**I: TITLE PAGE**

**Impact of Acute Endurance Exercise on Alternative Splicing in**

**Skeletal Muscle.**

Alexander Ahn, MS[1]

ORCID: 0009-0009-7865-2061

Ann Arbor, Michigan, USA

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Co-authors:

i. Jeongjin J. Kim, PhD[1,2] (ORCID: 0000-0002-6959-8544; now at Frederick, Maryland, USA)
ii. Aaron L. Slusher, PhD[1,3] (ORCID: 0000-0003-2082-4827; now at New Haven, Connecticut,
USA)
iii. Jeffrey Y. Ying[1] (no ORCID; Ann Arbor, Michigan, USA)
iv. Eric Y. Zhang[1] (ORCID: 0009-0000-7975-0303; Ann Arbor, Michigan, USA)

Corresponding author: Andrew T. Ludlow, PhD[1]

• ORCID: 0000-0003-0423-4800; Ann Arbor, Michigan, USA
• 830 North University Avenue, Ann Arbor, Michigan 48109-1048, USA
• atludlow@umich.edu
• +1 (734) 763-4720

Affiliation:

1. School of Kinesiology, University of Michigan, Ann Arbor, Michigan, USA
2. National Cancer Institute, National Institutes of Health, Frederick, Maryland, USA
3. School of Medicine, Yale University, New Haven, Connecticut, USA

# II: ABSTRACT

**Purpose:** Alternative RNA splicing (AS) is a highly conserved post-transcriptional mechanism, generating mRNA variants to diversify the proteome. Acute endurance exercise appears to transiently perturb AS in skeletal muscle, but transcriptome-wide responses are not well-defined. We aimed to better understand differential AS (DAS) in skeletal muscle by comparing short-read RNA sequencing (SRS) and long-read RNA sequencing (LRS) data.

**Methods:** Publicly accessible SRS of clinical exercise studies were extracted from the Gene Expression Omnibus. Oxford Nanopore LRS was performed on mouse gastrocnemius before and following treadmill exercise. Differential gene expression (DGE), DAS, and isoform switching were analyzed. Western blots were performed to validate expression changes of candidate genes.

**Results:** Both SRS and LRS illustrated significant DGE in skeletal muscle post-exercise, whereby 57 and 15 RNA-binding proteins (RBPs) were up-/down-regulated, respectively. rMATS analysis of SRS data revealed that exon-skipping and intron-retaining splicing events were the most common. Swan analysis of LRS data revealed 38 RBPs with significant isoform switching: one of these RBPs, *Hnrnpa3*, underwent a significant intron-retained to protein-coding switch. HnRNP-A3 protein levels validated nearly two-fold increases at 1 hour ($p=.0043$) and 24 hours ($p=.0103$) post-exercise.

**Conclusions:** This study illustrates that acute endurance exercise can elicit changes in AS-related responses and RBP expression in skeletal muscle. SRS is certainly a powerful tool for analyzing DGE but lacks AS detection. As such, "hidden" genes with no transcriptional changes but significant DAS and protein expression changes pose a major gap in knowledge. Our work highlights how LRS can uncover previously unknown transcript diversity and mechanisms influencing endurance exercise adaptations and responses.

**Keywords**

Endurance exercise, alternative RNA splicing, RNA-binding proteins, splicing factors, skeletal muscle.

**Abbreviations**

A3SS, alternative 3' splice site;

A5SS, alternative 5' splice site;

AS, alternative (RNA) splicing;

ATSS, alternative transcription start site;

ATTS, alternative transcription termination site;

DAS, differential alternative splicing;

DGE, differential gene expression;

hsAA, *homo sapiens* aged active;

hsAS, *homo sapiens* aged sedentary;

hsYS, *homo sapiens* young sedentary;

lncRNA, long non-coding RNA;

LRS, long-read RNA sequencing;

mmYS, *mus musculus* young sedentary;

MXE, mutually exclusive exons;

pcRNA, protein-coding RNA;

RBP, RNA-binding protein;

RI, retained intron;

SE, skipped exon;

SRS, short-read RNA sequencing.

**III: BODY**

**1 INTRODUCTION**

The positive impact of exercise on one's health is undeniable. With skeletal muscle

accounting for approximately 40% of body mass in adults, it is the most directly affected tissue

from both the beneficial effects of physical activity as well as the deleterious effects of

sedentarism. However, a large portion of the population fails to meet the minimum amount of

exercise to reduce health risks. The US Centers for Disease Control and Prevention reported

overall prevalence of physical inactivity was 25.3% in 2020,[1] while causing 9% of premature

death globally.[2] Why people fail to meet the minimum amount of exercise are varied but some

are simply unable to even if desired: for example, muscle dystrophy, motoneuron-related

sclerosis diseases, and obesity-induced osteoarthritis. To fully harness the health-promoting

power of endurance exercise, we must continue to uncover the fundamental mechanisms of

molecular responses and adaptations elicited by the exercise stimulus.

Endurance exercise promotes disease-free longevity via the enhancement of skeletal

muscle oxidative capacity among other important responses and adaptations.[3] Exercise is a

potent cellular stressor (eg, mechanical, metabolic, oxidative stress, etc) that triggers a series of

responses and adaptations.[4–7] Part of the adaptive process in skeletal muscle is changes in gene

expression regulation that, in part, regulates the protein landscape and alters structural and

functional outcomes. To date, reports have focused on changes in transcript levels, differential

gene expression (DGE).[8,9] For example, endurance exercise training increases mitochondrial

density, muscle-specific angiogenesis, and improves calcium handling in slow-twitch skeletal

myofibers by altering the expression of the genes encoding peroxisome proliferator-activated

receptor gamma coactivator 1 alpha (PGC-1α, *PPARGC1A*),[10] vascular endothelial growth factor

(*VEGF*),[11] and troponin T (ssTnT, *TNNT1*),[12] respectively. While *PPARGC1A*, *VEGF*, and

*TNNT1* are all differentially expressed, there is also evidence that exercise impacts the

expression of different transcript variants of each of these genes,[12–15] indicating that alternative

RNA splicing (AS) is impacted by exercise.[16,17] To date, however, only one group has

investigated mRNA isoform expression using SRS following exercise training in human skeletal

muscle and observed global training induced changes in mRNA isoform expression.[16]

RNA splicing and AS are RNA processing steps that offer additional regulatory layers in

gene expression. RNA splicing is mediated by a dynamic RNA-protein complex, the

spliceosome, that assembles on primary transcripts (ie, precursor messenger RNA, pre-mRNA)

to remove introns and splice exons together to form the final protein-coding transcript (ie, mature

messenger RNA, mRNA).[18] In conjunction with the spliceosome, RNA-binding proteins (RBPs)

provide tissue-/context-specific regulation of splicing.[19] While most exons of a pre-mRNA

undergo constitutive splicing to form full-length variants, many undergo AS: the choice of

including or excluding certain exons and/or introns in the mRNA.[20,21] AS is a highly conserved

co-/post-transcriptional mechanism that functions to generate multiple RNA transcript variants:

these transcript variants may be intended for either translation to respective protein isoforms,[22,23]

non-coding RNAs,[24,25] or degradation via RNA decay mechanisms.[26,27] Therefore, a single gene

can form several protein isoforms depending on the demands of the cells in a tissue.[22] For

instance, a significant change in AS can orchestrate a switch in the expression of certain protein

isoforms. These differential use of isoforms between conditions is often referred as isoform

switching,[13,14] which facilitate a functional change in cellular responses to stimuli. The

significance of AS is evident as nearly all mammalian genes undergo AS and generate two or

more protein isoforms, which vastly expands the protein-coding capacity of the genome and

greatly impacts the function of cells in a tissue and cells responses to homeostatic

perturbations.[22]

However, transcriptome-wide impact of endurance exercise on AS and isoform

generation is currently unknown. Previously, Tonevitsky et al[28] observed that acute aerobic

exercise with maximal intensity in trained skiers resulted in an increased gene expression from a

set of RBPs (*DDX17*, *DDX46*, *HNRNPR*, *PRPF4B*, and *SRPK2*) that regulate the formation of

the precatalytic spliceosome. Similarly, our laboratory also observed that exercise resulted in

reduced protein expression of splicing factor 3B subunit 4 (SF3B4) from young sedentary mouse

gastrocnemius in response to acute treadmill running.[29] These findings indicate that a single bout

of endurance exercise is sufficient to potentially instigate differential AS (DAS) and differential

isoform usage of many other genes through differential expression and regulation of RBPs.

Therefore, we set out to globally profile AS events (mRNA variants and exon-level events) in

skeletal muscle from a single bout of submaximal endurance exercise.

## 2 MATERIALS AND METHODS

### 2.1 Short-read RNA sequencing

The human SRS data had formerly been published by two different studies:

Pattamapraponont et al[30] and Rubenstein et al.[31] The raw FASTQ files were downloaded from

publicly accessible NCBI Gene Expression Omnibus database (RRID: SCR_005012) (accession

numbers GSE87749 and GSE151066, respectively). Briefly, Pattamapraponont et al consisted of

10 young (19-25 years) and healthy (BMI of 23.1 $\pm$ 2.8) Danish male participants with a

sedentary lifestyle (hsYS), and performed a single bout of intense (80% $V O_2 max$) cycling

(cycle ergometer) for 15 minutes; muscle biopsies of the vastus lateralis were obtained pre-

(hsYS-pre) and 4 hours post-exercise (hsYS-4pe).[30] Rubenstein et al studied two cohorts of older

individuals (65-90 years): 10 (8 males, 2 females) an active/endurance trained group (hsAA)

with a BMI of 24.2 $\pm$ 4.2; nine (7 males, 2 females)and a sedentary (hsAS) group with a BMI

of 28.7 $\pm$ 3.3. The participants performed a single bout of endurance exercise (cycling at 60-70%

of heart rate reserve) for 40 minutes. Muscle biopsies of the vastus lateralis were obtained pre-

(hsAA-pre & hsAS-pre) and 3 hours post-exercise (hsAA-3pe & hsAS-3pe).[31] To maintain

consistency for the initial processing and statistical analyses of the SRS data, only single-end

FASTQ files were used from the Pattamaprapanont et al study; similarly, only males at pre- and

3 hours post-exercise time points with paired-end FASTQ files were used from the Rubenstein et

al to maintain comparability between the two data sets (Figure 1A).

### 2.2 Animals

All animal experiments were approved by the University of Michigan Institutional

Animal Care and Use Committee (IACUC) and conducted as per the institutional guidelines.

C57BL/6-Tg(TERT)C10Hode/J (approximately 8 weeks old) were purchased from The Jackson

Laboratory (Bar Harbor, Maine, USA). The mice were housed at 25°C on a 12:12-hour light-

dark cycle, fed *ad libitum* laboratory mouse chow (Prolab® RMH 3000, 5P00, LabDiet by

Purina, Nestlé, Vevey, Switzerland), and given free access to water. The description of the

running protocol was previously published.[29] Animals were randomly assigned to each pre-/post-

exercise time points. All animals were included without exclusion nor attrition. Investigators

were not blinded to the groupings. Sample size and power analysis were determined based on our

previous study.[29] Briefly, 20 mice underwent acute treadmill running at 60% of maximal speed,

approximately 75% of mouse $VO_2max$ according to Fernando et al,[32] for 30 minutes (Figure

1B,S1M). Euthanasia practices were followed as suggested by the American Veterinarian

Medical Association guidelines (2020 edition). Gastrocnemius muscles were collected at pre-

(mmYS-pre; 3 males, 2 females), immediately post-exercise (mmYS-ipe; 3 males, 2 females), 1

hour post-exercise (mmYS-1pe; 2 males, 3 females), and 24 hours post-exercise (mmYS-24pe; 3

males, 2 females). Gastrocnemius muscles were flash frozen in liquid nitrogen and stored at –

80°C for subsequent tissue processing and RNA isolation.

**2.3 Tissue processing, RNA isolation, and poly(A)-mRNA isolation**

The gastrocnemius tissues were first powdered with a mortar and pestle in liquid nitrogen,

then either processed immediately or stored at –80°C, as described in Slusher et al.[29] Total RNA

from powdered tissues were isolated using the RNeasy Plus Universal Mini Kit (Qiagen, Cat#

73404) according to manufacturer instructions, and stored at -80°C. Isolated RNA was quantified

using the NanoDrop™ 2000 spectrophotometer and assessed using the Qubit™ RNA IQ Assay

Kits (Invitrogen, Cat# Q33221) with the Qubit 4 Fluorometer. Subsequently, 1.2 µg of total RNA

was used to isolate poly(A)-containing RNA with the NEBNext® Poly(A) mRNA Magnetic

Isolation Module (New England BioLabs, Cat# E7490S) accordingly. Poly(A)-mRNA isolates

were then quantified with Agilent Bioanalyzer (RRID: SCR_018043) and/or TapeStation,

NanoDrop™ 2000 spectrophotometry, and Qubit Fluorometry.

**2.4 Long-read RNA sequencing**

1 ng of poly(A)-mRNA isolates were used to synthesize barcoded PCR-cDNA libraries

(Oxford Nanopore Technologies®, ONT; Cat# SQK-PCB109) according to the manufacturer

instructions. Subsequently, the prepared PCR-cDNA libraries were quantified, multiplexed at

equal molar concentrations, loaded onto a MinION™ R9.4.1 Flow Cell (ONT, Cat# FLO-

MIN106) and sequenced (LRS) for 72 hours (protocol on the MinION™ Mk1C sequencer (ONT,

Cat# MIN-101C) under MinKNOW v22.03.4 (ONT, RRID: SCR_023196); Figure 1B). During

the sequencing period, the flow cell was "washed" with the Flow Cell Wash Kit (ONT, Cat#

EXP-WSH004) and reloaded with fresh multiplexed libraries as needed.

**2.5 Data preprocessing**

For the SRS retrieved data, the quality of the raw FASTQ files were checked and

trimmed to the minimum read length of 25 bases. Subsequently, RSEM-STAR[33,34] was used to

align and quantify the trimmed reads based on the human GENCODE release 42 (GRCh38.p13).

Matrices of "counts" (estimation of expected read counts), "abundance" (TPM-normalized

counts), and "length" (effective transcript lengths) were generated for statistical analyses (hsYS:

Figure S1A,E,I; hsAS: Figure S1B,F,J; and hsAS: Figure S1C,G,K).

For the LRS generated data, raw FASTQ (converted from FAST5) files, which passed the

MinKNOW quality check with minimum $q$-score threshold of 8, were used for read alignment.

minimap2 v2.14[35] (RRID: SCR_018550) and SAMtools v1.13[36] (RRID: SCR_002105) was used

to align the passed FASTQ files into SAM format; the mouse GENCODE release M29

(GRCm39) genome sequence assembly was used for the alignment step. The aligned SAM files

were sorted and "cleaned" (TranscriptClean[37]). TALON[38] was used to quantify reads and

generate an abundance matrix (coverage = 0.75, identity = 0.8) in GTF format to be used for

statistical analyses (Figure S1D,H,L and Figure S4D,E).

**2.6 Differential gene expression and differential alternative splicing analyses**

For the SRS-retrieved data, TXImport[39] was used to import the multidimensional RSEM-

STAR quantification matrix arrays at the gene-level to the R environment. Subsequently,

DESeq2[40] was used to perform gene-level differential expression (differential gene expression,

DGE) analyses with $\log_2$ fold changes ($\log_2$FC) and respective statistics ($p$-values adjusted with

default Benjamini-Hochberg method, BH; $p$-adj) on the quantification matrix arrays, and

enriched for significantly up-/down-regulated genes (Figure 2A–G). IsoformSwitchAnalyzeR[41]

was initially used (Figure S2) to identify genes with isoform-switching events with absolute

difference in isoform fraction (dIF) > 10% and $p$-adj < .05 (adjusted with BH). Splicing type

resulting in the isoform switches were annotated as skipped exon (SE), alternative 5' splice site

(A5SS), alternative 3' splice site (A3SS), mutually exclusive exons (MXE), multiple exon-

skipping (MES), retained introns (RI), alternative transcription start site (ATSS), and alternative

transcription termination site (ATTS). Additionally, rMATS-turbo v4.1.2[42,43] was used to

directly analyze exon-level splicing events with difference in percent spliced in ($\Delta\Psi$ or DPSI)

and respective statistics on the trimmed FASTQ files, and enriched for genes with significant

splicing events annotated as SE, A5SS, A3SS, MXE, and RI. The transcript-level rMATS data

frames were filtered based on the absolute $\Delta\Psi$ > 10% and $p$-adj < .05 (adjusted with BH) for the

significant splicing overlap analyses and for visualizing the proportions of splicing profile.

For the LRS-generated data, Swan v2.0[44] was used to generate data frames with $\log_2$FC

and respective significance statistics at the gene- and transcript-levels. Based on known genes

that were detected in at least half of the samples, the counts matrix was generated for the

downstream differential analyses. The corresponding DGE (gene-level) $log_2$FC and respective

statistics (adjusted with BH) from Swan were used for data visualizations (Figure 2H–J).

Similarly, differential isoform expression analyses generated absolute difference in percent

isoform use ($\Delta\Pi$ or DPI) to determine isoform-switching data, whereby respective statistics from

Swan were filtered based on $\Delta\Pi > 10\%$ and $p$-adj $< .05$ (adjusted with BH).

Functional enrichment analysis was performed on significantly up- and down-regulated

genes from the DGE analyses ($|log_2$FC$| > 1.5$ and $p$-adj $< .05$ for SRS; $|log_2$FC$| > 1$ and raw $p$

$< .05$ for LRS) using either Database for Annotation, Visualization, and Integrated Discovery

(DAVID)[45] or PANTHER[46] (for Figure S4A–C only) to generate top 10 gene ontology (GO)

terms. With the splicing and DIE data sets from both SRS and LRS data, multiple multivariate

overlap analyses across varying conditions and data sets were performed to identify any common

genes with potential biologically significant splicing events. Only overlapping genes with $p$-adj

$< .05$ from bivariate hypergeometric tests were considered significant. All code scripts used for

bioinformatical data analyses are available in the Deep Blue data repository (DOI will be

provided upon publication) or upon request.

**2.7 Protein lysate preparation, antibody validation, and western blot analyses**

To examine protein expression level of a candidate RBP, heterogeneous nuclear

ribonucleoprotein A3 (hnRNP-A3), HEK 293 fetal kidney cells (ATCC, Cat# CLR-1573, RRID:

CVCL_0045) were used as positive controls to verify cross-species specificity of the hnRNP-A3

antibody for the correct molecular weight at 42 kDa. Additionally, C2C12 murine myoblasts

(ATCC, Cat# CRL-1772, RRID: CVCL_0188) were transfected with 30 nM of either scrambled

(siCTL) or mouse *Hnrnpa3*-targeting (exon 10) siRNAs (ThermoFisher Scientific, Cat# 4390771)

in Lipofectamine™ RNAiMAX transfection reagent (Invitrogen, Cat# 13778075) for 24 and 48

hours to knock-down hnRNP-A3 and thus validate the protein specificity of hnRNP-A3 antibody.

All cell lines used were authenticated by the manufacturer (ATCC) and visually verified in-

house. The cell pellets were resuspended in an SDS-based lysis buffer, sonicated, and

centrifuged to extract the total protein lysate. Total protein lysates were prepared from

gastrocnemius, as described in Slusher et al,[29] were used to quantify protein expression level of

hnRNP-A3 in the skeletal muscle tissues. The protein concentrations were quantified using the

Pierce 660 nm Protein Assay Kit (ThermoFisher Scientific, Cat# 1861426). These protein lysates

from cell lines and the animal-derived tissues were then prepared using 2X Laemmli loading

buffer (Bio-Rad, Cat#1610737) and boiled for 10 minutes at 95°C.

All protein lysates from cells and tissues were resolved by SDS-polyacrylamide gel

electrophoresis, transferred to polyvinylidene fluoride membranes. To verify cross-species

specificity of the hnRNP-A3 antibody, protein lysates of wild-type HEK 293 was used (Figure

S5A). Loading control was normalized with GAPDH (Cell Signaling Technology, Cat# 2118,

RRID: AB_561053; 1:1000 dilution in 5% bovine serum albumin with 1X PBST). To validate

protein specificity of the hnRNP-A3 antibody, protein lysates of C2C12 myoblasts treated with

either siCTL or *Hnrnpa3* siRNA were used (Figure S5B,C). Loading control was normalized

with total protein quantification of bands at 40-45 kDa using Pierce™ Reversible Protein Stain

Kit (ThermoFisher Scientific, Cat# 24585). HnRNP-A3 from these cell lysates was detected with

a rabbit polyclonal antibody (Abcam, Cat# ab78300, RRID: AB_2041662; 1:1000 dilution factor

in 5% bovine serum albumin with 1X PBST and 0.02% sodium azide). Loading control of

protein lysates from the skeletal muscle tissue was normalized with total protein quantification of

bands at 40-45 kDa using Ponceau S stain (Sigma-Aldrich, Cat# P3504) and detected for

hnRNP-A3 with the validated polyclonal antibody. All blots were imaged with Bio-Rad

ChemiDoc XRS+ Molecular Imager (RRID: SCR_019690) and quantified with Bio-Rad Image

Lab software. Values from either the reversible Pierce-/Ponceau S-stained blots (tissue-based

lysates) or the loading control blots (cell-based lysates) were averaged and used to normalize the

target protein quantification. All images that were used to quantify hnRNP-A3 expression levels

are included in Figure S5D.

**2.8 Statistical analysis**

Unless otherwise noted, unpaired Student's *t* test was used for two group comparisons

using a statistical package on GraphPad Prism 10 (RRID: SCR_002798). One-way ANOVAs

were used to determine significance for multiple group comparisons of the western blot data,

whereby the groups (time points) had 1 level each. Subsequently, *post hoc* adjustments were

conducted with Tukey's HSD using GraphPad Prism 10.  Statistical significance was defined as

a $p < .05$.

**3 RESULTS**

**3.1 RNA-Seq identified differential gene expression in acutely exercised skeletal**

**muscle with and without training**

Differential gene expression (DGE) of vastus lateralis in hsYS-pre and hsYS-4pe was

analyzed with DESeq2 (Figure 2A): out of 13727 total detected genes, 19 were significantly up-

regulated ($\log_2$FC > 1.5, $p$-adj < .05) including *PPARGC1A* (i.e., PGC-1α), *NR4A3*, and

*HSPA1A/B* (i.e., HSP70), while 10 were significantly down-regulated ($\log_2$FC < −1.5, $p$-adj

< .05). These significantly up-regulated genes revealed top 10 gene ontology (GO) terms with

DAVID functional enrichment analysis (Figure 2B), including protein binding (GO:0005515, 15

genes, $p = 0.0596$), extracellular region (GO:0005576, 8 genes, $p = 7.6359e^{-4}$), and nucleoplasm

(GO:0005654, 7 genes, $p = 0.0773$). Three GO terms were revealed from the significantly down-

regulated genes (Figure 2C), including cell differentiation (GO:0030154, 3 genes, $p = 0.0419$),

positive regulation of JNK cascade (GO:0046330, 2 genes, $p = 0.0449$), and response to peptide

hormone (GO:0043434, 2 genes, $p = 0.0247$).

DGE of vastus lateralis in hsAS-pre and hsAS-3pe was analyzed (Figure 2D): out of

14082 total detected genes, 201 were significantly up-regulated ($\log_2$FC > 1.5, $p$-adj < .05)

including *PPARGC1A*, *NR4A3*, and *HSPA1B*, while 9 were significantly down-regulated ($\log_2$FC

< −1.5, $p$-adj < .05). These significantly up-regulated genes revealed top 10 GO terms with

DAVID functional enrichment analysis (Figure 2E), including protein binding (GO:0005515,

141 genes, $p = 1.1661e^{-4}$), nucleus (GO:0005634, 72 genes, $p = 0.0020$), and plasma membrane

(GO:0005886, 64 genes, $p = 0.0050$). Zero terms were significantly enriched from the down-

regulated genes.

DGE of vastus lateralis in hsAA-pre and hsAA-3pe was analyzed (Figure 2F): out of

14315 total detected genes, 112 were significantly up-regulated ($\log_2$FC > 1.5, $p$-adj < .05)

including *PPARGC1A*, *NR4A3*, *NR4A1*, and *HSPA1B*, while 4 were significantly down-regulated

($\log_2$FC < −1.5, $p$-adj < .05). These significantly up-regulated genes revealed top 10 GO terms

with DAVID functional enrichment analysis (Figure 2G), including protein binding

(GO:0005515, 79 genes, $p = 0.0058$), nucleus (GO:0005634, 47 genes, $p = 3.5854e^{-4}$), and

plasma membrane (GO:0005886, 34 genes, $p = 0.0856$). Zero terms were revealed from the

down-regulated genes.

DGE of gastrocnemius in mmYS-pre and mmYS-1pe was analyzed (Figure 2H): out of

2738 total detected genes, 6 were significantly up-regulated ($\log_2$FC > 1.0, raw $p$ < .05), while 20

were significantly down-regulated ($\log_2$FC < −1.0, raw $p$ < .05). These significantly up-regulated

genes revealed 4 GO terms with DAVID functional enrichment analysis (Figure 2I). Six GO

terms were revealed from the significantly down-regulated genes (Figure 2J).

**3.2 Differentially expressed RNA-binding proteins in acutely exercised skeletal**

**muscle with and without training**

Using a list of 1135 RBP genes generated in house, significant up- ($\log_2$FC > 0.5) and

down-regulated RBPs ($\log_2$FC < −0.5; raw $p$ < .05 for mouse, $p$-adj < .05 for human) in response

to an acute bout of exercise from all four cohorts (mmYS, hsYS, hsAS, and hsAA) were queried,

identifying 72 genes (57 were upregulated and 15 were downregulated, across all four groups).

The mmYS cohort had 8 and 3 RBPs were significantly up- and down-regulated, respectively, in

response to acute exercise. The hsYS cohort had a total of 11 and 1 RBPs were significantly up-

and down-regulated, respectively, in response to acute exercise. The hsAS cohort had a total of

39 and 6 RBPs were significantly up- and down-regulated, respectively, in response to acute

exercise. The hsAA cohort had a total of 23 and 5 RBPs were significantly up- and down-

regulated, respectively, in response to acute exercise. These genes were subsequently categorized

into the following categories: traditional RBPs, hnRNPs & splicing factors, RNA metabolism,

RNA helicase, and non-traditional RBPs (Figure 3). Raw *p* values were used to filter mmYS as

all 11 included genes did not have significant *p*-adj, except *Sf3b1* ($\log_2$FC = 1.1400, *p*-adj =

0.0336). Overall, these data indicate that acute endurance exercise results in DGE of some RBPs

in young organisms, the response of RBPs is much more robust in older individuals.

### **3.3 SRS identified differential splicing events in acutely exercised young and aged skeletal muscle with and without training**

Isoform switching, or differential isoform usage (dIF), analyses in human skeletal

muscles following acute exercise was first attempted with IsoformSwitchAnalyzeR. Firstly, dIF

revealed the most common AS event type of each human cohort (Figure S2A–F). Isoform

switching was also determined: compared to the respective baselines, 10 genes had significant

isoform-switching events in hsYS, 15 in hsAS, and 21 in hsAA from an acute bout of exercise

(Figure S2G).

Subsequently, potential changes in splicing events at the exon level were analyzed with

rMATS. The most common event across all three cohorts was SE followed by RI. The hsYS

cohort revealed 67 SE events (53.2% of total events, Figure 4A); the hsAS revealed 253 SE

events (38.4% of total events, Figure 4B); the hsAA revealed 217 SE events (42.6% of total

events, Figure 4C); all with statistical significance (*p*-adj < .05). When comparing the ratio of

splicing event types between the younger humans and the older humans, it is interesting to note

that exercise induced more A5SS and A3SS in older individuals compared to younger. Also,

these data illustrated a considerable difference in number of splicing events in skeletal muscle

between the younger and aged cohorts (younger cohort had 126 total events compared to greater

than 300 events in both aged cohorts). Overall, exercise impacts differential exon usage,

especially SE events, whereby age and exercise appear to interact to modify differential exon

usage to a greater extent.

Genes with statistically significant differential splicing events ($\Delta\Psi > 10\%$, $p$-adj $< .05$)

revealed significant GO terms with DAVID functional enrichment analysis (top 10 GO terms

illustrated in Figure S3A–C), predominantly pointing out protein binding (GO:0005515), nucleus

(GO:0005634), cytoplasm (GO:0005737), RNA/DNA binding (GO:0003723/GO:0003677),

ATP binding (GO:0005524), and mitochondrion (GO:0005739). The genes with statistically

significant differential splicing events were also compared to observe any overlaps (Figure 4D).

Out of 86, 341, and 272 known genes (unique gene IDs; some genes had multiple splicing events,

but each gene ID was only entered once in the overlap analysis) from the hsYS, hsAS, and hsAA

cohorts respectively, 4 (0.6%) overlapped between hsYS and hsAS, 3 (0.5%) between hsYS and

hsAA, 37 (5.7%) between hsAS and hsAA, and 1 (0.2%) across all. A bivariate hypergeometric

test between hsAS and hsAA cohorts revealed significant over-enrichment compared to

expectations (5.34-fold, $p = 4.606e^{-17}$). Furthermore, genes with significant SE events from these

cohorts revealed additional GO terms with the functional enrichment analysis (Figure S3D–F),

such as methylation (GO:0032259), ribonucleoprotein complex (GO:1990904), and protein

transport (GO:0015031).

**3.4 LRS identified differential gene expression, differential alternative splicing,**

**and isoform switching in young mice during recovery from acute exercise**

Significant DGE and DAS (SE and RI only) of gastrocnemius in mmYS were analyzed

using Swan ($\log_2$FC $\neq 0$, $\Delta\Pi > 10\%$, raw $p < .05$) to contrast how expressional changes of

transcription and AS differed across the three time points in recovery from acute exercise. Based

on mean normalized counts, mmYS-ipe compared to mmYS-pre illustrated DGE only (304,

63.2%), DAS only (143, 29.7%), both DGE and DAS (34, 7.1%) profiles (Figure 5A); mmYS-

1pe compared to mmYS-pre illustrated DGE only (231, 66.6%) DAS only (80, 23.1%) both

DGE and DAS (36, 10.4%) profiles (Figure 5B); and mmYS-24pe compared to mmYS-pre

illustrated DGE only (216, 61.7%), DAS only (107, 30.6%), both DGE and DAS (27, 7.7%)

profiles (Figure 5C). These data indicate that exercise not only perturbs transcript expression but

also impacts DAS in combination with transcriptional changes and independent of transcriptional

changes. This reveals a new source of exercise induced responses and adaptations that need to be

explored for their functional relevance in physiology of skeletal muscle and in their roles in

exercise induced health benefits.

Isoform switching in gastrocnemius of mmYS-ipe, mmYS-1pe, and mmYS-24pe

compared to mmYS-pre was analyzed with Swan. A total of 672, 1094, and 884 transcripts had

significant isoform switching events ($\Delta\Pi > 10\%$, $p$-adj $< .05$) at each timepoint, respectively

(Figure 5D). Furthermore, 156 (10.1%) overlapped between mmYS-ipe and mmYS-1pe, 114

(7.4%) between mmYS-ipe and mmYS-24pe, 243 (15.7%) between mmYS-1pe and mmYS-

24pe, and 295 (19.1%) across all three groups (Figure 5E). When unique gene identifiers of

significant isoform-switching genes at each time point were queried (mmYS-ipe = 612, mmYS-

1pe = 1009, and mmYS-24pe = 805 genes) for enriched pathways, enrichment of GO terms

predominantly included RNA splicing using PANTHER (top 10 GO terms are shown in Figure

S4A–C). The 295 common genes across time points post-exercise were independently queried

for enriched pathways, revealing enrichment of GO terms including RNA splicing, mRNA

processing, and mRNA splicing via spliceosome (top 10 GO terms are shown in Figure 5F).

Within these 295 common genes, 38 were RBPs as identified by overlapping the 295 gene

identifiers with a list of 1135 RBP genes generated in house (Figure 5G) and hypergeometric

testing revealed that this was significantly over-enriched compared to expectations (fold-change

$= 2.5, p = 2.7e^{-7}$).

We visualized the structures of AS transcript variants of the 38 RBPS across pre- and

post-exercise time points using Swan. The RBPs were then categorized based on the types of

exercise-induced isoform switching (identified from ENSEMBL genome browser transcript

identifiers) (Table 1): 11 genes had RI to protein-coding RNA (pcRNA); 9 had complex (ie,

multiple types of changes); 8 had pcRNA to pcRNA; 2 had pcRNA to RI; 2 had known to

potentially novel transcript variants; 2 had zero pcRNA to pcRNA; 1 had pcRNA to zero or less

pcRNA; 1 had potentially novel to known variants; 1 had pcRNA to premature termination

codon-containing transcript (bound for RNA decay); and 1 had RI to potentially novel variants.

We also investigated our isoform switching data for known exercise associated genes.

We generated a list of 37 well-established exercise-associated genes and overlapped with the list

of genes that had significant isoform-switching events at each time point. We observed isoform

switching in 22 of those 37 genes (46%) including myosin heavy chain IIX (*Myh4*) and IIA

(*Myh2*), *Myc*, *Nr4a1*, and *Mef2c* (Figure S6A–V). These data indicate that in addition to RBPs,

that genes that are associated with exercise responses and adaptations also undergo isoform

switching events that may be important to investigate their physiological relevance in future

mechanistic follow up studies.

**3.5 Validation of hnRNPA3 isoform switching and protein expression across timepoints post exercise**

Among the isoform-switching RBPs, *Hnrnpa3* had a splicing profile with biological significance according to the LRS data (Figure 6A,B). It was evident that a RI variant (*Hnrnpa3*-205) was dominant at baseline (mmYS-pre), there was a complete switch post-exercise (mmYS-ipe and -1pe), whereby the pcRNA variants (*Hnrnpa3*-203/-204) become the dominant forms. At the 24-hour time point, the proportions of the mRNA transcript variants were split 50% between RI (-205) and pcRNA (-204). Protein levels were determined for hnRNP-A3 to validate this isoform-switching event (Figure 6C). HnRNP-A3 was detectable at baseline according to the western blots, one-way ANOVA revealed statistical difference between the pre- and post-exercise time points ($F = 6.872$, $p = 0.0035$). *Post hoc* comparisons revealed no statistical difference between mmYS-pre and mmYS-ipe (23.1% increase, $p$-adj $= 0.6876$), but was found significant for mmYS-1pe and mmYS-24pe (95.6% and 84.9% increases, $p$-adj $= 0.0043$ and 0.0103, respectively).

**4 DISCUSSION**

The present study supports that, in addition to DGE in recovery from endurance exercise, there is a robust AS response across the transcriptome. Our data indicate that while some RBPs and spliceosome proteins undergo DGE in response to an acute bout of endurance exercise in untrained skeletal muscle, far more RBPs and spliceosome proteins undergo DAS and isoform switching in response to exercise. Our rMATS analysis of SRS data revealed that young individuals have splicing events in response to endurance exercise, but both sedentary and trained older individuals have a greater number of events detected compared to younger individuals. While SRS is excellent for detecting DGE and exon splicing events, it lacks the resolution to accurately detect transcript variants and/or isoform-switching events due to multi-read alignment and mapping ambiguity.[47] Finally, our data clearly points out the strengths of LRS for the detection of full-length transcript variants and opens an entirely new area of adaptive potential in skeletal muscle to explore in response to endurance exercise.

Recent literature has indicated changes in the expression of transcript variants with aging in skeletal muscle.[16,48–52] Since endurance exercise is a potent anti-aging intervention (ie, by maintaining V$\Box$O$_2$max), we surmised that the response of skeletal muscle gene expression at the level of AS would differ by age and training status. Our data clearly indicate that this is likely the case (Figure 3,4). First, since previous research has shown significant RNA and protein level differences in RBPs with age, we explored a biased DGE analysis of RBPs. This revealed that acute endurance exercise in young individuals had a minimal impact on DGE of RBPs in comparison to the effect acute endurance exercise in muscles of older individuals (Figure 3). Interestingly, older trained individuals had fewer differentially expressed RBPs in response to acute exercise compared to acute exercise in sedentary individuals (Figure 3). This finding is in

line with recently published data that indicated lower RBP expression levels in masters athletes

compared to age-matched non-athletes.[53]

Becoming or remaining physically active, as well as performing regular exercise, shifts to

play a more important role in health as one ages than during their youth. Recent findings have

indicated that AS becomes dysregulated with aging in several tissues, including skeletal

muscle.[16,54] When aged skeletal muscles were compared to younger muscles, proteins of the

spliceosome and several RBPs were overrepresented, leading to a change in the expressed

variants of mRNA.[16] Interestingly, when octogenarian masters athletes were compared to age-

matched non-athletes, the athletes had lower protein expression of the spliceosomal and several

RBPs.[53] The authors went on to hypothesize that the underrepresentation of the spliceosomal

proteins was related to the higher functioning mitochondria and the lower need for energy to be

expended for splice-isoform generation.[53] Thus, further research is needed to link exercise, AS

regulation, and mRNA variant generation to the adaptive process in skeletal muscle of both

younger and older adults.

Next, we used rMATS to explore the type and number of AS events at the exon level

from the SRS from humans (Figure 4). To our knowledge, rMATS has not previously been used

to explore how exercise may modify AS, allowing us to make several novel insights.

Collectively, it is apparent that SE is the dominant form of alternative splicing event category in

response to an acute bout of exercise while A5SS and A3SS are potentially subjected to other

factors, such as age. The second most abundant type of splicing event across all data sets was RI

(Figure 4). Both SE and RI events have important implications on the transcriptome and

proteome that should be explored in future studies, but these data provide novel mechanistic

insights into how acute endurance exercise is modifying gene expression and potentially skeletal

muscle responses and adaptations to exercise. Second, we observed that there were fewer

splicing events in the muscles of younger individuals compared to older individuals in response

to exercise. However, we interpret this cautiously due to technical limitations and differences

with how the samples were collected and the way the sequencing was performed between the

data sets. Future studies will be needed to test this important question more carefully. A third

observation is that older skeletal muscles utilized more A5SS and A3SS compared to younger

muscles in response to a bout of endurance exercise. This could be due to the different responses

of signal transduction pathways to modify the splicing machinery in older muscles compared to

younger muscles. Alternatively, this could indicate a greater energetic stress in older muscles

leading to different signaling pathways being activated, resulting in the utilization of weaker

splice sites. This could have important ramifications on the transcriptome and proteome

following exercise in older muscles and should be explored in more detail in future research.[55,56]

While SRS is a powerful technology and our data above illustrate its ability to detect

DGE and exon level splicing events, it lacks the ability to detect full-length transcripts, which

have great implications on the expression of protein isoforms. Thus, we next wanted to

determine if additional insights could be made concerning how exercise mechanistically impacts

skeletal muscle by using LRS. First, we were able to separate DGE and DAS using the LRS data

(Figure 5A–C). This revealed that a significant portion of genes only undergo DAS, meaning

previous post-exercise DGE analyses would not have detected these changes even though they

would have likely impacted the post-exercise protein levels in muscle. Next, we analyzed

isoform switching, specifically in genes that were not differentially expressed following exercise.

We observed a robust isoform-switching response at all three time points in recovery from

endurance exercise (Figure 5D). Further analysis illuminated a significant enrichment of RBPs

that undergo isoform-switching events during recovery from endurance exercise (Figure 5E–G).

In other words, RBPs and splicing factors undergo regulatory alteration by genes encoding these

proteins via AS. Such regulatory process is referred to as either auto-regulation (whereby a RBP

regulates the splicing of its own transcripts) or cross-regulation (whereby a RBP regulates the

splicing of other RBP-coding transcripts). This idea of auto- and cross-regulation as a means of

regulating functional levels of RBPs is not a novel concept in the field of RNA biology, as

previously demonstrated in neuronal (NOVA1)[57] and cancer (PTBP1/2 and SRSF3)[58] cells.

Interestingly, several of the isoform-switching events lasted at least 24 hours into

recovery from exercise, indicating a lasting (ie, not transient) re-wiring of the transcriptome that

likely impacts the proteome as we have shown is the case for hnRNP-A3 (Figure 6A–C).

Splicing and AS are regulated by a multitude of factors including (but not limited to)

transcriptional rate, chromatin structure, the spliceosome, and RBPs.[4,5] The potential for exercise

to modify the activity of the spliceosome, as well as post-translational modification of RBPs

which may impact binding to their respective target RNAs (and thus modify their splicing), is

particularly important. RBPs bind to RNAs and impact their entire lifecycle: from splicing to

localization, to translation, and degradation.[18] Specifically, RBPs bind to *cis*-regulatory elements

(ie, intronic/exonic splicing enhancers and silencers) to regulate the inclusion of specific exons,

resulting in the expression of different transcript variants and protein isoforms.  Differential use

of isoforms between conditions (isoform switching) can have profound biological impacts, even

if they are only transiently induced by exercise, due to the difference in functions of the isoforms.

Functional consequences of isoform switches can include gain or loss of protein domains or

signal peptides, loss of protein coding sequence, and change in propensity for nonsense-mediated

decay.[13] Isoform switches are implicated in many diseases, and it has already been observed

following exercise (PGC-1α),[15] however the full extent and impact of isoform switching post-

exercise is far from understood.

It is highly likely, but not yet tested, that exercise remodels the binding patterns of RBPs

either through post-translational modifications (PTMs) of the RBPs themselves or through

isoform switching and AS changes to RBPs themselves, which would modify the target genes of

RBPs. Metabolic stress responsive pathways, such as AMPK, are already known to regulate

PTMs of RBPs.[21] Interestingly, many RBPs tend to regulate their protein abundance through AS

and isoform switching. Our isoform switching data indicate an enrichment of events in RBPs

post-exercise. This indicates that exercise may remodel the expression of protein isoforms by

modifying the function of RBPs. Our findings not only support the preceding study from our

laboratory that focused on SF3B4 and SRSF2,[29] but others that have observed similar

phenomenon in a separate setting: Henrich et al[59] illustrated 9 weeks of microgravity conditions

leading to AS-driven diversification of the transcriptome in mouse skeletal muscle, including

RBPs (eg, *Mbnl1* and *Rbfox1*). This mechanism is important in shaping the transcriptome and

proteome in response to specific cellular stresses. Bringing this idea to the study of skeletal

muscle adaptations in response to exercise is an innovative and novel molecular mechanism of

adaptation (Figure 7).

The present study is not without limitations. The human SRS data utilized for this study

included on average 20 million reads per sample, which is insufficient/minimum threshold to

yield biologically true isoform-switching analyses with IsoformSwitchAnalyzeR. Hence, there is

a growing need for employing LRS technologies to better examine alternative splicing and

isoform switching in the field of exercise biology. Additionally, the mice cohort had mixed sexes

unlike the human cohorts utilized for analyses, which may further limit the comparability. Indeed,

protein analysis was only conducted for our candidate RBP, hnRNP-A3, but not at the global

level for this study. To better validate the significance of DAS and isoform-switching events,

future studies will incorporate proteomics data with these LRS data via proteogenomic

approaches.

In summary, the present data supports recent evidence of divergence in the skeletal

muscle AS-related responses and RBP expression by age and training status. Moreover, LRS is

the preferrable method of transcriptomics study when exploring AS and isoform-switching

events, whereas utilizing SRS may require cost prohibitive read depth per sample for many

groups (at least 100 million reads per sample) to proficiently conduct the isoform switching

analyses. Additionally, our acute endurance exercise mouse model demonstrated that, even

without any changes in overall gene expression, the protein expression of hnRNP-A3 was

increased by nearly two-fold in response to exercise for at least 24 hours via isoform switching

with the power of LRS. Therefore, our study points out that AS following exercise in skeletal

muscle is an underexplored and untapped area of ripe to increase our mechanistic understanding

of exercise.

## IV: DATA AVAILABILITY STATEMENT

The human SRS data were extracted from deposits by Pattamaprapanont et al[30] and Rubenstein et al[31] in the NCBI Gene Expression Omnibus database with the accession numbers GSE87749 and GSE151066, respectively. The mouse LRS data are deposited in the NCBI Gene Expression Omnibus database with the accession number GSE279359. All data used to generate the figures in this manuscript will be deposited at the Deep Blue Data repository with a permanent DOI (DOI will be provided upon publication).

## V: CONFLICT OF INTEREST STATEMENT

The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest. The authors declare no competing interests.

## VI: AUTHOR CONTRIBUTIONS

AA, ALS, JJK, and ATL conceived and/or designed the research. AA, ALS, JJK performed the research and acquired the data, AA, JJK, JYY, EYZ, and ATL analyzed and interpreted the data. All authors were involved in drafting and revising the manuscript.

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# IX: FIGURE LEGENDS

**Figure 1.** Layout of RNA-Seq study. (A) Publicly accessible human SRS data (hsYS, hsAS, and

hsAA) were downloaded from NCBI Gene Expression Omnibus, preprocessed, and analyzed for

differential expression. (B) Young C57BL/6 mice (mmYS) underwent an acute bout (30 minutes)

of treadmill running, sacrificed, and their gastrocnemius skeletal muscle tissues were harvested

for RNA sequencing cDNA library prep. Following LRS, the data were preprocessed and

analyzed for differential expression. Biologically significant genes from (A) and (B) were

retrieved for subsequent pathway and biased analyses.

**Figure 2.** Differential gene expression (DGE) of hsYS (A-C), hsAS (D,E), hsAA (F,G), and

mmYS (H-J) in the skeletal muscle comparing pre- and post-acute exercise. (A) Volcano plot of

hsYS-pre and hsYS-4pe DGE. (B) Top 10 GO terms from significantly up-regulated genes of

hsYS-pre and hsYS-4pe DGE. (C) Top GO terms from significantly down-regulated genes of

hsYS-pre and hsYS-4pe DGE. (D) Volcano plot of hsAS-pre and hsAS-3pe DGE. (E) Top 10

GO terms from significantly up-regulated genes of hsAS-pre and hsAS-3pe DGE. (F) Volcano

plot of hsAA-pre and hsAA-3pe DGE. (G) Top 10 GO terms from significantly up-regulated

genes of hsAA-pre and hsAA-3pe DGE. (H) Volcano plot of mmYS-pre and mmYS-1pe DGE.

(I) Top 10 GO terms from significantly up-regulated genes of mmYS-pre and mmYS-1pe DGE.

(J) Top GO terms from significantly down-regulated genes of mmYS-pre and mmYS-1pe DGE.

**Figure 3.** Biased differential gene expression of biologically significant ($|\log_2 FC| > 0.5$; raw $p$

$< .05$ for mouse, $p$-adj $< .05$ for human) RNA-binding proteins in response to an acute bout of

exercise in skeletal muscle with and without training. The 72 genes were binned to one of

traditional RBPs, hnRNPs & splicing factors, RNA metabolism, RNA helicase, and non-

traditional RBPs.

**Figure 4.** Differential splicing events in acutely exercised young and aged skeletal muscle with

and without training. (A) Level of potential splicing change detected between hsYS-pre and

hsYS-4pe, categorized into 5 common event types (SE, RI, MXE, A5SS, and A3SS). (B) Level

of potential splicing change detected between hsAS-pre and hsAS-3pe, categorized into 5

common event types. (C) Level of potential splicing change detected between hsAA-pre and

hsAA-3pe, categorized into 5 common event types. (D) Euler overlap of genes with differences

in potential splicing events detected pre- and post-acute exercise across the three human SRS

cohorts.

**Figure 5.** Splicing and isoform switching in acutely exercised young sedentary skeletal muscle

in a temporal manner. (A) Expressional changes in genes with significant (raw $p < .05$) DGE and

DAS between mmYS-pre and mmYS-ipe. (B) Expressional changes in genes with significant

DGE and DAS between mmYS-pre and mmYS-1pe. (C) Expressional changes in genes with

significant DGE and DAS between mmYS-pre and mmYS-24pe. (D) Isoform switching genes

with statistical significance ($\Delta\Pi > 10\%$, $p$-adj $< .05$) between pre- and post-acute exercise time

points. (E) Euler overlap of isoform switching genes with statistical significance between pre-

and post-acute exercise time points. (F) Top 10 GO terms from the 295 common genes across the

three post-acute exercise time points found in Figure 4E. (G) Overlap of the 295 common genes

with in-house list of 1135 RBP genes, highlighting significant DAS of 38 RBP genes without

significant DGE.

**Figure 6.** Acute bout of treadmill running increased expression of splicing factor hnRNP-A3 in

skeletal muscle without training. (A) Transcript expressional and splicing profile of Hnrnpa3

obtained from LRS data, illustrating RI (Hnrnpa3-205) to pcRNA (Hnrnpa3-203/-204) in

response to acute exercise. (B) Transcript expressional and splicing profile of Hnrnpa3 in $\Delta\Pi$

from Figure 6A illustrated as a bar chart. (C) Western blot validation of significant isoform

switching of hnRNP-A3 at the protein level, normalized to total protein at 40-45 kDa band

detection then normalized to mmYS-pre for relative quantification in arbitrary units (AU),

included with representative image of western blots. *, p-adj < 0.05 compared to mmYS-pre. **,

p-adj < 0.01 compared to mmYS-pre. All experiments were conducted with n = 5 per cohort

(Figure S5D).

**Figure 7.** Current model on the effects of acute endurance exercise on the AS regulatory

mechanism with key *trans*-factors/RBPs.

**X: TABLES**

**Table 1.** Biologically significant RNA-binding proteins selected and categorized based on the

types of exercise-induced changes in isoform switching events.

| Types of exercise-induced changes in isoforms | RI to pcRNA | Complex to complex | pcRNA to pcRNA | pcRNA to RI | Known to novel transcript | lncRNA to pcRNA | pcRNA to lncRNA/ less pcRNA | Novel transcript to known | pcRNA to NMD | RI to novel transcript |
|---|---|---|---|---|---|---|---|---|---|---|
| **Gene Names** | Eif4g2 Hnrnpa3 Hnrnpc Mrpl37 Mthfsd Noc4l Nosip Rnps1 Rpl3 Tia1 U2af1l4 | Mbnl1 Hnrnpa2b1 Hnrnpf Rack1 Rpl10a Rpl18a Rsrc2 Srsf5 Srsf7 | Arhgdip Grsf1 Ivns1abp Mtpap Ppil3 Pqbp1 Rps13 Snrnpa | Hnrnpr Mphosph | Mbnl2 Pfn1 | Dnajc8 Rbm39 | Rpl37 | Cpsf4 | Hnrnpa1 | Hnrnpk |
| **Final count** | 11 | 9 | 8 | 2 | 2 | 2 | 1 | 1 | 1 | 1 |

# XI: SUPPLEMENTAL FIGURE LEGENDS

**Figure S1.** RNA-Seq data quality metrics and animal acute treadmill running model. Bar graph of total read count of (A) hsYS, (B) hsAS, (C) hsAA, and (D) mmYS cohort data by sample in millions. Euclidean hierarchical heatmap analysis of (E) hsYS, (F) hsAS, (G) hsAA, and (H) mmYS cohort data by sample. Principal component analysis of (I) hsYS, (J) hsAS, (K) hsAA, and (L) mmYS cohort data by sample. (M) Overview of treadmill acclimation protocol, max speed test, and pre-/post-acute exercise time points of skeletal muscle harvests.

**Figure S2.** Violin plots of genome-wide differences in isoform fraction (IF) across (A) hsYS, (B) hsAS, and (C) hsAA cohorts compared between pre- and post-acute bout of exercise using IsoformSwitchAnalyzeR. Differences in IF revealed enrichment of genes stratified in AS event type across (D) hsYS, (E) hsAS, and (F) hsAA cohorts compared between pre- and post-acute bout of exercise. (G) Isoform switching genes with statistical significance ($\Delta\Pi > 10\%$, $p$-adj $< .05$) between pre- and post-acute exercise time points across the human cohorts. (H) Isoform switching genes with statistical significance and predicted biological outcomes between pre- and post-acute exercise time points across the human cohorts.

**Figure S3.** Differential splicing events of hsYS (A,D), hsAS (B,E), and hsAA (C,F) in the skeletal muscle comparing pre- and post-acute exercise using rMATS. (A) Top 10 GO terms of enriched genes with splicing events of hsYS-pre and hsYS-4pe. (B) Top 10 GO terms of enriched genes with splicing events of hsAS-pre and hsAS-3pe. (C) Top 10 GO terms of enriched genes with splicing events of hsAA-pre and hsAA-3pe. (D) Top 10 GO terms of enriched genes with skipped exons of hsYS-pre and hsYS-4pe. (E) Top 10 GO terms of enriched genes with skipped exons of hsAS-pre and hsAS-3pe. (F) Top 10 GO terms of enriched genes with skipped exons of hsAA-pre and hsAA-3pe.

**Figure S4.** Significant isoform-switching genes and additional DGE data of mmYS in the

skeletal muscle comparing pre- and post-acute exercise using Swan. (A) Top 10 GO terms of

enriched genes with isoform-switching events of mmYS-pre and mmYS-ipe using PANTHER.

(B) Top 10 GO terms of enriched genes with isoform-switching events of mmYS-pre and

mmYS-1pe using PANTHER. (C) Top 10 GO terms of enriched genes with isoform-switching

events of mmYS-pre and mmYS-24pe using PANTHER. (D) Volcano plot of mmYS-pre and

mmYS-ipe DGE. (E) Volcano plot of mmYS-pre and mmYS-24pe DGE.

**Figure S5.** Western blot validation of anti-hnRNP-A3 antibody in human and mouse samples.

(A) Wild-type HEK 293 cells were used to verify cross-species specificity of the hnRNP-A3

antibody and was loaded by 50k, 25k, and 10k cells. (B,C) C2C12 myoblasts were transfected

with 30 nM of either siCTL or *Hnrnpa3* siRNA for 24 and 48 h to validate protein specificity of

the antibody. (D) Full collection of western blots used to analyze significant isoform switching

of hnRNP-A3 at the protein level, normalized to total protein at 40-45 kDa band detection then

normalized to mmYS-pre for relative quantification in AU. \*\*\*\*, $p < 0.0001$ compared to siCTL.

**Figure S6.** Transcript expressional and splicing profile of 22 well-established exercise-

associated genes with significant isoform switching obtained from LRS data. (A)

Myelocytomatosis oncogene; *Myc*. (B) Nuclear receptor subfamily 4, group A, member 1; *Nr4a1*.

(C) Pyruvate dehydrogenase kinase, isoenzyme 4; *Pdk4*. (D) Sirtuin 2; *Sirt2*. (E) Sirtuin 3; *Sirt3*.

(F) Sirtuin 5; *Sirt5*. (G) Heat shock protein 5; *Hspa5*. (H) Heat shock protein 70 family, member

13; *Hspa13*. (I) Heat shock protein 70 family, member 11; *Hspa11*. (J) Insulin-like growth factor

1; *Igf1*. (K) Insulin-like growth factor 2; *Igf2*. (L) Interlukin-11 receptor subunit α 1; *Il11ra1*. (M)

Interlukin-15 receptor, α chain; *Il15ra*. (N) Interlukin-33; *Il33*. (O) Muscleblind-like splicing

regulator 1; *Mbnl1*. (P) Muscleblind-like splicing regulator 2; *Mbnl2*. (Q) Myocyte enhancer

factor 2C; *Mef2c*. (R) Mitochondrial transcription termination factor; *Mterf2*. (S) Myosin, heavy

polypeptide 2, skeletal muscle, adult; MYH type IIA; *Myh2*. (T) Myosin, heavy polypeptide 4,

skeletal muscle, adult; MYH type IIX; *Myh4*. (U) Heat shock protein 2; *Hspb2*. (V) Nuclear

receptor subfamily 2, group F, member 2; *Nr2f2*.

# Figure 1.

**Figure 2.**

**Figure 3.**

**Figure 4.**

**(A)** hsYS-pre vs hsYS-4pe

RI, 20
MXE, 18
A3SS, 8
A5SS, 13
SE, 67

**(B)** hsAS-pre vs hsAS-3pe

RI, 149
MXE, 46
A3SS, 131
A5SS, 79
SE, 253

**(C)** hsAA-pre vs hsAA-3pe

RI, 107
MXE, 30
A3SS, 83
A5SS, 72
SE, 217

**(D)**

hsAA−pre:3pe
231
(35.4%)

3
(0.5%)

37
(5.7%)

1
(0.2%)

hsYS−pre:4pe
78
(11.9%)

hsAS−pre:3pe
299
(45.8%)

4
(0.6%)

# Figure 5.

# Figure 6.

## (A)

| Transcript Name | Novelty | B | IPE | 1hPE | 24hPE | Transcript Model |
|---|---|---|---|---|---|---|
| *Hnrnpa3*-204 pcRNA 379 AA (39.7 kDa) | Known | 0.0 | 50.0 | 33.33 | 50.0 | |
| *Hnrnpa3*-203 pcRNA 357 AA (37.1 kDa) | Known | 0.0 | 50.0 | 66.67 | 0.0 | |
| *Hnrnpa3*-205 No protein (RI) | Known | 100.0 | 0.0 | 0.0 | 50.0 | |

Percent of isoform use ($\pi$)

## (B)

*Hnrnpa3*-204 (protein-coding)
*Hnrnpa3*-203 (protein-coding)
*Hnrnpa3*-205 (non-coding)

ΔΠ (%)

PRE  IPE  1hPE  24hPE

## (C)

AU (Normalized to PRE)

PRE  IPE  1hPE  24hPE

hnRNP-A3        42 kDa
Total Protein   40-45 kDa

**Figure 7.**