *grb10a* KD, consistent with the role of grb10a as a negative regulator of this pathway (50,51). Transient disruption of grb10a signalling was sufficient to induce morphological, physiological, and transcriptomic changes which persisted to the late-juvenile stage, despite no further manipulation to the organism. E3i3 treated zebrafish were significantly larger during embryonic development, with significantly elevated metabolic rate, and depressed heart rate. This suggests a clear link between embryonic growth, metabolism, and cardiac phenotype, indicating that grb10a may play a fundamental role in coordinating these distinct pathways.

Additionally, metabolic rate remained elevated in the juvenile zebrafish, supporting the concept that disruptions to embryonic growth and development have a lasting impact on health and disease. Both embryonic and adult cardiac systems were impacted by *grb10a* KD. The ability of grb10a disruption to modify growth, metabolism, and cardiac phenotype supports a fundamental link between these three distinct aspects. As gene expression remained significantly perturbed by 30 dpf, it is clear that transient g*rb10a* KD has persistent long-term impacts following attenuation of the morpholino, potentially indicating a lasting epigenetic remodelling. This is the only study to our knowledge to report this impact.

Transcriptomic data analysis not only confirmed a prolonged impact of transient KD, persisting after morpholino attenuation, but also revealed important gene expression trends regarding life history phase transitions in WT zebrafish. Two key transitionary phases (5 to 10 dpf and 15 to 20 dpf) were identified, with WT zebrafish undergoing a transcriptomic shift between three distinct gene clusters. These clusters correlate with the transition between larval and juvenile phases. Further investigation into these clusters will provide insight into the major factors regulating early growth and development compared to later life homeostasis.

In contrast, KD zebrafish only displayed one transitionary phase, indicating grb10a may

coordinate this life-history phase transition. There was no clear transition in gene expression

between 5 and 10 dpf. This suggests falling levels of grb10a (post 48 hpf peak) in WT zebrafish

may induce this gene expression transition, and ablation of this grb10a gradient is sufficient

to persistently remodel gene expression and to impact cardiometabolic function in later life.

Hypernetwork analysis allowed quantification of the coordination of expression within the

transcriptome. There was an increase in connectivity in the hypernetwork model of KD

transcriptome activity compared to controls, indicating a greater degree of interaction

between age-related genes in the KD zebrafish. The hypernetwork entropy in age-related

genes compared with randomly selected genes was reduced to a greater extent in the SC than

the KD. A reduction in interactome entropy, as seen in SC zebrafish, is associated with more

highly differentiated cell populations, corresponding to narrower biological function (36).

Therefore, in KD zebrafish there will be a broader range of biological functions consistent with

the increase in connectivity in the hypernetwork. In previous work looking at prepubertal

growth in children we noted that greater entropy in growth hormone secretion was

associated with better growth (37); these results imply that a broad range of pathways would

be contributing to the increased growth hormone secretion.

The co-ordination between age-related gene expression and the wider transcriptome was

assessed by measuring all genes correlated with the hypernetwork cluster (Galois

correspondence). This revealed a 27.8-fold increase in co-ordinated genes in the KD zebrafish

compared with SC zebrafish, and highlighted a range of associated pathways. This included

cardiovascular development and metabolism in the KD, compared to immunological and

growth-associated pathways in the SC. Taken together, these data indicate an ongoing impact

of *grb10a* KD on biological functions.

Findings from this study may also provide important insight for the agri- and aquaculture

industries. Embryonic heart rate was significantly depressed in KD zebrafish embryos, despite

increased body length, indicating increased cardiac efficiency over SC individuals. Myl7

expression, a cardiac specific myosin light chain protein, was upregulated in the mature KD

cardiac tissue, while pcna, a marker of proliferation, was not significantly different between

the two groups. This suggests the difference in myl7 gene expression is due to an increase in

cardiac cell size (hypertrophy) rather than cell number (hyperplasia).

In addition, the promotion of embryonic growth induced by *grb10a* KD may be a key
alternative to growth hormone treatment for improving meat yield and production efficiency.
This may be particularly useful for fisheries, as larger juvenile fish will be more capable of
overwintering (52,53), and thus improve fish stocks.

Cardiac development was also linked to the persistent changes observed in the transcriptome
in the KD animals. The previously described molecular cardiac phenotype markers, while not
present in the clusters of genes showing persistent dysregulation, were shown to display
altered age-related expression in early life. This suggests an indirect action on later life cardiac
physiology.

Finally, this model of embryonic growth perturbation may yield significant insights into the
propensity for early growth disruption in SGA and LGA new-borns to convey elevated risk of
disease in later life. It is widely accepted that many disorders may have their origins during
embryonic development (often termed the developmental origins of adult disease hypothesis
(54)). Early life growth disruption and non-average for gestational age status convey elevated
risk of cardiac and metabolic disorders in later life (1,55–57). While this has been observed
across multiple human populations (3,58,59), the mechanisms involved are not fully
understood. As grb10a modulation is sufficient to alter embryonic growth trajectory,
metabolic rate, and cardiac function, this model may prove key in understanding the
mechanisms involved in the developmental origins of health and disease and identifying novel
avenues for prevention and treatment.

While mammalian models have been used to show the immediate impact of embryonic
growth disruption, replicated in this study, their use for longitudinal study is limited, and little
research has been conducted into later life impacts of early growth disruption. Due to the
nature of human data collection, matched data for embryonic growth rate and later life
disease risks is not possible, with measurements limited to mass and body size at birth. While
this is somewhat informative, multiple distinct growth trajectories may yield similar birth
weights, such as growth restriction followed by catch-up growth, or overgrowth followed by
catch-down growth (55). Both catch-up and catch-down growth have been reported to
correlate with increased risk of chronic health disorders (1,60,61). Furthermore, the growth
profile was shifted to an earlier age in the KD zebrafish, reflecting similar growth profiles
observed in cases of precocious puberty (62). This suggests the KD zebrafish may mature at a

greater rate than SCs and presents an interesting model for investigating growth and
maturation. This model not only facilitates growth rate measurements, but due to the short
generation time is also highly suitable for longitudinal study throughout adult life.

As key physiological measurements and the transcriptomic landscape is persistently
remodelled following transient *grb10a* disruption, this model may provide the link between
embryonic development and later disease risk (63). Investigation into the metabolic and
cardiac performance of the adult is the next key step.

Conclusion

This study proves transient knockdown of *grb10a* expression alters growth trajectory and
cardiometabolic phenotype in embryonic zebrafish. This impact persists into adulthood,
correlating with a measurable remodelling of the transcriptomic landscape. This provides
significant evidence to suggest grb10a plays a fundamental role in the coordination of these
distinct physiological pathways and could represent a promising avenue for production
enhancement in an agricultural setting. The novel model of early growth disruption generated
in this study, featuring easily measurable phenotypic characteristics, a short developmental
window, and rapid generation time, provides much needed groundwork for thorough
longitudinal study into the mechanisms underpinning the developmental origins of health and
disease.

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Competing Interests

The authors declare the research was conducted in the absence of any conflicts of interest.

Data availability

Transcriptomic data is available from the Gene Expression Omnibus (GSE162474).

References

1. Lei X, Zhao D, Huang L, Luo Z, Zhang J, Yu X, et al. Childhood Health Outcomes in

Term, Large-for-Gestational-Age Babies with Different Postnatal Growth Patterns. Am

J Epidemiol [Internet]. 2018 Jul 13;187(3):507–14. Available from:

https://doi.org/10.1093/aje/kwx271

2. Kimm SYS. Fetal origins of adult disease : the Barker hypothesis revisited — 2004.

Curr Opin Endocrinol Diabetes. 2004;11(192–196):245–9.

3. Barker DJP, Osmond C, Kajantie E, Eriksson JG. Growth and chronic disease: Findings

in the Helsinki Birth Cohort. Ann Hum Biol. 2009;36(5):444–58.

4. Harding J. The nutritional basis of the fetal origins of adult disease. Int J Epidemiol

[Internet]. 2001;30(1):15–23. Available from: https://academic.oup.com/ije/article-

lookup/doi/10.1093/ije/30.1.15

5. Desbuquois B, Carré N, Burnol A-FF, Carre N, Burnol A-FF. Regulation of insulin and

type 1 insulin-like growth factor signaling and action by the Grb10/14 and SH2B1/B2

adaptor proteins. FEBS J. 2013 Feb;280(3):794–816.

6. Charalambous M, da Rocha ST, Hernandez A, Ferguson-Smith AC. Perturbations to

the IGF1 growth pathway and adult energy homeostasis following disruption of

mouse chromosome 12 imprinting. Acta Physiol. 2014;210(1):174–87.

7. Murdaca J, Treins C, Monthouel-Kartmann M-N, Pontier-Bres R, Kumar S, Van

Obberghen E, et al. Grb10 prevents Nedd4-mediated vascular endothelial growth

factor receptor-2 degradation. J Biol Chem. 2004 Jun;279(25):26754–61.

8. Tezuka N, Brown AMC, Yanagawa S ichi. GRB10 binds to LRP6, the Wnt co-receptor

and inhibits canonical Wnt signaling pathway. Biochem Biophys Res Commun

[Internet]. 2007 May 11 [cited 2020 Oct 20];356(3):648–54. Available from:

https://pubmed.ncbi.nlm.nih.gov/17376403/

9.   Wick KR, Werner ED, Langlais P, Ramos FJ, Dong LQ, Shoelson SE, et al. Grb10 inhibits

insulin-stimulated insulin receptor substrate (IRS)-phosphatidylinositol 3-kinase/Akt

signaling pathway by disrupting the association of IRS-1/IRS-2 with the insulin

receptor. J Biol Chem. 2003 Mar;278(10):8460–7.

10.   Charalambous M, Cowley M, Geoghegan F, Smith FM, Radford EJ, Marlow BP, et al.

Maternally-inherited Grb10 reduces placental size and efficiency. Dev Biol [Internet].

2010 Jan 1 [cited 2017 Nov 6];337(1):1–8. Available from:

http://linkinghub.elsevier.com/retrieve/pii/S0012160609012548

11.   Everson TM, Marable C, Deyssenroth MA, Punshon T, Jackson BP, Lambertini L, et al.

Placental expression of imprinted genes, overall and in sex-specific patterns,

associated with placental cadmium concentrations and birth size. Environ Health

Perspect [Internet]. 2019 May;127(5):57005. Available from:

https://pubmed.ncbi.nlm.nih.gov/31082282

12.   Depetris RS, Hu J, Gimpelevich I, Holt LJ, Daly RJ, Hubbard SR. Structural basis for

inhibition of the insulin receptor by the adaptor protein Grb14. Mol Cell [Internet].

2005;20(2):325–33. Available from: http://ac.els-cdn.com/S1097276505015984/1-

s2.0-S1097276505015984-main.pdf?_tid=11727a1a-b532-11e5-96b1-

00000aacb360&acdnat=1452166415_c128af004e062d38d997f991a691a7be

13.   Crippa M, Bonati MT, Calzari L, Picinelli C, Gervasini C, Sironi A, et al. Molecular

Etiology Disclosed by Array CGH in Patients With Silver-Russell Syndrome or Similar

Phenotypes. Front Genet [Internet]. 2019 Oct 15;10:955. Available from:

https://pubmed.ncbi.nlm.nih.gov/31749829

14.   Clayton P, Chatelain P, Tato L, Yoo HW, Ambler GR, Belgorosky A, et al. A

pharmacogenomic approach to the treatment of children with GH deficiency or

Turner syndrome. Eur J Endocrinol. 2013 Sep;169(3):277–89.

15.   De Leonibus C, Murray P, Garner T, Hanson D, Clayton P, Stevens A. The in vitro

functional analysis of single-nucleotide polymorphisms associated with growth

726  hormone (GH) response in children with GH deficiency. Pharmacogenomics J

727  [Internet]. 2019 Apr 1 [cited 2020 Oct 12];19(2):200–10. Available from:

728  https://www.nature.com/articles/s41397-018-0026-4

729 16. De Leonibus C, Chatelain P, Knight C, Clayton P, Stevens a. Effect of summer daylight

730  exposure and genetic background on growth in growth hormone-deficient children.

731  Pharmacogenomics J [Internet]. 2016;16(6):540–50. Available from:

732  http://www.nature.com/doifinder/10.1038/tpj.2015.67

733 17. Calkins K, Devaskar SU, Angeles L. Fetal Origins of Adult Disease. Curr Probl Pediatr

734  Adolesc Heal Care. 2011;41(6):158–76.

735 18. Robinson R. The fetal origins of adult disease: No longer just a hypothesis and may be

736  critically important in south Asia. BMJ. 2001;322(7283):375–6.

737 19. Barker DJP, Martyn CN. The maternal and fetal origins of cardiovascular disease. J

738  Epidemiol Community Heal. 1992;46:8–11.

739 20. Sun Y, Liu Y, Sun X, Lin Y, Yin D, Xu S, et al. Insights into body size variation in

740  cetaceans from the evolution of body-size-related genes. BMC Evol Biol [Internet].

741  2019 Jul 27;19(1):157. Available from: https://pubmed.ncbi.nlm.nih.gov/31351448

742 21. Xu L, Yang L, Wang L, Zhu B, Chen Y, Gao H, et al. Probe-based association analysis

743  identifies several deletions associated with average daily gain in beef cattle. BMC

744  Genomics [Internet]. 2019 Jan 10;20(1):31. Available from:

745  https://pubmed.ncbi.nlm.nih.gov/30630414

746 22. Magee DA, Sikora KM, Berkowicz EW, Berry DP, Howard DJ, Mullen MP, et al. DNA

747  sequence polymorphisms in a panel of eight candidate bovine imprinted genes and

748  their association with performance traits in Irish Holstein-Friesian cattle. BMC Genet

749  [Internet]. 2010 Oct 13;11:93. Available from:

750  https://pubmed.ncbi.nlm.nih.gov/20942903

751 23. Smith FM, Garfield AS, Ward A. Regulation of growth and metabolism by imprinted

752  genes. Cytogenet Genome Res. 2006;113(1–4):279–91.

753 24. Charalambous M, Smith FM, Bennett WR, Crew TE, Mackenzie F, Ward A. Disruption

of the imprinted Grb10 gene leads to disproportionate overgrowth by an Igf2-
independent mechanism. Proc Natl Acad Sci U S A. 2003 Jul;100(14):8292–7.

25. Stainier DYR, Raz E, Lawson ND, Ekker SC, Burdine RD, Eisen JS, et al. Guidelines for
morpholino use in zebrafish. PLoS Genet. 2017;13(10).

26. Ye J, Coulouris G, Zaretskaya I, Cutcutache I, Rozen S, Madden TL. Primer-BLAST: a
tool to design target-specific primers for polymerase chain reaction. BMC
Bioinformatics. 2012 Jun;13:134.

27. Schindelin J, Arganda-Carreras I, Frise E, Kaynig V, Longair M, Pietzsch T, et al. Fiji: An
open-source platform for biological-image analysis. Nat Methods [Internet]. 2012 Jun
28;9(7):676–82. Available from: https://www.ncbi.nlm.nih.gov/pubmed/22743772

28. Fink M, Flekna G, Ludwig A, Heimbucher T, Czerny T. Improved translation efficiency
of injected mRNA during early embryonic development. Dev Dyn an Off Publ Am
Assoc Anat. 2006;235(12):3370–8.

29. Avey SR, Ojehomon M, Dawson JF, Gillis TE. How the expression of green fluorescent
protein and human cardiac actin in the heart influences cardiac function and aerobic
performance in zebrafish danio rerio. J Fish Biol [Internet]. 2018 Jan 1 [cited 2020 Oct
15];92(1):177–89. Available from: https://pubmed.ncbi.nlm.nih.gov/29194605/

30. SigmaAldrich. Assay Optimization and Validation A Technical Guide to PCR
Technologies Table of Contents [Internet]. MERCK. 2015 [cited 2020 Mar 1]. p. 1–11.
Available from: https://www.sigmaaldrich.com/technical-
documents/articles/biology/assay-optimization-and-validation.html#validating

31. Durinck S, Spellman PT, Birney E, Huber W. Mapping identifiers for the integration of
genomic datasets with the R/ Bioconductor package biomaRt. Nat Protoc [Internet].
2009 [cited 2020 Sep 8];4(8):1184–91. Available from:
/pmc/articles/PMC3159387/?report=abstract

32. Fontes M, Soneson C. The projection score - an evaluation criterion for variable
subset selection in PCA visualization. BMC Bioinformatics [Internet]. 2011;12(1):307.
Available from: https://doi.org/10.1186/1471-2105-12-307

33. Battiston F, Cencetti G, Iacopini I, Latora V, Lucas M, Patania A, et al. Networks

beyond pairwise interactions: Structure and dynamics. Physics Reports. Elsevier B.V.;

2020.

34. Zhang B, Horvath S. A general framework for weighted gene co-expression network

analysis. Stat Appl Genet Mol Biol [Internet]. 2005 Aug 12 [cited 2020 Sep 8];4(1).

Available from: https://pubmed.ncbi.nlm.nih.gov/16646834/

35. Luo F, Yang Y, Chen CF, Chang R, Zhou J, Scheuermann RH. Modular organization of

protein interaction networks. Bioinformatics [Internet]. 2007 Jan 15 [cited 2020 Sep

8];23(2):207–14. Available from:

https://academic.oup.com/bioinformatics/article/23/2/207/204437

36. Banerji CRS, Miranda-Saavedra D, Severini S, Widschwendter M, Enver T, Zhou JX, et

al. Cellular network entropy as the energy potential in Waddington's differentiation

landscape. Sci Rep [Internet]. 2013 Oct 24 [cited 2020 Aug 28];3(1):1–7. Available

from: www.nature.com/scientificreports

37. Gill MS, Tillmann V, Veldhuis JD, Clayton PE. Patterns of GH Output and Their

Synchrony with Short-Term Height Increments Influence Stature and Growth

Performance in Normal Children. J Clin Endocrinol Metab [Internet]. 2001 Dec 1 [cited

2020 Oct 20];86(12):5860–3. Available from: https://academic.oup.com/jcem/article-

lookup/doi/10.1210/jcem.86.12.8116

38. Zhang JD, Hatje K, Sturm G, Broger C, Ebeling M, Burtin M, et al. Detect tissue

heterogeneity in gene expression data with BioQC. BMC Genomics [Internet]. 2017

Apr 4 [cited 2020 Sep 8];18(1):277. Available from:

http://bmcgenomics.biomedcentral.com/articles/10.1186/s12864-017-3661-2

39. Subramanian A, Tamayo P, Mootha VK, Mukherjee S, Ebert BL, Gillette MA, et al.

Gene set enrichment analysis: A knowledge-based approach for interpreting genome-

wide expression profiles. Proc Natl Acad Sci U S A [Internet]. 2005 Oct 25 [cited 2020

Aug 28];102(43):15545–50. Available from:

www.pnas.orgcgidoi10.1073pnas.0506580102

40. Liao Y, Wang J, Jaehnig EJ, Shi Z, Zhang B. WebGestalt 2019: gene set analysis toolkit

with revamped UIs and APIs. Nucleic Acids Res [Internet]. 2019 Jul 1 [cited 2020 Aug

28];47(W1):W199–205. Available from: http://www.webgestalt.org.

41.   Liberzon A, Birger C, Thorvaldsdóttir H, Ghandi M, Mesirov JP, Tamayo P. The

Molecular Signatures Database Hallmark Gene Set Collection. Cell Syst [Internet].

2015 Dec 23 [cited 2020 Sep 8];1(6):417–25. Available from:

http://dx.doi.org/10.1016/j.cels.2015.12.004http://dx.doi.org/10.1016/j.cels.2015.12

.004

42.   Package "ggpubr" Type Package Title "ggplot2" Based Publication Ready Plots

[Internet]. 2020 [cited 2020 Sep 8]. Available from:

https://rpkgs.datanovia.com/ggpubr/

43.   Benjamini Y, Hochberg Y. Controlling the False Discovery Rate: A Practical and

Powerful Approach to Multiple Testing. Vol. 57, Source: Journal of the Royal

Statistical Society. Series B (Methodological). 1995.

44.   Motulsky H, Brown R. Detecting outliers when fitting data with nonlinear regression -

a new method based on robust nonlinear regression and the false discovery rate.

BMC Bioinformatics [Internet]. 2006;7(123). Available from:

http://www.biomedcentral.com/1471-2105/7/123

45.   Banerji CRS, Severini S, Teschendorff AE. Network transfer entropy and metric space

for causality inference. Phys Rev E - Stat Nonlinear, Soft Matter Phys [Internet]. 2013

May 31 [cited 2020 Aug 28];87(5):052814. Available from:

https://journals.aps.org/pre/abstract/10.1103/PhysRevE.87.052814

46.   Cheng C, Liu H, Tan C, Tong D, Zhao Y, Liu X, et al. Mutation in NPPA causes atrial

fibrillation by activating inflammation and cardiac fibrosis in a knock-in rat model.

FASEB J [Internet]. 2019 Aug 1 [cited 2020 Oct 12];33(8):8878–91. Available from:

https://pubmed.ncbi.nlm.nih.gov/31034774/

47.   Riedel H. Grb10 exceeding the boundaries of a common signaling adapter. Front

Biosci. 2004 Jan;9(JAN):603–18.

48.   Shiura H, Miyoshi N, Konishi A, Wakisaka-Saito N, Suzuki R, Muguruma K, et al.

Meg1/Grb10 overexpression causes postnatal growth retardation and insulin

resistance via negative modulation of the IGF1R and IR cascades. Biochem Biophys
Res Commun. 2005 Apr;329(3):909–16.

49.   Holt LJ, Brandon AE, Small L, Suryana E, Preston E, Wilks D, et al. Ablation of Grb10
Specifically in Muscle Impacts Muscle Size and Glucose Metabolism in Mice.
Endocrinology. 2018;159(3):1339–51.

50.   Dufresne AM, Smith RJ. The adapter protein GRB10 is an endogenous negative
regulator of insulin-like growth factor signaling. Endocrinology. 2005
Oct;146(10):4399–409.

51.   Mori K, Giovannone B, Smith RJ. Distinct Grb10 domain requirements for effects on
glucose uptake and insulin signaling. Mol Cell Endocrinol. 2005;230(1–2):39–50.

52.   Francová K, Ondračková M. Overwinter Body Condition, Mortality and Parasite
Infection in Two Size Classes of 0+ Year Juvenile European Bitterling Rhodeus Amarus.
J Fish Biol. 2013;82(2):555–68.

53.   Shoup D, Wahl D. Body Size, Food, and Temperature Affect Overwinter Survival of
Age-0 Bluegills. Trans Am Fish Soc. 2011;140(5):1298–304.

54.   Barker DJ. The fetal and infant origins of adult disease. BMJ. 1990;301(6761):1111.

55.   Godfrey KM, Inskip HM, Hanson MA. The long-term effects of prenatal development
on growth and metabolism. Semin Reprod Med. 2011;29(3):257–65.

56.   Devaskar SU, Chu A. Intrauterine growth restriction: Hungry for an answer.
Physiology. 2016 Feb 17;31(2):131–46.

57.   Jaquet D, Gaboriau A, Czernichow P, Levy-Marchal C. Insulin Resistance Early in
Adulthood in Subjects Born with Intrauterine Growth Retardation [1]. J Clin Endocrinol
Metab [Internet]. 2000;85(4):1401–6. Available from:
https://academic.oup.com/jcem/article-lookup/doi/10.1210/jcem.85.4.6544

58.   Savanur MS, Ghugre PS. BMI, body fat and waist-to-height ratio of stunted v. non-
stunted Indian children: A case-control study. Public Health Nutr [Internet].
2016/02/19. 2016;19(8):1389–96. Available from:
https://www.cambridge.org/core/article/bmi-body-fat-and-waisttoheight-ratio-of-

stunted-v-nonstunted-indian-children-a-casecontrol-

study/3B83DFA36072ED691FC09FF3B2068D2F

59.   Painter RC, Osmond C, Gluckman P, Hanson M, Phillips DIW, Roseboom TJ.

Transgenerational effects of prenatal exposure to the Dutch famine on neonatal

adiposity and health in later life. BJOG An Int J Obstet Gynaecol. 2008;115(10):1243–

9.

60.   Finkielstain GP, Lui JC, Baron J. Catch-up growth: Cellular and molecular mechanisms.

World Rev Nutr Diet. 2013;106:100–4.

61.   Singhal A. Long-Term Adverse Effects of Early Growth Acceleration or Catch-Up

Growth. Vol. 70, Annals of Nutrition and Metabolism. 2017. p. 236–40.

62.   Tirumuru SS, Arya P, Latthe P, Kirk J. Understanding precocious puberty in girls.

Obstet Gynaecol [Internet]. 2012 Apr 1 [cited 2020 Oct 20];14(2):121–9. Available

from: http://doi.wiley.com/10.1111/j.1744-4667.2012.00094.x

63.   Turan N, Ghalwash MF, Katari S, Coutifaris C, Obradovic Z, Sapienza C. DNA

methylation differences at growth related genes correlate with birth weight : a

molecular signature linked to developmental origins of adult disease ? BMC Med

Genomics [Internet]. 2012;5(1):10. Available from:

http://www.biomedcentral.com/1755-8794/5/10

Tables

Table 1. Oligonucleotide sequences

A) Morpholino-modified antisense oligonucleotides

Name	Accession no.	Sequence	
e3i3	BX571825	CATACAGTATGCATTACCTGACAGC	
e4i4		GTGTCTGTTTTCAGCTCTTACATGT	
Standard Control		CCTCTTACCTCAGTTACAATTTATA	

B) Primers for cloning *grb10a* cDNA and for validating splicing interruption

Name	Accession no.	Forward	Reverse
grb10a cDNA	NM_0010042	gacagaatcgatGACTGAGTATGGC	gacagatctagaTCATAAGGCC
grb10a exon3-	BX571825	TGGTGAATGACATGGCCTCT	CTGCATGGTCAAGACACAC
grb10a exon3-		TGGTGAATGACATGGCCTCT	CTGACGGATAATAGCTACA

B) Primers for qPCR

Gene	Accession no.	Forward	Reverse
grb10a	NM_0010042	TGGATGACTGCTTTTAGACTGC	CGACCAGTCCTTCCAGAAA
actb1	NM_131031.	CTTCCAGCAGATGTGGATCA	GCCATTTAAGGTGGCAACA
myl7	NM_131329.	TCACTGTCTTCCTCACCCTC	CACGTCTATTGGAGCCACT
pcna	NM_131404.	AGGCAACATCAAGCTCTCAC	ATTTGACGTGTCCCATGTCT
nppa	NM_198800.	AAGCAAAAGCTTGTCTGG	ACTGTATCCGCGTATTGCA

888 **Table 2. Microinjection Solutions**

Injection	Oligonucleotide	nCerulean	Phenol Red
Standard Control (5	0.5 mM human beta globin morpholino	50 ng/µl	1 µl
grb10a KD (5 µl)	0.5 mM e3i3 or e4i4 morpholino	50 ng/µl	1 µl
grb10a OE (5 µl)	500 ng/µl *grb10a* RNA	50 ng/µl	1 µl

889 **Table 3. Thermocycling Parameters**

Procedure	Temperature (°C)	Time (S)	Cycles
NEB Q5 Hot Start	95	300	
	95	30	35
	55	30	
	72	120	
	72	600	
NEB Taq	95	30	
	95	15	30
	55	15	
	68	30	
	68	300	
SyBr Green qPCR	95	30	
	95	5	40
	51	15	
	72	10	

890 **Table 4. Western Blot Antibodies**

Target	Species	Supplier	Dilution
AKT	Mouse	Cell Signalling #2920	1:1000
p-AKT	Rabbit	Cell Signalling - #5831	1:1000
ERK1/2	Mouse	Santa Cruz Biotechnology sc-135900	1:1000
p-ERK1/2	Rabbit	Cell Signalling #4370	1:1000
S6	Mouse	Cell Signalling - #2317	1:1000
p-S6	Rabbit	Cell Signalling - #2215	1:1000
Anti-Mouse HRP linked IgG	Horse	Cell Signalling - #7076	1:5000
Anti-Rabbit HRP linked IgG	Goat	Cell Signalling - #7074	1:5000

Supplementary Figures

A) Analysis Pipeline

B) Hypernetworks

C) Hypernetwork Matrix Representation

Supplementary Figure 1. Pipeline of transcriptomic analysis and hypernetworks. 1a. Analysis pipeline of transcriptomic data. **(i)** Unsupervised hierarchical clustering was performed using a projection score to capture the most informative age-associated gene clustering in principal component analysis under a variance strip. Hypernetwork analysis was generated using the age associated genes identified in both SC and KD animals. **(ii)** Hypernetworks were quantified by comparing cluster structure, connectivity, and entropy. **(iii)** The impact of co-ordinated gene expression on the whole transcriptome was measured by identifying the Galois correspondence within the hypernetwork. 1***b.*** A general model of a hypernetwork, shown as a three dimensional representation of genes (coloured tetrahedra) correlating with the expression of four other genes (black spheres). Shared correlations are represented by matching vertices, edges, and faces of the tetrahedra. ***1c.*** A hypernetwork representation of the "higher order" interactions within the transcriptome. This summary of the genes with shared correlations can be considered as an incidence matrix of a multi-dimensional network.

a.

b.

Supplementary Figure 2. Connectivity (left) and entropy (right) of 20-30 dpf associated genes in the SC and KD
zebrafish compared with randomly selected gene sets. 2***a.*** Connectivity in the experimental data was
significantly greater than in the random iterative data, and greater in the KD data than SC ($p<0.0001$). 2***b.*** Entropy
was significantly lower in the experimental data than the random iterative data. Entropy was lower in the KD
than SC, though the reduction in entropy between the experimental data and interated data was greater in the
SC than the KD.

Supplementary Tables

Supplementary Table 1. Gene set enrichment analysis on age related gene expression in KD and SC zebrafish. 75212 probe ids mapped to 3733 human orthologues. Probe sets were collapsed to gene summary by averaging and group ANOVAs were performed by age groups. Q-values are reported as the false discovery rate modified p-value of the GSEA, performed in Qlucore Omics Explorer (v3.6) using Gene Ontology Biological Process pathways.

Supplementary Table 2. 12775 and 459 genes defined by the Galois correspondence from the 20-30 dpf KD and SC hypernetwork clusters respectively, together with rank regression scores and p-values. Zebrafish gene symbol and corresponding human orthologue shown.

Supplementary Table 3. A subset of 3460 genes from the Galois correspondence showing fluctuating gene expression from 15 to 30 dpf and associating with metabolism and development gene ontology pathways. Displayed as zebrafish gene symbols, corresponding human orthologues, R-statistics of age rank regression analysis, and p-values.

Supplementary Table 4. Dysregulated expression of cardiac phenotype marker genes in the KD zebrafish. False discovery rate modified p-value (q-value) shown for age group ANOVA.