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3	Single-cell transcriptomic analysis of skeletal muscle regeneration across mouse
4	lifespan identifies altered stem cell states associated with senescence
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18	Abstract: Skeletal muscle regeneration is driven by the interaction of myogenic and non-
19	myogenic cells. In aging, regeneration is impaired due to dysfunctions of myogenic and non-
20	myogenic cells, but this is not understood comprehensively. We collected an integrated atlas of
21	273,923 single-cell transcriptomes from muscles of young, old, and geriatric mice (~5, 20, 26
22	months-old) at six time-points following myotoxin injury. We identified eight cell types, including T
23	and NK cells and macrophage subtypes, that displayed accelerated or delayed response
24	dynamics between ages. Through pseudotime analysis, we observed myogenic cell states and
25	trajectories specific to old and geriatric ages. To explain these age differences, we assessed
26	cellular senescence by scoring experimentally derived and curated gene-lists. This pointed to an
27	elevation of senescent-like subsets specifically within the self-renewing muscle stem cells in aged
28	muscles. This resource provides a holistic portrait of the altered cellular states underlying skeletal
29	muscle regenerative decline across mouse lifespan.

30 EXTENDED SUMMARY

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32 Skeletal muscle regeneration relies on the orchestrated interaction of myogenic and non-33 myogenic cells with spatial and temporal coordination. The regenerative capacity of skeletal 34 muscle declines with aging due to alterations in myogenic stem/progenitor cell states and functions, non-myogenic cell contributions, and systemic changes, all of which accrue with age. 35 A holistic network-level view of the cell-intrinsic and -extrinsic changes influencing muscle 36 37 stem/progenitor cell contributions to muscle regeneration across lifespan remains poorly resolved. To provide a comprehensive atlas of regenerative muscle cell states across mouse 38 lifespan, we collected a compendium of 273,923 single-cell transcriptomes from hindlimb muscles 39 40 of young, old, and geriatric (4-7, 20, and 26 months-old, respectively) mice at six closely sampled time-points following myotoxin injury. We identified 29 muscle-resident cell types, eight of which 41 42 exhibited accelerated or delayed dynamics in their abundances between age groups, including T 43 and NK cells and multiple macrophage subtypes, suggesting that the age-related decline in 44 muscle repair may arise from temporal miscoordination of the inflammatory response. We 45 performed a pseudotime analysis of myogenic cells across the regeneration timespan and found age-specific myogenic stem/progenitor cell trajectories in old and geriatric muscles. Given the 46 47 critical role that cellular senescence plays in limiting cell contributions in aged tissues, we built a series of tools to bioinformatically identify senescence in these single-cell data and assess their 48 49 ability to identify senescence within key myogenic stages. By comparing single-cell senescence scores to co-expression of hallmark senescence genes Cdkn2a and Cdkn1a, we found that an 50 51 experimentally derived gene-list derived from a muscle foreign body response (FBR) fibrosis 52 model accurately (receiver-operator curve AUC = 0.82-0.86) identified senescent-like myogenic 53 cells across mouse ages, injury time-points, and cell-cycle states, in a manner comparable to 54 curated gene-lists. Further, this scoring approach pinpointed transitory senescence subsets within the myogenic stem/progenitor cell trajectory that are related to stalled MuSC self-renewal states 55 across all ages of mice. This new resource of mouse skeletal muscle aging provides a 56 comprehensive portrait of the changing cellular states and interaction network underlying skeletal 57 58 muscle regeneration across mouse lifespan.

59 INTRODUCTION

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61 Skeletal muscle is heterogeneously composed of interacting immune, stromal, and myogenic cells that contribute to the maintenance and regeneration of muscle by regulating muscle stem cell 62 63 (MuSC) guiescence, proliferation, and differentiation.¹ MuSCs are found between the basal lamina and the plasma membrane of myofibers and are essential for the initial development of 64 muscle and in muscle regeneration.^{2,3} The MuSC population is maintained across multiple cycles 65 of growth and regeneration by asymmetrical division which generates additional MuSCs and 66 *Myod1*+ myoblasts.^{2,3} Myoblasts further expand, differentiate, and fuse to form new *Myoq*+ 67 myocytes.^{2,3} The paired box protein 7 (Pax7) transcription factor, predominantly expressed in 68 MuSCs, regulates the expression of myogenic regulatory factors such as Myf5 and Myod1.³ 69

During homeostasis, the skeletal muscle microenvironment maintains signals to keep 70 MuSCs in a non-cycling state and resident mast cells and macrophages monitor for damage.^{1,4} 71 72 Following muscle injuries, the mature myofibers undergo necrosis and the individual myonuclei undergo apoptosis.^{5,6} Once damage is detected by resident immune cells, inflammatory cells like 73 neutrophils and macrophages are recruited to the damaged site.^{1,2} First, resident macrophages 74 75 release Cxcl1 and Ccl2, neutrophil chemoattractants, to signal for neutrophils to invade.^{1,4} 76 Neutrophils reach their maximum abundance in the damaged muscle between 12-24 hours post-77 injury, after which they quickly return to basal levels.⁴ Resident Cd8+ T cells also respond early 78 to muscle injury by producing Cc/2 and recruiting macrophages to the injured muscle.⁴ Circulating 79 monocytes and macrophages enter the muscle environment which is enriched with proinflammatory cytokines that activate macrophages.^{1,4} These activated macrophages clear cellular 80 debris and promote myogenic cell proliferation.^{1,5} The active phagocytic macrophages peak in 81 82 abundance at 2 days post-injury (dpi) and they are replaced by non-phagocytic macrophages that peak in abundance at 4-7 dpi.⁴ The non-phagocytic macrophages help maintain myogenic cell 83 differentiation, resolve inflammation, and support the production of connective tissue.^{1,4,5} If 84 macrophages do not clear cellular debris and promote myogenic cell proliferation and 85 differentiation, the muscle remains inflamed and there are repeated cycles of necrosis and 86 regeneration.⁵ The damaged myofibers are then replaced with adipose tissue, fibrotic tissue, or 87 bone, instead of new myofibers.⁵ A prior study found that there was an increase in the number of 88 anti-inflammatory macrophages which can contribute to an increase in fibrosis in aged muscle.⁷ 89 It remains controversial how monocytes and macrophages should be classified and whether 90 91 broad pro- and anti-inflammatory definitions should be used or whether more varied phenotypic

92 identities better capture their molecular and functional plasticity.⁸ In this work, we sought to
93 distinguish monocyte/macrophage populations by markers and by resident status.

Prior studies have found that both CD8+ and CD4+, especially FoxP3+ regulatory T cells,
infiltrate and help repair damaged muscle.⁹ In aging, there is a decline in new naive T cells
released from the Thymus.¹⁰ To compensate for this loss, CD4+ T cells in the periphery proliferate
resulting in a shift towards more memory T cell populations throughout aging.⁹ Within the memory
T cell population, an increase in senescent and exhausted T cells is observed in aging.⁹

In addition to resident immune cells, fibro-adipogenic progenitors (FAPs), bipotent 99 progenitor cells that can differentiate into fibroblasts and adipocytes, are a part of the skeletal 100 muscle microenvironment.¹ FAPs are quiescent during homeostasis and activate upon injurv.⁴ 101 There is some evidence that in the early stages of injury response FAPs control immune infiltration 102 and in later stages FAPs control muscle remodeling.¹¹ They reach peak abundance at 3 dpi and 103 return to homeostatic levels by 14 dpi.⁴ The expansion and decline of FAPs is regulated by 104 105 myeloid cells and FAPs that are activated to the fibrogenic phenotype are regulated by antiinflammatory macrophages.⁴ Fibrogenic FAPs are the primary producers of connective tissue in 106 injured muscle.⁴ 107

Multiple factors that contribute to the reduced functionality of MuSCs in aged tissues have 108 been reported, including an excess of FAPs and fibroblasts, misbalanced cell division, and the 109 establishment of senescent MuSCs.^{2,4,12,13} Senescence is characterized by a combination of 110 111 hallmarks. These include prolonged DNA damage response activation, upregulation of the cell 112 cycle inhibitors p16^{INK4a} (encoded by Cdkn2a and referred to as p16 hereafter) and p21^{Cip1} (encoded by Cdkn1a and referred to as p21 hereafter) and anti-apoptotic BCL-2 proteins, an 113 increase in reactive oxygen species levels and of senescence-associated-β-galactosidase (SA-114 β -gal), and a senescence-associated secretory phenotype (SASP).¹⁴ Prior studies have used the 115 cell cycle proteins p16, p21, p53, and Rb to differentiate between dividing and non-diving cells, 116 but the non-diving cells can include senescent cells and guiescent cells.¹⁵ SA-β-gal is also 117 commonly used to identify senescent cells, but it is also detected in quiescent cells and in stressed 118 cells.¹⁵ Because these markers are not unique to senescent cells and because senescent cells 119 are heterogeneous, it has been challenging to identify biomarkers that can accurately and 120 121 consistently identify senescent cells.¹⁶

There are extrinsic changes, such as an increase in FAPs, and intrinsic factors, such as a reduction in asymmetrical self-renewal and an increase in senescent MuSCs, that disrupt skeletal muscle homeostasis and regeneration in aging.² Aged MuSCs exhibit a decline in selfrenewal and ability to differentiate, thus reducing the MuSC pool.^{2,4,12,13} Compared to young MuSCs, fewer aged MuSCs are found in quiescence, due to either elevated activation or entering a pre-senescent state.^{12,13} It remains unclear how these extrinsic and intrinsic changes are integrated systematically and how heterogeneities related to cellular senescence within both myogenic and non-myogenic cell populations contribute, in part due to a paucity of holistic analyses of these alterations. Further, it has been posited that temporal and spatial discoordination between the dynamics in key cell types during the repair process leads to inefficient outcomes.²

Single-cell methods have been used previously to understand skeletal muscle 133 homeostasis and regeneration at various ages.^{11,17–32} Recent reports have provided insights into 134 MuSC dysfunction with aging. A recent human skeletal muscle study observed a decline in the 135 proportion of MuSCs with age and that IGFN1, which is needed for myoblast fusion and 136 differentiation, is decreased in old (~75 years old) muscle.²⁸ This report found no difference in 137 Cdkn2a expression by age, but did identify a senescent myonuclei population that expressed 138 Cdkn1a that was more frequent in old than young human samples.²⁸ A recent study on mouse 139 skeletal muscle aging based on mass cytometry observed that CD47^{hi} MuSCs occur with a higher 140 frequency in aged mice and exhibit poor regenerative capacity.³³ Another report demonstrated 141 142 that guiescent MuSCs in aged mice have reduced expression of Cyclin D1, which is needed for proper MuSC activation and muscle regeneration.³⁴ 143

144 To evaluate the factors that contribute to the age-related decline in skeletal muscle 145 regeneration in a more comprehensive manner, we have generated a new single-cell RNA 146 sequencing (scRNA-seq) analysis of uninjured (day 0) and myotoxin-injured (days 1, 2, 3.5, 5, 147 and 7) tibialis anterior (TA) muscles from young, old, and geriatric mice. We identified a total of 29 cell types, 8 of which had a significant difference in their abundances throughout regeneration 148 149 by age. We confirmed changes in age-specific T cell abundance by immunohistochemistry and flow cytometry. Given the role that cellular senescence plays in limiting cell contributions in aged 150 tissues, we tested a series of tools to bioinformatically identify senescence in these single-cell 151 152 data and found a transfer-learning based scoring approach accurately classified senescent-like myogenic cells across ages and cell cycling states. This scoring approach revealed that 153 senescent-like subsets exist at key transitional self-renewal states within the myogenic 154 stem/progenitor cell pseudotime trajectory across all ages but are elevated in aged muscles. This 155 156 resource of mouse skeletal muscle aging provides a more comprehensive portrait of the changing 157 cellular states underlying skeletal muscle regeneration across mouse lifespan.

158 **RESULTS**

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160 Single-cell RNA-sequencing analysis of skeletal muscle regeneration across mouse lifespan. To comprehensively evaluate skeletal muscle homeostasis and regeneration 161 throughout aging, we performed single-cell RNA sequencing (scRNA-seq) on 65 mouse skeletal 162 muscle samples with the 10x Chromium v2 and v3 platforms. Muscle damage was induced in 163 young (4-7 months-old [mo]), old (20 mo), and geriatric (26 mo) C57BL/6J mice by injecting the 164 tibialis anterior (TA) muscles with notexin. The injured and uninjured muscles were collected at 165 six time points (days 0, 1, 2, 3.5, 5, and 7) (Figure 1A, B). Together, these 65 scRNA-seq 166 samples, newly reported here and from our two prior reports^{20,35}, contained a total of 365,710 cell 167 barcodes prior to quality control and filtering (Supplementary Figure 1A, Extended Data File 168 1). All samples were processed by aligning sequencing reads to the mm10 mouse reference 169 genome, removing ambient RNA signatures with SoupX³⁶, removing low quality cells, and 170 identifying and removing doublets with DoubletFinder³⁷ (Figure 1C, Supplementary Figure 1). 171 The samples were integrated with Harmony³⁸ to correct for batch effects (**Figure 1C**). The final 172 dataset contained 273,923 cells. We observed that the cell number was relatively evenly 173 174 distributed across the three age groups (Figure 1D,G), and within each age group, the number 175 of cells from each time point was relatively consistent (Figure 1E).

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177 Multi-step identification of diverse cell types by clustering. After data integration, shared 178 nearest neighbor (SNN) clustering was performed, and canonical marker genes were used to 179 manually identify cell types. The initial clustering resulted in 24 clusters that each received a 180 unique cell type annotation. Of these, nine were myeloid cell clusters (monocytes, macrophages, 181 dendritic cells, and neutrophils) that exhibited similar expression profiles. To further clarify the myeloid cells found in the final dataset, the 9 myeloid cell clusters were subset out, re-clustered, 182 and re-embedded (Supplementary Figure 2A-C). This resulted in 15 clusters that each received 183 a unique cell type annotation based on known myeloid markers (Supplementary Figure 2C-D). 184 Although this re-clustering did not further clarify the monocyte and macrophage annotations, it did 185 help to identify more specific dendritic cell and T cell subtypes (Supplementary Figure 2C-D). 186 The dendritic cell and T cell subtype annotations were transferred from the myeloid subset back 187 188 to the final dataset based on the cell barcode. The monocyte and macrophage annotations were 189 not changed based on the myeloid subset. With the additional myeloid subset annotations, we 190 identified 29 distinct cell types in the final dataset (Figure 1F, Supplementary Figure 3).

Compared to prior scRNA-seq and snRNA-seq skeletal muscle studies we identified similar broad
 cell types and we identified more specific endothelial, FAP, and immune cell subsets.^{11,18–30}

193 Lymphoid cell types were 5 of the 17 immune cell clusters. We identified a rare B cell cluster (0.47% of the final dataset) that expressed Cd19, Cd22, and Ms4a1 (Supplementary 194 195 Figure 3A). We identified a natural killer (NK) cell cluster that expressed Nkq7, Gzma, Klra4, and Klre1 but, importantly, did not express T cell markers (Supplementary Figure 3A). We identified 196 197 three T cell clusters all of which expressed Cd8a and Cd8b1. One of the T cell populations more 198 strongly expressed Cd4 while the other two T cell populations expressed Cd3e. One of the Cd3e+ clusters also strongly expressed the cycling markers Cdk1 and Hmgb2 and were thus identified 199 200 as cycling Cd3e+T cells (Supplementary Figure 3A). The other Cd3e+T cell population appears 201 to be non-cycling. The B cells, NK cells, and the non-cycling Cd3e+T cells were identified as 202 unique clusters in the initial clustering of the final dataset. The Cd4+ and cycling Cd3e+ T cells 203 were identified when we subset and re-clustered the myeloid populations (Supplementary 204 Figures 2C-D and 3A).

Although we incubated the single-cell suspension in erythrocyte lysis buffer, we did see a small (0.42% of the final dataset) erythrocyte cluster that uniquely and strongly expressed a variety of hemoglobin genes, including *Hba-a1* and *Hbb-bs* (**Supplementary Figure 3A**). Erythrocytes are not a native cell type in skeletal muscle, so we have excluded them from the cell type dynamics analysis.

210 We identified three FAPs populations (adipogenic, pro-remodeling, and stem), a tenocytes 211 population, and a Schwann and neural/glial cell population. All three of the FAPs populations 212 expressed Pdgfra and Col3a1 (Supplementary Figure 3B). The adipogenic FAPs also expressed Adam12, Bmb5, Myoc, Col1a1, Dcn, Mmp2, and Apod. The pro-remodeling FAPs 213 214 uniquely expressed cycling genes like Cdk1 and Tyms in addition to other FAPs markers like 215 Tnfalp6, II33, Adam12, Bgn, and Hdlbp. The stem FAPs also expressed lgfbp5, Dpp4, Cd34, Gsn, and *Mmp2*. The tenocyte population expressed some FAPs markers like *Col1a1*, *Dcn*, and *Apod* 216 217 and they expressed tenocyte-specific markers *Tnmd* and *Scx*. The Schwann and neural/glial cell cluster expressed *Ptn* and *Mpz* (**Supplementary Figure 3B**). 218

We identified a pericytes and smooth muscle cells cluster which expressed the pericytespecific gene *Rgs5* and *Acta2*, *Myl9*, and *Myh11* (**Supplementary Figure 3C**).³⁹ Four endothelial clusters were identified, and they shared strong expression of *Cdh5* and *Pecam1* (**Supplementary Figure 3C**). The arterial endothelial cells uniquely expressed *Alpl* and *Hey1*, the capillary endothelial cells strongly expressed *Lpl*, and the venous endothelial cells expressed *Vwf*, *Hlf1a*, *Icam1*, *Lrg1*, and *Aplnr* (**Supplementary Figure 3C**). The fourth endothelial cluster

expressed endothelial markers like *Cdh5* and *Pecam1* and myeloid markers like *S100a8/9*, *Csf1*,
and *Itgam* (**Supplementary Figure 3C**). This cluster was small (0.073% of the final dataset) and
was made up of cells from multiple replicates from the three ages at 0-2 dpi (**Supplementary Figure 5E**). Because this cluster was not unique to a single replicate, or single age, or single time
point, we have maintained it in our analysis.

230

231 Comparison of cell type dynamics in skeletal muscle regeneration across mouse ages. For each time point independent of age, we calculated the percent of cells from each cell type. In 232 agreement with previous findings, uninjured skeletal muscle (day 0) was mainly composed of 233 234 endothelial cells (49.2%), FAPs (20.4%), and myonuclei (15.1%) and there were small populations of immune cells (2.7%) and MuSCs and progenitors (2.0%) (Supplementary Figure 235 **4A**, **Supplementary Table 1A**).^{20,40} Of the endothelial cells at day 0, the most prominent subtype 236 were the capillary endothelial cells (42.4%) (Supplementary Figure 4B, Supplementary Table 237 1B). The FAPs present at day 0 were mainly adipogenic FAPs (15.6%) (Supplementary Figure 238 239 **4B**, **Supplementary Table 1B**). Of the immune cells present at day 0, there were a variety of monocytes and macrophages (47.2%), B cells (14.6%), non-cycling Cd3e+ T cells (11.6%), 240 241 Cd209a+ Dendritic cells (10.6%), and Neutrophils (9.3%) (Supplementary Figure 4D, 242 Supplementary Table 1D).⁴⁰

243 Following injury (days 1, 2, 3.5, and 5), the most abundant general cell type was the 244 immune cells (60.9%, 79.7%, 75.2%, 63.2%, respectively) (Figure 2K, Supplementary Figure 245 **4B**, **Supplementary Table 1B**). As in previous studies^{20,40}, non-immune cells like endothelial 246 cells, FAPs, and myonuclei were present following injury, but at transiently lower relative 247 abundances. As expected, the most abundant immune cells immediately after injury (day 1) were neutrophils (32.0%), Ccr2+ monocytes/macrophages (19.7%), and Ctsa+ patrolling 248 monocytes/macrophages (13.7%) (Supplementary Figure 4C, Supplementary Table 1C).^{20,40} 249 250 Immediately following injury (days 1 and 2), there was a more pro-inflammatory environment, as 251 evident by the abundance of Ccr2+ monocytes/macrophages. This was followed by a shift at days 3.5 and 5 to a more anti-inflammatory cell population, as evident by the peak in abundance of 252 Cx3cr1+ monocytes/macrophages at day 5 (28.7%) (Supplementary Figure 4C, 253 Supplementary Table 1C).^{20,40} By day 7 the cell type abundances were returning to the 254 abundances observed at day 0, but there was still a substantial immune cell population (32.1%) 255 256 (Supplementary Figure 4A, Supplementary Table 1A). The immune population at day 7 mainly 257 consists of Cx3cr1+ monocytes/macrophages (24.1%), Ctsa+ patrolling monocytes/macrophages

(13.2%), and non-cycling *Cd3e*+ T cells (17.8%) (Supplementary Figure 4D, Supplementary
 Table 1D).

260 We next conducted an analysis of cell-type dynamics across age groups by comparing the abundance of a given cell type over the entire injury time course. Of the 28 cell types, eight 261 262 were identified as having significantly different cell type dynamics across the three ages using a 263 non-linear modeling approach with multiple hypotheses correction (Figure 2J, Supplementary 264 Table 2). In response to injury, we first observed an increase in neutrophils which peaked in 265 abundance at day 1 and returned to day 0 levels by day 3.5 (Supplementary Figure 5N). We also observed a peak in the abundance of the Ccr2+ monocytes/macrophages at days 1 and 2 266 267 (Figure 2A) while the cycling monocytes/macrophages peaked in abundance at day 3.5 (Figure 268 **2D**) and the *Cx3cr1*+ monocytes/macrophages peaked in abundance at days 3.5 and 5 (Figure 269 monocyte/macrophage 2C). We observed two populations. Mrc1+ and Ctsa+ 270 monocytes/macrophages, that responded early to injury (day 2) and remained high through day 271 5 (Figure 2B,E). The geriatric Mrc1+ monocytes/macrophages maintained a higher abundance 272 from day 2 to day 7 compared to the young and old cells (Figure 2B,J). Additionally, some lymphoid cell types like NK cells, Cd3e+ non-cycling T cells, and B cells started to increase in 273 274 abundance at day 2, day 3.5, and day 5, respectively (Figure 2F-H). We observed a similar 275 pattern when looking at all three T cell populations combined (Supplementary Figure 5T). The 276 geriatric NK cells did not increase in abundance within the 7-day time course, unlike the young 277 and old cells (Figure 2F).

278 When looking at all three T cell populations combined, we detected very few T cells and 279 no age-specific differences in abundance at day 0. However, at day 5 we observed a higher 280 abundance of T cells in old samples, with a significant difference between the old and geriatric 281 samples (Figure 2L; Student's t-test, p-value = 0.01*). To confirm this, we performed 282 immunohistochemistry on sectioned TA muscles and observed that CD3+ T cells are detected more abundantly at day 5 compared to day 0 in the TAs of young, old, and geriatric mice (Figure 283 2M). We further used flow cytometry to quantify CD45+CD11c–CD11b–TCRβ+ T cells at days 0 284 and 5 from dissociated TA muscles of young, old, and geriatric mice (Figure 2N). We detected a 285 low abundance of TCRβ+ T cells out of all CD45+ hematopoietic cells at day 0, but still detected 286 a significantly higher T cell abundance in old mice compared to young (Figure 20; Student's t-287 test, p-value = 0.02^{*}). Further, we observed an increase in T cell abundance from day 0 to day 5 288 289 and a significant difference between the old and young samples at 5 dpi (Figure 20; Student's t-290 test, p-value = 0.03*). Together, these results suggest the abundance of the T cell pool is elevated specifically in older muscles (20-months of age), but not preserved in geriatric ages. 291

292 Independent of age, we detected few MuSCs and progenitors immediately following injury 293 (days 1 and 2; 2.1%, 1.1%, respectively) and the abundance of MuSCs and progenitors peaked 294 at day 5 (9.7%) (Supplementary Figure 4A, Supplementary Table 1A). This was in agreement with previous studies.^{20,40} The peak in MuSCs and progenitors abundance did vary by age with 295 296 the young cells peaking at day 5, the old cells peaking at day 3.5, and the geriatric cells peaking 297 at day 7 (Figure 2I). This difference in peak abundance did not result in a statistically significant 298 difference in the MuSCs and progenitors dynamics by age, but it did demonstrate a delayed response by the geriatric MuSCs and progenitors. Independent of age, we detected the most 299 Myonuclei at days 0 and 7 (15.1%, 10.6%, respectively) (Supplementary Figure 4A, 300 301 **Supplementary Table 1A**). The Myonuclei dynamics were very similar between the three ages, 302 but we detected more Myonuclei in old and geriatric samples at both days 0 and 7 compared to 303 young (Figure 2J, Supplementary Figure 5M).

304

305 Senescence scoring based on single-cell transcriptomic signatures. Next, we sought to 306 investigate age-specific differences in senescence within skeletal muscle regeneration. Hallmarks of mammalian aging include stem cell exhaustion, altered cellular communication, and cellular 307 senescence.⁴¹ Identifying senescent cells in scRNA-seg data is challenging because the markers 308 309 traditionally used to identify senescent cells are either lowly expressed, expressed in select cell 310 types in single-cell data, and/or assayed in terms of cellular localization and enzymatic function (Figure 3A).⁴² For example, senescent cells are commonly identified by persistent expression of 311 312 cell cycle regulators p16 (*Cdkn2a*), p21 (*Cdkn1a*), p53, and/or Rb.¹⁵ Senescent cells are also 313 marked by the senescent associated secretory phenotype (SASP) which includes proinflammatory cytokines and chemokines, growth modulators, angiogenic factors, and matrix 314 metalloproteinases (e.g., Mmp3).⁴³ To examine individual gene signatures of senescence, we 315 quantified the abundance of Cdkn2a (encodes p16), Cdkn1a (encodes p21), Mmp3 (a 316 senescence-associated matrix metalloproteinase), *Glb1* (encodes senescence-associated β-317 318 galactosidase) across all cell types and ages.

Expression of these genes depended more on cell type than age, when considering all time-points and samples together (**Figure 3A**). Given *Cdkn1a*, *Mmp3*, and *Glb1* were widely expressed across many cell types, we focused on the common senescence hallmark gene *Cdkn2a*. *Cdkn2a* transcripts were rarely detected, in agreement with previous observations in the Tabular Muris Senis project¹⁷, and primarily observed in the MuSCs/progenitors, cycling T cells, and FAPs. We observed age-associated changes in the relative abundance of *Cdkn2a*+ cells within any given cell type infrequently significant (**Figure 3B-D**). There was no significant

difference in the fraction of *Cdkn2a*+ MuSCs and progenitors by age or in the fraction of *Cdkn2a*+ cycling T cells by age (**Figure 3B-C**). However, we did observe a significant difference in the fraction of *Cdkn2a*+ adipogenic FAPs between the young and geriatric ages (**Figure 3D**; Student's t-test, p-value = 0.03^*).

330 Within the MuSCs and progenitors, we observed an increase in the fraction of cells that co-expressed Cdkn2a and Cdkn1a from day 0 to day 3.5, after which it returned to near day 0 331 levels (Figure 3E). Although there was no significant difference by age in the abundance of these 332 333 double-positive cells across all timepoints, there was a significant difference at day 3.5 between the young and old ages (Student's t-test, p-value = 0.03*) and the young and geriatric ages 334 (Student's t-test, p-value = 0.01*) (Figure 3E-F). Although Cdkn2a and Cdkn1a are both cell cycle 335 336 inhibitors and senescent markers, their expression was not correlated in MuSCs and progenitors at day 3.5 on the individual cell level in this dataset, possibly due to transcript detection dropout 337 (Figure 3G). We considered the double-positive Cdkn2a+ and Cdkn1a+ cells as candidate 338 senescent MuSCs/progenitors and performed Gene Set Enrichment Analysis (GSEA) on day 3.5 339 340 at their peak abundance. GSEA found that double-positive MuSCs/progenitors are enriched for gene-sets associated with muscle weakness and various mitosis-related processes but 341 diminished in muscle contraction and cytoskeletal processes (Figure 2H). Collectively, these 342 343 GSEA results suggest that double-positive MuSCs/progenitors have signatures of dysregulated 344 muscle function and stalled cell cycle-related gene expression.

345 We then used the Cdkn2a+ Cdkn1a+ MuSCs/progenitors as a candidate cell population to evaluate broader senescence signatures at the single-cell level. We tested two senescence 346 scoring methods^{44,45} and ten senescence-signature (SenSig) gene lists^{44,46–49} (**Extended Data** 347 File 2). We refer to the first method as the Two-way Senescence Score (Sen Score) because it 348 349 calculates a score based on a list of up- and down-regulated genes. Within this method we tested 350 six gene lists that were generated from bulk RNA-seg datasets comparing cells with senescence conditions or markers to control cells from various tissues and cell types.^{44,46} We refer to the 351 second method as the One-way Sen Score because it calculates a score based on a list of up-352 regulated genes. Within this method we tested four gene lists, three of which were taken from 353 gene-ontology databases or curated in other reports.⁴⁷⁻⁴⁹ We refer to the Methods, 354 Supplementary Figure 7, and Extended Data File 2 for more details on these two methods and 355 356 the gene lists. We note that two of these gene lists are derived from bulk RNA-seq differential 357 expression analyses of p16+ and p16- cells selected based on transgenic reporter status. One 358 gene list ("FBR") was generated by Cherry et al from p16+ versus p16– CD29+ cells isolated from a foreign body response-driven skeletal muscle fibrosis model in adult *p16-CreER*⁷²;*Ai14* reporter 359

mice.44 A second gene list ("Aged Chondrocytes") was generated from p16+ versus p16-360 361 Aggrecan+ chondrocytes isolated from 20-mo p16-tdTom:Aggrecan-CreER^{T2}:Ai6 mice (B.O. Diekman, personal communication).^{50–52} To compare how the choice of gene list and method 362 impacted senescence scoring across different cell types, we examined the FBR two-way and one-363 364 way scores in the final scRNA-seg dataset. The Two-way FBR scores were more consistently low across most cell clusters and exhibited high scores most notably in the FAP and MuSC clusters 365 (Figure 31,K). The One-way FBR scores had broader distribution, with many more cell types 366 exhibiting high scores, including FAP, MuSCs, endothelial cell, pericytes and smooth muscle cell, 367 and monocytes/macrophages clusters (Figure 3J,L). Whereas the Two-way FBR scores were 368 mean-centered around zero from each cell type cluster due to their z-scored counts (Figure 3K), 369 370 One-way FBR scores had varied cell type averages (Figure 3L). These differences complicate 371 establishing threshold for senescence positivity between cell types in the one-way scores.

372 We established a scoring approach calibrated for sensitivity and specificity in 373 discriminating Cdkn2a+ Cdkn1a+ MuSCs/progenitors across all ages and timepoints and present 374 the results in receiver-operator curves with performance reported using an area-under-the-curve 375 (AUC) metric (Figure 3M-O). Between the two senescence scoring methods and the ten SenSig 376 gene sets, the One-way FBR method performed the best of any experimentally derived approach 377 (AUC = 0.86), and was comparable to the ontology-curated One-way GO: SASP approach (AUC 378 = 0.88; Figure 3M-N). Notably, it performed far better than the recently described SenMayo list 379 while using the same ssGSEA method (AUC = 0.63). Moreover, the One-way FBR score accurately discriminated double-positive senescent-like MuSCs across all three ages (AUCs = 380 381 0.85-0.88), suggesting it captures common features of senescence irrespective of age (Figure 382 **30**). We concluded that the One-way FBR method was able to accurately identify senescent-like 383 cells in a manner that is not biased by a highly curated gene list.

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Refined analysis of myogenic subsets. In the final dataset, we identified two broad myogenic 385 clusters (Figure 1F). We observed a cluster of MuSCs and progenitors that expressed the 386 myogenic transcription factor Pax7⁵³ and a cluster of myonuclei that expressed Acta1, Myh1, and 387 *Myh4*, genes critical for the contractile function of mature skeletal muscle cells⁵⁴ (**Supplementary**) 388 Figure 3C). We subsetted out these myogenic clusters and re-clustered and re-embedded the 389 390 cells, resulting in nine distinct sub-clusters for refined annotation (Figure 4A-B). We identified four progenitor populations that expressed Pax7, Myf5, Myod1, Myog, Mymk, and Mymx and 391 three myonuclei subtypes (IIx, IIb, IIx/IIb) that expressed Acta1, Ckm, and Tnnt3.54 We observed 392 393 two transcriptomically variant clusters, which expressed both myogenic markers and either

394 endothelial cell markers like Cd34, Cdh5, and Pecam1 or monocyte and macrophage markers 395 like Ccr2 and C1qa (Supplementary Figure 8). We suspected these clusters were dominated by 396 doublets. The first doublet sub-cluster contained cells that co-expressed Pax7 and Pecam1, suggesting that these were MuSCs/progenitors and endothelial cell doublets (Supplementary 397 398 Figure 8A). The second doublet sub-cluster contained cells that co-expressed Acta1 and C1ga, suggesting that these were myonuclei and monocyte/macrophage doublets (Supplementary 399 Figure 8B). We designated these sub-clusters as 'Doublets 1' and 'Doublets 2', respectively, and 400 401 excluded them from subsequent analyses involving the myogenic subset.

- The type IIx cluster expressed *Myh1*, the type IIb cluster expressed *Myh4*, and the type 402 IIx/IIb cluster expressed both Myh1 and Myh4 (Figure 4B, Supplementary Figure 9A-G).⁵⁵ A 403 previous study also identified a myonuclei cluster that expressed both Myh1 and Myh4, but this 404 405 studied concluded that this cluster represented cells with high metabolic activity, not cells that represent a transitional state between types IIx and IIb.¹⁸ We interpret that the type IIx/IIb cluster 406 407 identified here represents a transitional state between types IIx and IIb because 39% of the cells 408 in this cluster co-express *Myh1* and *Myh4* and because this cluster does not differentially express markers of high metabolic activity (Tnnc2, Tnni2, Mb, Cox6a2, Cox6c, Atp5e, Atp5g1) 409 (Supplementary Figure 9F-H).^{18,56,57} Additionally, this transitional fiber type is the most common 410 transitional fiber type in rat and mouse muscle fibers.^{58,59} Notably, the type IIx/IIb cluster had a 411 412 lower percentage of mitochondrial reads than the type IIx and type IIb clusters, indicating that 413 these cells were not clustering together due to being lower quality (Supplementary Figure 9I). 414 We did not identify a cluster of neuro-muscular junction or myotendinous junction cells due to a lack of Chrne or Col22a1 expression (Supplementary Figure 9H).^{18,29} 415
- We then re-embedded the myogenic subset using PHATE⁶⁰ and these embeddings were 416 used by Monocle3^{61–63} to organize the cells in pseudotime (**Figure 4B-C**). The pseudotime values 417 418 were grouped into 25 bins that contain approximately equal numbers of cells. As the cells progressed through pseudotime, the order in which myogenic markers were expressed followed 419 420 a typical trajectory of myogenesis. Early pseudotime bins had predominant expression of Pax7 421 and *Myf5*, but no strong expression of activation markers (Supplementary Figure 10A-F). Further in the pseudotime progression, cells still expressed Pax7 and Myf5, but they also 422 expressed cycling markers such as Cdk1/4. In later pseudotime bins, cells expressed Myod1, 423 424 *Myog, Mymx*, and *Mymk*, markers of committed and fusing progenitors. In the latest pseudotime 425 bins, cells expressed Acta1, Ckm, Myh1, and Myh4, markers of myogenic maturation.
- 426

427 **Pseudo-temporal analysis of myogenesis progression across mouse age and injury time.**

428 To directly compare myogenesis in regeneration responses, we assembled an annotated 429 "cartography" of myogenic progression arrayed across both day post-injury and myogenic pseudotime. We first examined the percent of cells that fell within each of the 25 initial pseudotime 430 431 bins by time-point and age, and then used expression frequency of myogenic marker genes to 432 inform myogenic cell-state annotations (Supplementary Figure 10A-H). Pseudotime bins 1-6 433 exhibited age-specific cell abundances, with bins 1-2 predominantly containing cells from young 434 mice, bin 3 from young and old mice, bin 4 contained cells from old mice, bin 5 from old and geriatric mice, and bin 6 from geriatric mice only. Bins 1-6 cells expressed Pax7 and Myf5, which 435 436 we annotated as MuSCs (with sub-stages 1-6 preserved). Bins 7-13 at 0 dpi expressed Pax7, 437 Myf5, and Myod1 and lowly expressed cycling markers Cdk1 and Cdk4, which we annotated as Non-cycling MPCs. Cells in bin 7 and dpi 1-3.5 and cells in bins 8-11 and dpi 1-7 expressed 438 439 Myod1 and cycling markers Cdk1 and Cdk4, which we annotated as Cycling MPCs. Cells in bin 12 at dpi 0-7 and cells in bin 13 at dpi 1-2 have diminishing expression of Myf5, Cdk1 and Cdk4, 440 441 and increasing expression of Myog and Mymk, which we annotated as Committing MPCs. Cells in pseudotime bin 13 and dpi 3.5-7 highly expressed Myog and Mymk and lowly expressed Cdk1 442 443 and Cdk4, which we annotated as Fusing Myocytes. Cells in pseudotime bins 14-25 and dpi 0-7 444 expressed Acta1, which we annotated as Myonuclei. These pseudotime-informed myogenic cell 445 stage aggregates (summarized in Supplementary Figure 10I) were used in subsequent 446 analyses.

To infer the cell-cycle phases, we first assigned each myogenic cell S-phase and G2M-447 phase scores using Seurat's standard Cell-Cycling Scoring method⁶⁴ (Figure 4D). We treated 448 these scores as polar coordinates, which were converted to cartesian coordinates and normalized 449 450 to be within a range from 0 to 1 ("normalized theta"; Figure 4E-G, Supplementary Figure 11A-451 B). We assessed all myogenic cells within this cell cycle progression from a normalized theta of 0 to 1, corresponding to the continuum of G1–S–G2M stages (Figure 4E, Supplementary Figure 452 453 **11A-B**). When considering all MuSCs/progenitors, the distribution of normalized theta values 454 increased from day 0 to day 3.5 and nearly returned to day 0 levels by day 7 in all age groups. 455 suggesting a return to quiescence as expected (Supplementary Figure 11E). We observed a shift to higher normalized theta values at 1 dpi in the geriatric samples compared to the young 456 457 and old myogenic cells, suggesting an age-skewed cell-cycle induction in early injury-response 458 that may represent a precocious activation phenotype. Differences by age group were minimal 459 after 3.5 dpi. When examining all myogenic cells by the 25 pseudotime bins, we observed a shift 460 in normalized theta values at bin 7 persisting through bin 13 (Supplementary Figure 11F).

461 Notably, pseudotime bins 7-13 also highly expressed the cycling markers *Cdk1* and *Cdk4*462 (Supplementary Figure 10G-H).

We then found that *Cdk1* and *Cdk4* are more highly expressed in cells predicted to be in S or G2M than in cells predicted to be in G1 (**Figure 4F-G**). Seurat's standard G1 cutoff is at a normalized theta value of 0.25. Based on the expression of cycling markers *Cdk1* and *Cdk4* and the distribution of cells across the normalized theta values, we extended the G1 cutoff to 0.375 for this analysis (**Figure 4F-G**, **Supplementary Figure 11C-D**). For simplicity, cells with a normalized theta below and above 0.375 were classified as "G1" and "Non-G1" (S/G2/M), respectively (**Supplementary Figure 11C-D**).

470 We then calculated the percent of cells within each myogenic cell stage and time-point by 471 age group. Within the MuSC 1-6 stages at 0-1 and 5-7 dpi, we observed high levels of Pax7 472 (Figure 4H). We also detected a high fraction of Non-G1 cells in MuSCs 1-6, especially at 1-3.5 473 dpi in the old and geriatric mice (Figure 4K). This suggested that more of the old and geriatric MuSCs were actively cycling post-injury compared to the young MuSCs. We compared the 3.5 474 475 dpi cells in the MuSC 1 and MuSC 2-6 stages by differential gene expression and found that the quiescence-associated genes *Cdkn1c* (encoding p57^{Kip2}) and *Socs3* were upregulated in MuSCs 476 477 1 and numerous translation-associated genes such as Rps29 were upregulated in MuSCs 2-6 478 (Figure 4L). These expression profiles suggest that MuSCs 1 cells are in a less activated state 479 MuSCs 2-6 cells.

480 We observed an inverse relationship between the average Myog expression and the fraction of Non-G1 cells in the Cycling MPCs, Committing MPCs, and Fusing Myocytes, as 481 482 expected for differentiating myogenic cells (Figure 4I,K). In all ages we detected the highest average expression of Myog in the Fusing Myocytes population (Figure 4I). We detected 483 484 Myonuclei in all ages and at every dpi, but there were fewer Myonuclei with lower average expression of Acta1 at dpi 1-3.5 in the geriatric mice compared to the young and old mice (Figure 485 **4J**). Together, these results present an integrated cellular cartography of myogenic trajectories 486 487 through regeneration, which exhibits age-associated cellular trajectories, particularly within the MuSC pool. 488

489

490 Scoring cell senescence across the myogenic cell cycle. To explore how cellular senescence 491 manifests within this organized cartography of myogenesis, we focused on the One-way FBR Sen 492 Score which performed well across ages (Figure 30). To identify cells with senescence-like 493 identities, we defined a threshold within the One-way FBR Sen Score based on its relationship 494 with *Cdkn2a* and *Cdkn1a* expression which exhibited correlation (Supplementary Figure 11G- H). We set a One-way FBR score threshold at 2412, where 50% of cells above this value coexpressed *Cdkn2a* and *Cdkn1a*, and classified cells above this threshold as 'Sen Score high' and
senescence-like (Figure 5A). We further observed through ROC analysis that the One-way FBR
Sen Score could accurately identify double-positive *Cdkn2a* and *Cdkn1a* cells from both the G1
and Non-G1 fractions of MuSCs/progenitors (Figure 5B).

We aimed to quantify the prevalence of cellular senescence within the cartography of 500 501 myogenesis by age using both double-positive expression status and Sen Score, reasoning that 502 the scores might capture a more expansive set of senescence-like cells. We observed a correspondence between the fraction of cells that co-express Cdkn2a and Cdkn1a and the 503 504 fraction of cells that have a high Sen Score in most ages, cell stages, and timepoints (Figure 5C-D). Focusing on 3.5 dpi, we found a significantly higher fraction of Cdkn2a+ and Cdkn1a+ cells in 505 both the old and geriatric MuSCs 1 compared to young MuSCs 1 (Student's t-tests, p-values = 506 0.02* and 0.003*, respectively; Figure 5E). We did not observe age-specific differences in the 507 508 fraction of Cdkn2a+ and Cdkn1a+ in MuSCs 2-6 (Figure 5F). We found a significantly higher 509 fraction of Cdkn2a+ and Cdkn1a+ in both old and geriatric MPCs (from both Cycling and Committing stages) compared to young MPCs (Student's t-tests, p-values = 0.04* and 0.02*, 510 511 respectively; Figure 5G). Likewise, we observed a similar pattern in the fraction of One-way FBR 512 Sen Score high cells, with significantly higher frequencies in the old compared to young MuSCs 513 1 (Student's t-test, p-value = 0.002*; Figure 5H). We did not observe age-specific differences in 514 the fraction of Sen Score high MuSCs 2-6 or MPCs (Figure 5I-J). Together, these observations point to a transitory senescent-like cell population that is abundant at the self-renewing MuSC 1 515 516 stage across all ages, but increases in older mice, potentially underlying a stalled stem-cell self-517 renewal in mouse muscle aging.

518 **DISCUSSION**

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520 We utilized the profiling depth and complexity of scRNA-seg and associated computational analyses to generate a comprehensive compendium of 273,923 single-cell transcriptomes from 521 522 regenerating tibialis anterior muscles throughout mouse lifespan. To date, our dataset is the most 523 comprehensive portrait of muscle repair at the single-cell level, as it includes three ages (young, 524 old, and geriatric), six time points (days 0, 1, 2, 3.5, 5, and 7), and includes 29 different cell type clusters (Figure 1, Supplementary Figures 1 and 3). Additionally, compared to previous scRNA-525 seq and snRNA-seq skeletal muscle studies, we have identified more specific endothelial, FAPs, 526 and immune cell sub-types.^{11,18-30} 527

The immune, stromal, and myogenic cells found in skeletal muscle contribute to muscle 528 529 maintenance and regeneration by regulating MuSC guiescence, proliferation, and differentiation.¹ It has been shown that an imbalance in immune cell populations during injury response can 530 disrupt proper muscle repair.^{1,2} To investigate this we compared the change in cell type 531 532 abundances over our regeneration time course between young, old, and geriatric muscles. As expected, Neutrophils are one of the first immune cell types to peak in abundance 533 (Supplementary Figure 5L).⁴ We also observe monocyte and macrophage populations that 534 535 express pro-inflammatory markers like Ccr2 and patrolling markers like Ctsa responding soon 536 after injury (days 1-2) when we expect the muscle environment to be enriched with pro-537 inflammatory cytokines (Figure 2A,E).^{1,4} Monocytes and macrophages that express pro-538 inflammatory markers clear cellular debris and promote myogenic cell proliferation.^{1,5} There should be a shift to monocytes and macrophages that express anti-inflammatory marker C1ga at 539 4-7 dpi (Figure 2B-C, Supplementary Figure 3A).⁴ We do broadly observe a shift from 540 541 monocytes and macrophages that express pro-inflammatory markers to anti-inflammatory 542 markers, but there are significant differences by age (Figure 2A-E). This difference in monocyte 543 and macrophage dynamics could explain the age-related decline in muscle repair because if macrophages do not clear cellular debris or promote myogenic cell proliferation and 544 differentiation, the muscle remains inflamed and there are repeated cycles of necrosis and 545 regeneration.⁵ The damaged myofibers are then replaced with adipose tissue, fibrotic tissue, or 546 bone, instead of new myofibers.⁵ 547

In addition to age-specific differences in the dynamics of the monocyte and macrophage populations, we observe age specific differences in the T cell dynamics (**Figure 2L-O**, **Supplementary Figure 5T**). It has previously been shown that Treg cells, marked by *Cd4* and *Foxp3*, accumulate in injured muscle and to peak in abundance at day 4.⁴ We detected *Foxp3* expression in a few T cells, specifically in the T cell (Cycling) and T cell (Non-Cycling) populations which both highly express *Cd3e* (**Supplementary Figure 3A**). Although we cannot confidently identify any of our three T cell populations as Tregs, we do observe a peak in T cell abundances at days 5 and 7 (age-specific). There is miscoordination of T cell response which in turn could impact the ability of aged muscle to repair itself.

One factor that has been shown to contribute to the reduced functionality of MuSCs in 557 aged tissues is the establishment of senescent MuSCs.^{2,13} Prior studies have used the cell cycle 558 proteins p16, p21, p53, and Rb to differentiate between dividing and non-diving cells, but the non-559 diving cells can include senescent cells and quiescent cells.¹⁵ SA- β -gal is also commonly used to 560 identify senescent cells, but it is also detected in guiescent cells and in stressed cells.^{15,65} Because 561 562 these markers are not unique to senescent cells and because senescent cells are heterogeneous, 563 it has been challenging to identify biomarkers that can accurately and consistently identify senescent cells across species, tissues, and conditions.¹⁶ Indeed, recent large consortia have 564 been established to develop new tools to detect and bioinformatically identify senescent cells with 565 robustness and precision throughout mammalian tissues and lifespans.⁶⁶ Given the role that 566 cellular senescence plays in limiting cell contributions in aged tissues, we tested a series of tools 567 568 to bioinformatically identify senescence in these single-cell data and found a transfer-learning 569 based scoring approach accurately classified senescent-like myogenic cells across ages and cell 570 cycling states. The approach described here to quantitatively assess various senescence scoring 571 approaches and reference gene lists in discriminating senescent or senescent-like cells (Figures 572 **3** and **5**) may provide a template for future studies using single-cell data. Notably, here we 573 concluded that a skeletal muscle FBR gene list more accurately and robustly discriminated 574 senescent-like Cdkn2a+ and Cdkn1a+ MuSC/progenitors in these muscle regeneration datasets 575 than did a variety of experimental and curated gene lists, including the recently described SenMavo list.⁴⁷ In particular, at day 3.5 post-injury, we observed a significantly higher fraction of 576 Cdkn2a+ and Cdkn1a+ cells in the aged and geriatric MuSCs associated with a self-renewing cell 577 stage (MuSC stage 1; Figure 5E,G). Likewise, we observed a similar pattern in the fraction of 578 One-way FBR Sen Score high cells, with significantly higher frequencies in the old compared to 579 young MuSCs 1 (Figure 5H). These observations point to a transitory senescence-like cell 580 population that is abundant at the self-renewing MuSC stage across all ages, but increases in 581 582 older mice, potentially underlying a stalled stem-cell self-renewal in mouse muscle aging.

583 METHODS

584

585 Mouse muscle injury and single-cell isolation. Muscle injury was induced in young (4-7 months-old [mo]), old (20 mo), and geriatric (26 mo) C57BL/6J mice (Jackson Laboratory # 586 587 000664; NIA Aged Rodent Colonies) by injecting both tibialis anterior (TA) muscles with 10 µl of notexin (10 µg/ml; Latoxan, France). The mice were sacrificed, and TA muscles were collected at 588 0, 1, 2, 3.5, 5, and 7 days post-injury (dpi). Each TA was processed independently to generate 589 single cell suspensions. At each time point, the young and old replicates are biological replicates, 590 and the geriatric replicates are two pairs of technical replicates (n = 3-4). Muscles were digested 591 592 with 8 mg/ml Collagenase D (Roche, Basel, Switzerland) and 10 U/ml Dispase II (Roche, Basel, 593 Switzerland) and then manually dissociated to generate cell suspensions. Myofiber debris was 594 removed by filtering the cell suspensions through a 100 µm and then a 40 µm filter (Corning Cellgro # 431752 and # 431750). After filtration, erythrocytes were removed by incubating the cell 595 596 suspension in erythrocyte lysis buffer (IBI Scientific # 89135-030).

597

Single-cell RNA-sequencing library preparation. After digestion, the single-cell suspensions 598 were washed and resuspended in 0.04% BSA in PBS at a concentration of 10⁶ cells/ml. A 599 600 hemocytometer was used to manually count the cells to determine the concentration of the 601 suspension. Single-cell RNA-sequencing libraries were prepared using the Chromium Single Cell 602 3' reagent kit v3 (10x Genomics, Pleasanton, CA) following the manufacturer's protocol.⁶⁷ Cells 603 were diluted into the Chromium Single Cell A Chip to yield a recovery of 6,000 single-cell transcriptomes with <5% doublet rate. Libraries were sequenced on the NextSeg 500 (Illumina, 604 San Diego, CA).⁶⁸ The sequencing data was aligned to the mouse reference genome (mm10) 605 using CellRanger v5.0.0 (10x Genomics).⁶⁷ 606

607

608 Preprocessing and batch correction of single-cell RNA sequencing data. From the gene expression matrix, the downstream analysis was carried out in R (v3.6.1). First, ambient RNA 609 signal was removed using the default SoupX (v1.4.5) workflow (autoEstCounts and adjustCounts; 610 github.com/constantAmateur/SoupX).³⁶ Samples were then preprocessed using the standard 611 Seurat (v3.2.3) workflow (NormalizeData, ScaleData, FindVariableFeatures, RunPCA, 612 FindNeighbors, FindClusters, and RunUMAP; github.com/satijalab/seurat).⁶⁴ Cells with fewer 613 than 200 genes, with fewer than 750 UMIs, and more than 25% of unique transcripts derived from 614 mitochondrial genes were removed. After preprocessing, DoubletFinder (v2.0.3) was used to 615 identify putative doublets in each dataset.³⁷ The estimate doublet rate was 5% according to the 616

617 10x Chromium handbook. The putative doublets were removed from each dataset. Next, the 618 datasets were merged and then batch-corrected with Harmony (github.com/immunogenomics/harmony) (v1.0).³⁸ Seurat was then used to process the integrated 619 data. Dimensions accounting for 95% of the total variance were used to generate SNN graphs 620 621 (FindNeighbors) and SNN clustering was performed (FindClusters). A clustering resolution of 0.8 622 was used resulting in 24 initial clusters.

623

624 **Cell type annotation in single-cell RNA sequencing data.** Cell types were determined by expression of canonical genes. Each of the 24 initial clusters received a unique cell type 625 626 annotation. The nine myeloid clusters were challenging to differentiate between, so these clusters 627 were subset out (Subset) and re-clustered using a resolution of 0.5 (FindNeighbors, FindClusters) 628 resulting in 15 initial clusters. More specific myeloid cell type annotations were assigned based on expression of canonical myeloid genes. This did not help to clarify the monocyte and 629 macrophage annotations, but it did help to identify more specific dendritic cell and T cell subtypes. 630 631 These more specific annotations were transferred from the myeloid subset back to the complete 632 integrated object based on the cell barcode.

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634 Analysis of cell type dynamics. We generated a table with the number of cells from each sample 635 (n = 65) in each cell type annotation (n = 29). We removed the erythrocytes from this analysis 636 because they are not a native cell type in skeletal muscle. Next, for each sample, we calculated the percent of cells in each cell type annotation. The mean and standard deviation were calculated 637 638 from each age and time point for every cell type. The solid line is the mean percentage of the 639 given cell type, the ribbon is the standard deviation around the mean, and the points are the 640 values from individual replicates. We evaluated whether there was a significant difference in the 641 cell type dynamics over all six time points using non-linear modeling. The dynamics for each cell type were fit to some non-linear equation (e.g., quadratic, cubic, quartic) independent and 642 643 dependent on age. The type of equation used for each cell type was selected based on the confidence interval and significance (p < 0.05) for the leading coefficient. If the leading coefficient 644 645 was significantly different from zero, it was concluded that the leading coefficient was needed. If the leading coefficient was not significantly different than zero, it was concluded that the leading 646 647 coefficient was not needed, and the degree of the equation went down one. No modeling equation 648 went below the second degree. The null hypothesis predicted that the coefficients of the nonlinear equation were the same across the age groups while the alternative hypothesis predicted 649 650 that the coefficients of the non-linear equation were different across the age groups. We

651 conducted a likelihood ratio test to see if the alternative hypothesis fits the data significantly better652 than the null hypothesis and we used FDR as the multiple comparison test correction.

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Muscle immunohistochemical analysis. Muscle injury was induced in young, old, and geriatric 654 655 C57BL/6J mice by injecting both TA muscles with 10 µl of notexin (10 µg/ml; Latoxan, France). The mice were sacrificed, and TA muscles were collected at 0 and 5 dpi. The TA muscles were 656 657 coated in Tissue-Tek O.C.T. Compound (Sakura Finetek # 4583), snap-frozen in liquid nitrogen cooled isopentane (Thermo Scientific Chemicals # AA19387AP), and then stored at -80C. Frozen 658 659 TA muscles were sectioned with a cryostat transversely at 5 µm thickness and section slides were stored at -20C until stained. Sections were fixed with 4% PFA (Electron Microscopy Sciences # 660 15710) for 10 minutes, washed with 1X PBS, and blocked with 3% BSA (Rockland 661 662 Immunochemicals # RLBSA50) at room temperature for 1 hour. Sections were washed with 1X 663 PBS and then stained with rat anti-mouse CD3 (eBiosciences # 14-0032-82) at 1:100 dilution in blocking buffer overnight at 4C. Sections were then washed and stained with Alexa Fluor Plus 664 665 750 Phalloidin (Life Technologies # A30105) at 1:500 dilution and goat anti-rat 488 (Invitrogen # A-11006) at 1:250 dilution in blocking buffer for 1 hour at room temperature protected from light. 666 667 Sections were then washed with 1X PBS and stained with 5 mg/mL DAPI (Life Technologies # 668 D3571) at 1:1000 dilution. Slides were mounted with Glycergel mounting medium (Agilent # 669 C056330-2) and stored at 4C before imaging. Images were acquired using a Nikon Eclipse Ti-E 670 microscope (Micro-Video Instruments, Inc.), and were analyzed using NIS Elements 5.11.03 671 software and ImageJ 2.1.0.

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673 **Immune cell flow cytometric analysis.** Single cell suspensions of uninjured day 0 and injured 674 day 5 TAs and gastrocnemius muscles were collected in the same way as the single cell 675 suspensions for scRNA-seq library preparation. However, the single cells were suspended in 90% FBS and 10% DMSO and frozen at -80C. When ready to use, the single cell suspensions were 676 677 thawed in a 37C water bath and then transferred to 15 mL conical tubes. The cells were washed with staining buffer (1X PBS + 0.5% BSA + 2 mM EDTA) before being spun at 500g for three 678 679 minutes and transferred to a 96 well round bottom plate. Cells were incubated with FC block (TruStain FcX PLUS (anti-mouse CD16/32), Biolegend # 156604) at 4C for five minutes. Cells 680 681 were then washed with staining buffer, spun at 500g for three minutes, and incubated with viability 682 dye (Fixable viability dye APCe780, eBiosciences # 65-0865-14) and surface antibody (see 683 antibody table) in BSB (Brilliant Stain Buffer Plus, BD Biosciences # 566385) and staining buffer 684 for 30 minutes at 4C in the dark. Aliguots of cell samples were counted on a MoxiZ Mini Automated

685 Cell Counter. After incubating we followed the manufacturer's protocol (FOXP3 Transcription 686 factor fixation/permeabilization kit, eBioscience # 00-5521-00) and cells were washed with 687 staining buffer, spun, and resuspended in FoxP3 1x perm solution (10x Permeabilization buffer, Invitrogen # 00-8333-56) and incubated for 30 minutes at 4C in the dark. Cells were washed with 688 689 1x perm solution, spun twice, and resuspended in an intracellular antibody stain. Cells were incubated in intracellular antibody stain for 30 minutes at 4C in the dark. Cells were washed with 690 1x perm and spun twice before being resuspended in staining buffer and transferred to 40 µM 691 692 blue capped flow tubes. FMO controls were prepared using a mixture of young, old, and geriatric uninjured and injured TA and gastrocnemius muscles. Flow cytometry was performed using a 693 694 FACSymphony A3 (BD) and data was analyzed in FlowJo 10.5.3. Gates were determined using 695 FMO controls.

696

697 Flow cytometry antibodies

Antibody	Clone	Fluorophore	Manufacturer catalog
CD45	30-F11	PECy7	Invitrogen # 25-0451-82
CD11b	M1/70	BUV395	BD Biosciences # 563553
CD11c	N418	PerCPCy5.5	Invitrogen # 45-0114-82
τςrβ	H57-597	APC	eBiosciences # 17-5961-82
CD19	1D3	BV650	BD Biosciences # 563235

698

699 Senescence scoring. We tested two senescence scoring methods along with ten senescence 700 gene lists (Extended Data File 2) to identify senescent-like cells within the scRNA-seq dataset. 701 The Two-way senescence score was calculated using a transfer-learning method developed by Cherry et al 2023.⁴⁴ For this score, all genes in a cell type cluster (Figure 1F) were z-scored. The 702 703 provided senescence gene list was split into genes that are up- and down-regulated in p16+ cells. 704 The scale.data slot, which contains the z-scored counts, was extracted from the full dataset. The 705 genes that were in the up- and down-regulated gene lists were identified and subset out of the 706 extracted scale.data matrix. Two scores were calculated, one being the sum of the z-scored 707 counts of the down-regulated genes multiplied by negative one and the other score being the sum 708 of the z-scored counts of the up-regulated genes. The overall score is the sum of the down-709 regulated gene score and the up-regulated gene score scaled by the length of the gene set. With 710 this method we tested six gene lists: Stimulation Independent, Replicative, Oncogene, Ion-

Radiation Induced, Aged-Chondrocyte, and Two-way foreign body response (FBR). The gene
lists were the result of differential expression analysis of bulk RNA-seq experiments comparing
p16+ to p16– cultured fibroblasts (Stimulation Independent, Replicative, Oncogene, and IonRadiation Induced)⁴⁶, uninjured aged chondrocytes (Aged-Chondrocytes) (B.O. Diekman,
personal communication).^{50–52}, and CD29+ cells from a FBR model (Two-way FBR)⁴⁴.

716 The One-way Senescence Score was calculated using Single-Sample GSEA as per Saul et al., 2022.⁴⁷ This method uses the raw counts of genes that are upregulated in p16+ cells. With 717 this method we tested four gene lists: One-way FBR, SenMayo, GO: Senescence, and GO: 718 SASP. The One-way FBR gene list contains only the upregulated genes found in the Two-way 719 FBR gene list.⁴⁴ The SenMayo gene list is a literature-curated list of genes commonly used to 720 cells.47 721 identify senescent The GO: Senescence gene list is the GO: FRIDMAN SENESCENCE UP⁴⁸ gene list and the GO: SASP gene list is the GO: 722 REACTOME SENESCENCE ASSOCIATED SECRETORY PHENOTYPE SASP⁴⁹ gene list. 723

724 We evaluated the ability of the two methods and the ten gene lists to accurately identify 725 senescent-like MuSCs and progenitors by calculating a receiver operator characteristic (ROC) curve. For each MuSCs and progenitor cell, we evaluated whether it expressed both Cdkn2a and 726 727 Cdkn1a. For each method and gene list, the scores were ranked from highest to lowest and then 728 grouped into 100 bins with approximately the same number of MuSCs and progenitors. We 729 evaluated the specificity and the sensitivity in each bin where a true positive expresses both 730 Cdkn2a and Cdkn1a and has a high senescent score. This analysis was done for all MuSCs and 731 progenitors (Figure 3M-N), MuSCs and progenitors split by age (Figure 3O, Supplementary 732 Figure 7A-F), and MuSCs and progenitors split by G1-Status (Figure 5B, Supplementary 733 Figure 7G-J). The area under the curve (AUC) was calculated for each ROC curve (Figures 3M-734 O and 5B, Supplementary Figure 7K).

735 Given that the One-way Senescence Score with the FBR gene list performed the best (AUC = 0.86), we focused on that for further analyses. We next set a threshold of senescence 736 737 based on the One-way FBR. We ranked the MuSCs and progenitors from highest to lowest Oneway FBR Sen Score and then grouped the cells into 100 bins with approximately the same number 738 739 of MuSCs and progenitors. Within each bin we calculated the fraction of MuSCs and progenitors 740 that co-express Cdkn2a and Cdkn1a. The One-way FBR Sen Score where 50% of the MuSCs 741 and progenitors with at least that score co-express Cdkn2a and Cdkn1a was set as the senescence threshold. For the One-way FBR Sen Score, MuSCs and progenitors with a score 742 743 >= 2412.562 were called "senescent-like" while all other cells were called "not senescent-like" 744 (Figure 5A. Supplementary Figure 11G-H).

745

746 **Cell cycle scoring.** To each cell in the final dataset, we assigned an S phase score, a G2M phase 747 score, and a discrete phase classification (G1/S/G2M) using Seurat's standard Cell-Cycling Scoring method.⁶⁴ We have treated the S phase and G2M phase score as polar coordinates to 748 749 help us visualize how cells are progressing through the cell cycle (Figure 4D). We have converted 750 the polar coordinates to cartesian coordinates and normalized the theta values so that they range 751 from 0 to 1 so that cells in G1 have the lowest theta values followed by cells in S and G2M (Figure **4E**, **Supplementary Figure 11A-B**). This enables us to see how cells are progressing linearly 752 through the cell cycle. Seurat's standard cutoff between cells classified as G1 versus cells 753 754 classified as S is at the normalized theta value of 0.25. Looking at the distribution of cells across 755 the normalized theta values as well as the expression of cell cycle markers Cdk1 and Cdk4, we 756 decided to extend the G1 to S cutoff to 0.375 (Figure 4E-G, Supplementary Figure 11C-D). Cells with a normalized theta value ≥ 0.375 are considered Non-G1 (S/G2/M). 757

758

759 Myogenic cell subsets. From the final dataset, the cells with the cell type IDs 'MuSCs and progenitors' and 'Myonuclei' were subset out and the Seurat workflow was partially re-run 760 761 (ScaleData, FindVariableFeatures, RunPCA, FindNeighbors, FindClusters, and RunUMAP). 762 Dimensions accounting for 95% of the total variance were used to generate SNN graphs (FindNeighbors) and SNN clustering was performed (FindClusters).⁶⁴ A clustering resolution of 763 764 0.7 was used resulting in 9 clusters. These 9 clusters were assigned general cell type IDs based 765 on canonical myogenic markers. Of the 9 clusters, 4 were progenitor subtypes, 3 were myonuclei 766 subtypes, and 2 were doublets (Figure 4A).

To more specifically ID the doublet clusters we looked at the co-expression of myogenic and non-myogenic markers (**Supplementary Figure 8**). Using GetAssayData, we extracted the log-normalized expression values of *Pax7*, *Pecam1*, *Acta1*, and *C1qa* in each cell in the 9 myogenic clusters. For each of the 9 clusters, we plotted cells by their expression values of *Pax7* and *Pecam1* and by their expression values of *Acta1* and *C1qa*. A density plot was plotted along the x- and y-axes using ggmarginal(type = "density") (**Supplementary Figure 8**). The two clusters identified as doublets were excluded from the remaining myogenic subset analyses.

To identify the myonuclei clusters more specifically, we looked at the expression of myonuclei markers, markers of high metabolic activity, and the percent of unique transcripts derived from mitochondrial genes (**Supplementary Figure 9**). Using GetAssayData, we extracted the log-normalized expression values of *Myh1* and *Myh4* in each cell in the three myonuclei clusters. For every cell, as defined by the cell barcode, we determined whether the expression

value equaled zero (no expression) or exceeded zero (expression) for both *Myh1* and *Myh4*independently. For each of the three myonuclei clusters, the fraction of cells that expressed *Myh1*and *Myh4*, only *Myh1*, only *Myh4*, and neither *Myh1* nor *Myh4* were calculate by dividing the
number of cells that expressed *Myh1* and *Myh4*, only *Myh1*, only *Myh4*, and neither *Myh1* nor *Myh4* by the total number of cells within each myonuclei cluster (Supplementary Figure 9D-G).

Harmony embedding values from the dimensions accounting for 95% of the total variance 784 were used for further dimensional reduction with PHATE, using phateR (v1.0.7) (Figure 4B-C).⁶⁰ 785 The PHATE embedding values were used by monocle3 (v1.0.0).^{61–63} The normal monocle3 786 workflow was used (cluster cells, estimate size factors, learngraph, order cells) where 787 788 L1.sigma = 0.4 and the root cell was in the Progenitor 1 cluster. The pseudotime values for each 789 cell as defined by monocle3 were transferred from the monocle3 CDS object to the myogenic 790 cells only Seurat object by cell barcode. The pseudotime values were divided into 25 bins with 791 approximately equal numbers of cells (1089-1090 cells per bin) (Figure 4C).

792 We assigned myogenic cell type IDs based on known myogenic marker expression in 793 each pseudotime bin and dpi. We visualized this with dot plots where the size of the dot corresponds to the percent of cells in each pseudotime bin and dpi normalized by the dpi. The 794 795 color of the dots corresponds to the average log-normalized expression of a select myogenic 796 marker in each pseudotime bin and dpi (Supplementary Figure 10A-H). Cells in pseudotime bin 797 1 and dpi 0, 1, 2, 3.5, 5, and 7 were classified as 'MuSCs 1', cells in pseudotime bin 2 and dpi 0, 798 1, 2, 3.5, 5, and 7 were classified as 'MuSCs 2', cells in pseudotime bin 3 and dpi 0, 1, 2, 3.5, 5, 799 and 7 were classified as 'MuSCs 3', cells in pseudotime bin 4 and dpi 0, 1, 2, 3.5, 5, and 7 were 800 classified as 'MuSCs 4', cells in pseudotime bin 5 and dpi 0, 1, 2, 3.5, 5, and 7 were classified as 801 'MuSCs 5', and cells in pseudotime bin 6 and dpi 0, 1, 2, 3.5, 5, and 7 and cells in pseudotime bin 802 7 and dpi 5 and 7 were classified as 'MuSCs 6' based on expression of Pax7 and Myf5 803 (Supplementary Figure 10A-B,I). Cells in pseudotime bins 7-13 and dpi 0 were classified as 804 'Non-Cycling MPCs' based on the expression of Pax7, Myf5, and Myod1 and the lack of 805 expression of cycling markers Cdk1 and Cdk4 (Supplementary Figure 10A-C,G-I). Cells in pseudotime bin 7 and dpi 1, 2, and 3.5 and cells in pseudotime bins 8-11 and dpi 1, 2, 3.5, 5, and 806 7 were classified as 'Cycling MPCs' based on the expression of Myod1 and cycling markers Cdk1 807 808 and Cdk4 (Supplementary Figure 10C,G-I). Cells in pseudotime bin 12 and dpi 0, 1, 2, 3.5, 5, and 7 and cells in pseudotime bin 13 and dpi 1 and 2 were classified as 'Committing MPCs' based 809 810 on the low expression of *Myod1*, *Myoq*, *Mymk* and the still high expression of cycling markers 811 Cdk1 and Cdk4 (Supplementary Figure 10C-E,G-I). Cells in pseudotime bin 13 and dpi 3.5, 5, 812 and 7 were classified as 'Fusing Myocytes' based on the high expression of Myog and Mymk and

low expression of cycling markers *Cdk1* and *Cdk4* (Supplementary Figure 10D-E,G-I). Cells in
pseudotime bins 14-25 and dpi 0, 1, 2, 3.5, 5, and 7 were classified as 'Myonuclei' based on the
expression of *Acta1* (Supplementary Figure 10F,I).

We focused on dpi 3.5 and compared the cells in MuSCs 1, MuSCs 2-6, and all MPCs (this includes cells classified as Cycling MPCs and cells classified as Committing MPCs). For each sample, we calculated the fraction of cells that had log-normalized *Cdkn2a* and *Cdkn1a* counts greater than 0 (**Figure 5E-G**). Within these same groupings we also calculated the fraction of cells that had a One-Way FBR score greater than 2412.562 (**Figure 6H-J**). We conducted unpaired, two-sided Student's t-tests to evaluate whether there was a significant difference between ages.

823

824 Differential expression analysis and pre-ranked Gene Set Enrichment Analysis. For select 825 comparisons we used Seurat's FindAllMarkers() function to identify genes that were differentially expressed between groups. In the myogenic subset with all ages at day 3.5, we did this analysis 826 827 between the cells in 'MuSCs 1' and the cells in 'MuSCs 2-6' (Figure 4L). In the MuSCs and progenitors with all ages at day 3.5, we did this analysis between cells that co-expressed Cdkn2a 828 829 and Cdkn1a (we refer to these cells as 'Double positive') and all other cells (we refer to these 830 cells as 'other'). Genes that had an FDR-corrected p-value <=0.05 were ranked by average log2 831 fold change and used in a Gene Set Enrichment Analysis (GSEA, v4.1.0). The gene set databases 832 used included h.all.v2023.1.Hs.symbols.gmt, c2.all.v2023.1.Hs.symbols.gmt, 5.all.v2023.1.Hs.symbols.gmt, and c8.all.v2023.1.Hs.symbols.gmt. Significant GO Terms (FDR 833 834 q-value <= 0.25) were ranked by the normalized enrichment score (enrichment scores normalized 835 by the size of the gene set) (Figure 3H).

836

837 Key resource availability. A complete list of metadata and GEO accessions for the scRNA-seq data can be found in **Extended Data File 1**. Previously published scRNA-seq data are deposited 838 in GEO under accessions GSE143437, GSE159500, and GSE162172. Newly collected scRNA-839 seg data from young (4.7 mo; days 1 and 3.5) and geriatric (26 mo) mice are deposited in GEO 840 under accession GSE232106. Fully processed Seurat objects for the final dataset (Figure 1) and 841 the myogenic subset (Figures 4 and 5) will be available for download on Dryad upon publication. 842 843 Gene lists used in the Senescence Scoring analysis are compiled in the Extended Data File 2. 844 All newly developed code (Senescence Scoring, Cell Cycle Scoring, Pseudotime Binning) will be 845 available on Github upon publication.

846 **AUTHOR CONTRIBUTIONS**

847 L.D.W., V.I.M., B.D.R., J.H.E., and B.D.C. designed the study. L.D.W., J.L.O., E.H.H.F., and V.I.M. carried out the experiments. L.D.W. performed computational analyses. L.D.W. and J.L.O. 848 analyzed experimental data and prepared figures. B.D.R., J.H.E., and B.D.C. supervised the data 849 850 analyses. L.D.W. and B.D.C. wrote the manuscript. All authors provided feedback and comments. 851

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870

871 **COMPETING INTERESTS**

872 J.H.E. was previously a consultant and holds equity in Unity Biotechnology, Aegeria Soft Tissue and is an advisor for Tessera Therapeutics, HapInScience, Regenity, and Font Bio. All other 873 874 authors declare no competing interests.

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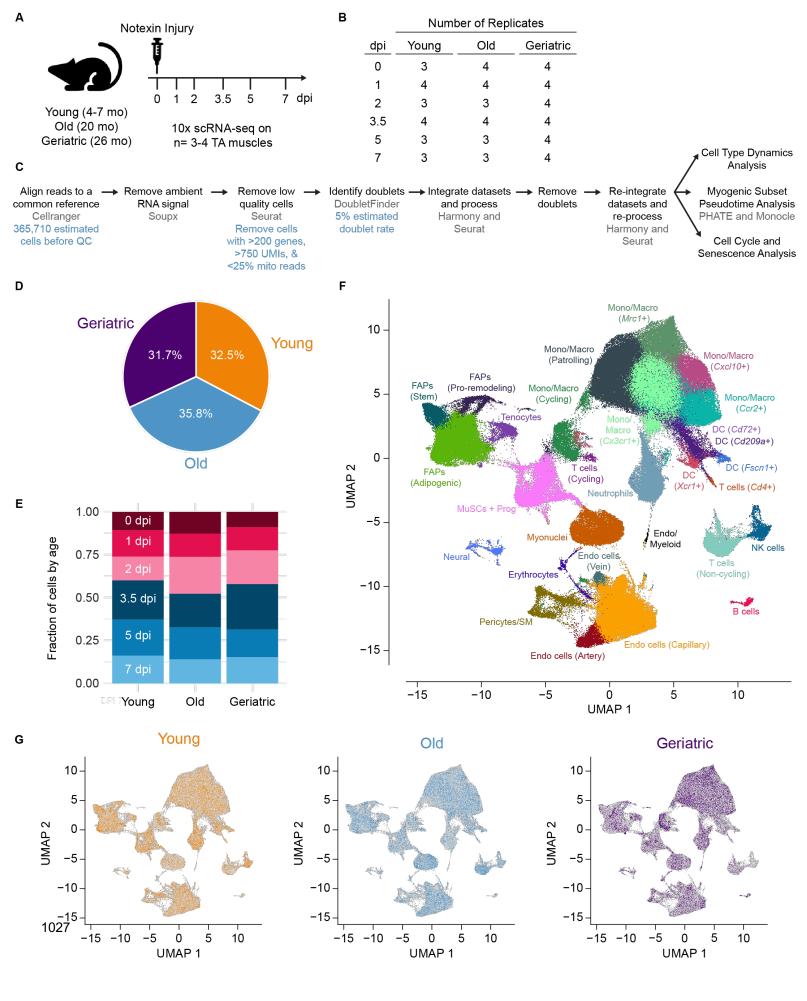
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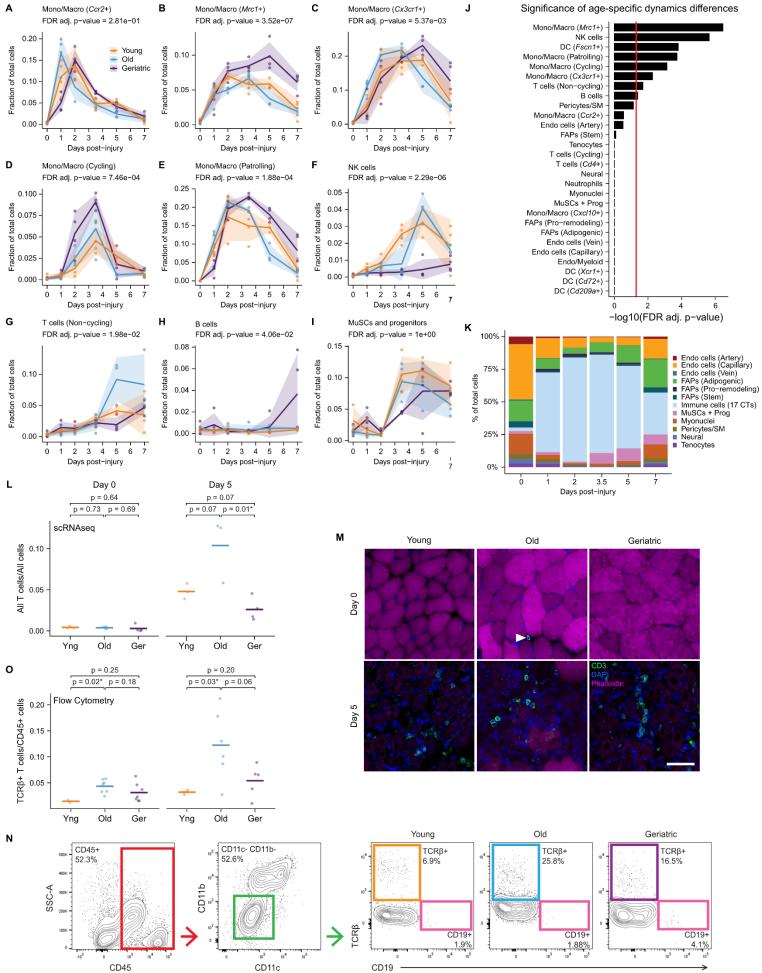
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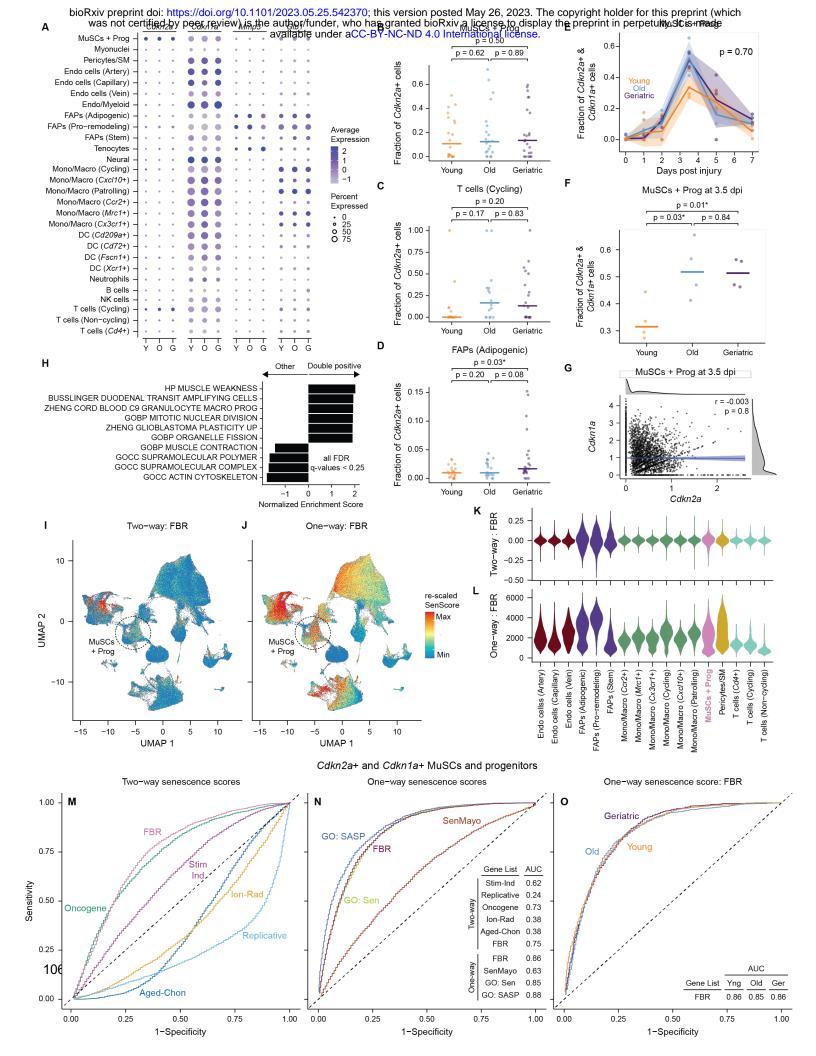


1028 Figure 1: Assembly of scRNA-seq atlas of skeletal muscle regeneration across mouse

1029 aging. (A-B) Overview of experimental design. 3' scRNA-seg (10X Chromium v2 and v3) was 1030 performed on dissociated tibialis anterior (TA) muscles from young (4-7 mo), old (20 mo), and geriatric (26 mo) mice (both sexes) 0-7 days post-notexin injury (dpi) with n = 3-4 replicates per 1031 1032 age and dpi (B). (C) Processing workflow. Each scRNA-seg sample was aligned to the mm10 mouse reference genome, ambient RNA was removed by SoupX, low quality cells were identified 1033 1034 and removed, and doublets were identified and removed. All samples were then integrated with Harmony, resulting in a final dataset containing 273,923 cells from 65 samples. See 1035 Supplementary Figure 1 and Extended Data File 1 for additional detail. (D) Fraction of cells 1036 1037 from each age group. (E) Fraction of cells from each dpi within each age group. (F-G) UMAP representations of the final dataset. Cells colored by manually assigned cell type IDs based on 1038 1039 the expression of hallmark skeletal muscle genes (see Supplementary Figures 2 and 3) (F). Cells are colored by age group, with all other cells in gray (G). 1040



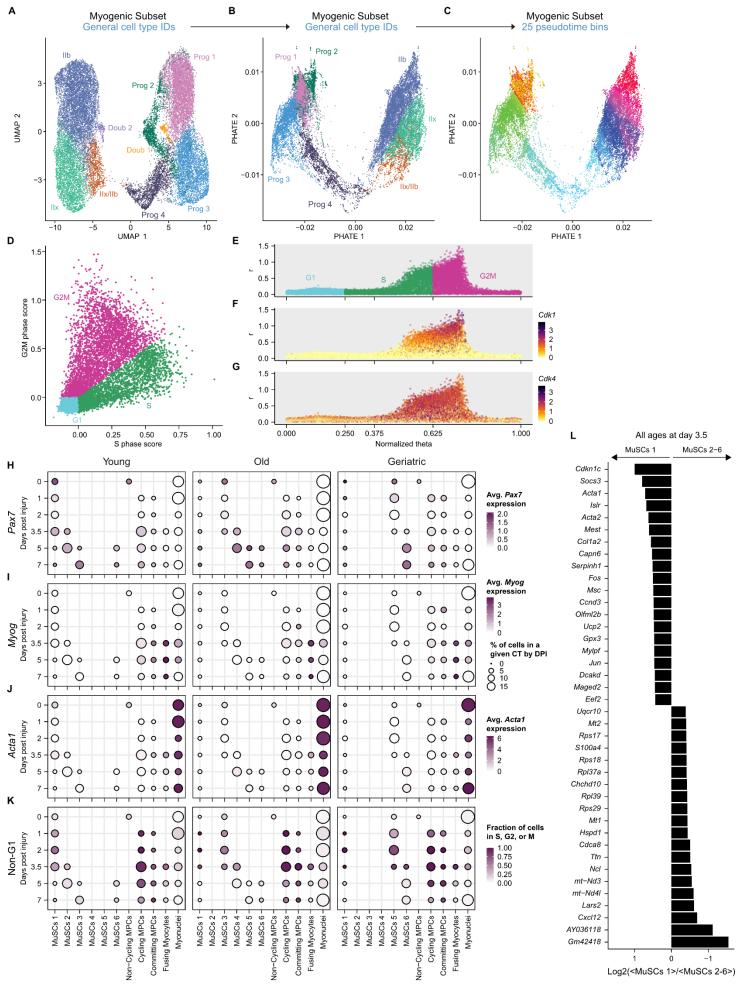
1042 Figure 2: Age-related changes to cell dynamics during skeletal muscle regeneration. (A-I) 1043 Line plots showing cell type relative abundance as a fraction of total cells from 0-7 days post injury 1044 (dpi). For each sample, the number of cells of the reported type was divided by the total number of cells (excluding erythrocytes). Points are each sample (n = 3-4). Ribbon is the standard 1045 1046 deviation. Statistical significance of age-specific cell type dynamics was evaluated using non-1047 linear modeling and FDR-corrected p-values are reported (see Supplementary Figure 6). (J) Statistical significance of age-specific cell type dynamics differences as reported by FDR-1048 1049 corrected p-values from non-linear modeling (see **Supplementary Figure 6**). Red line denotes the FDR-adjusted p = 0.05 threshold. (K) Stacked bar plot of the fraction of cell types across all 1050 1051 dpis. All 17 immune cell clusters were grouped into a unified "Immune cells (17 CTs)" cluster, which is separated out in **Supplementary Figure 4**. (L) Scatter plots of the fraction of all T cells 1052 1053 (3 CTs) at 0 and 5 dpi from the scRNA-seg data. For each sample, the number of all T cells (3 CTs) was divided by the total number of cells (excluding erythrocytes). Points are each sample 1054 1055 (n = 3-4). Line is the mean for each age group. Significance was evaluated using the Student's t-1056 test. (M) Immunohistochemical analysis of CD3+ T cells (green) at day 0 and day 5 post-injury in tibialis anterior (TA) muscles from young (5 mo), old (20 mo), and geriatric (26 mo) mice with 1057 1058 DAPI (blue) as a nuclear counterstain and Phalloidin-750 (pink) as myofiber counterstain. Scale 1059 bar, 50 μm. Arrow denotes CD3+ T cell. (N) Flow cytometric analysis of TCRβ+ T cells. After 1060 gating single viable cells by FSC/SSC and a fixable viability dye (not shown), CD45+ 1061 hematopoietic cells, CD11b- CD11c- non-myeloid cells, and TCRβ+ CD19- T cells were gated 1062 sequentially. (**O**) Scatter plots of the fraction of TCR β + cells out of all CD45+ cells at 0 and 5 dpi. 1063 Points are each sample (n = 2-7). Line is the mean for each age group. Significance was evaluated 1064 using the Student's t-test.



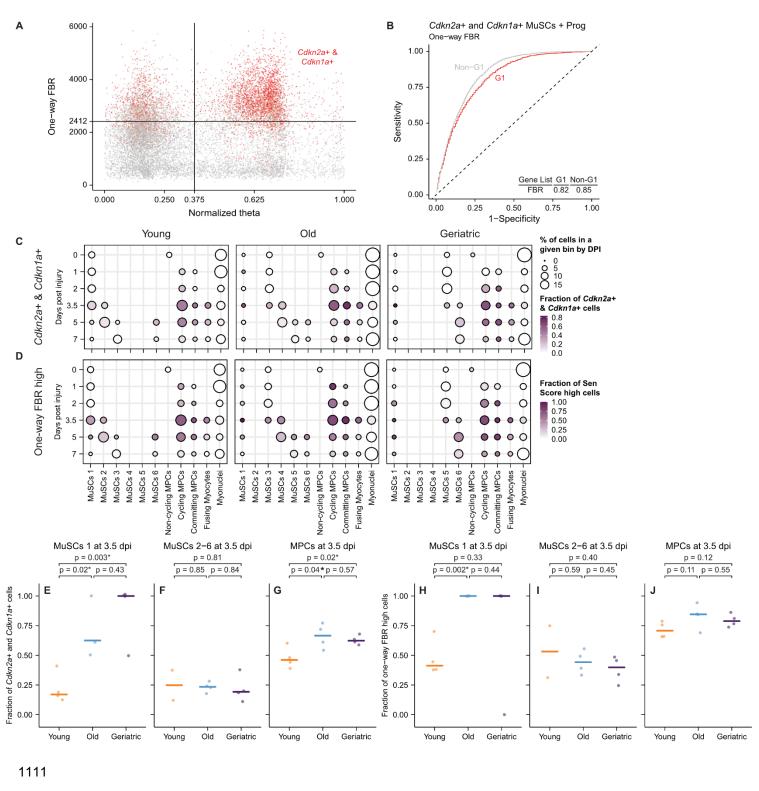
1066 Figure 3: Identification of senescent-like cells using an informatic scoring approach. (A)

1067 Dot plot showing the expression frequency and average expression level of select senescence-1068 associated genes by cell type and age (across all time-points). (B-D) Scatter plots of the fraction of Cdkn2a+ cells within the MuSCs and progenitors (**B**), T cells (Cycling; Cd3e+) (**C**), and FAPs 1069 1070 (Adipogenic) (**D**) across all samples within each age group (n = 20-24). Points are the fraction for 1071 each sample. Horizontal line is the median for each age group. Significance was evaluated using 1072 the Student's t-test. (E) Line plot of the fraction of MuSCs and progenitors that co-express Cdkn2a and Cdkn1a from 0-7 days post injury (dpi). Points are the fraction for each sample (n = 4). Ribbon 1073 1074 is the standard deviation. Statistical significance of age-specific dynamics was evaluated using 1075 non-linear modeling and the FDR-corrected p-values is reported. (F) Scatter plot of the fraction of 1076 MuSCs and progenitors at 3.5 dpi that co-express Cdkn2a and Cdkn1a by age. Points are the 1077 fraction for each sample (n = 4). Horizontal line is the median for each age group. Significance was evaluated using the Student's t-test. (G) Scatter plot of the normalized expression level of 1078 1079 Cdkn2a and Cdkn1a transcripts in all individual MuSCs and progenitors at 3.5 dpi. The density is 1080 shown on the top and to the right of the plot. Blue line represents the linear trend. Ribbon is the 1081 confidence interval. The inset contains the Pearson correlation coefficient and its statistical 1082 significance. (H) Significantly up- or down-regulated gene ontology terms between Cdkn2a+ and 1083 Cdkn1a+ (Double Positive) and all other (Other) MuSCs and progenitors at day 3.5. The 1084 normalized enrichment score and the FDR-corrected g-values were obtained from gene set 1085 enrichment analysis (GSEA). (I-J) Feature plots of the final dataset with the cells colored by the re-scaled Two-way FBR senescence score (I) and the re-scaled One-way FBR senescence score 1086 (J). The cells are randomly plotted. (K-L) Violin plots of the Two-way (K) and One-way (L) FBR 1087 1088 senescence scores in select cell types. (M-O) Receiver Operator Characteristic (ROC) curves 1089 based on the co-expression of Cdkn2a and Cdkn1a for the six Two-way senescence scores (**M**), 1090 the four One-way senescence scores (N), and for each age group using the One-way FBR 1091 senescence score (**O**). The area under the curve (AUC) is reported for each ROC curve.

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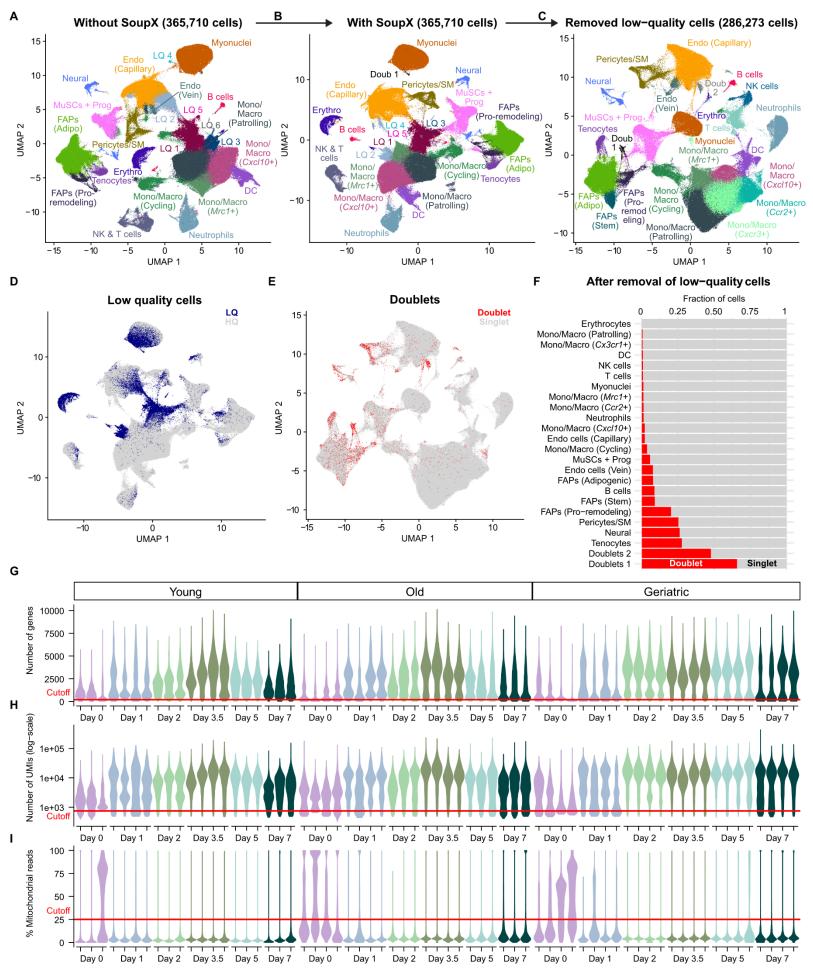


1093 Figure 4: Age-specific trajectories through myogenesis following injury. (A-C) Pseudotime 1094 organization of the myogenic cell subset after re-clustering. Myogenic cells were re-embedded 1095 with UMAP (A) and with PHATE (B) and are colored by general myogenic IDs. PHATE embeddings were used by Monocle3 to organize the cells in pseudotime where the earliest 1096 1097 pseudotime is in the upper left corner and the latest pseudotime in the upper right corner. 1098 Myogenic cells were organized into 25 approximately equal bins of increasing pseudotime values (C). (D) Each cell was assigned an S phase score and a G2M phase score using Seurat's Cell 1099 1100 Cycle Scoring method. Scatter plot of the two scores with the cells colored by the predicted cell cycle phase based on the two scores. (E-G) Polar coordinates (in D) were converted to cartesian 1101 1102 coordinates and rescaled to fit in a range from 0 to 1. Cells are colored by the predicted cell cycle 1103 phase based on the two scores (E) and by the log-normalized expression of Cdk1 (F) and Cdk41104 (G). (H-K) Dot plots of the average log-normalized expression of Pax7 (H), Myod1 (I), and Acta1 (J) and by the fraction of non-G1 (S, G2, and M) cells (K) in each day post injury (dpi) and 1105 1106 pseudotime-based myogenic cell state bin. The size of the circle is the percent of cells in each 1107 pseudotime-based myogenic cell state bin for each age and dpi combination. (L) Top 40 differentially up- and down-regulated genes between cells in MuSCs 1 and MuSCs 2-6 at day 1108 1109 3.5. All genes highlighted here have an FDR-corrected q-value < 0.05.

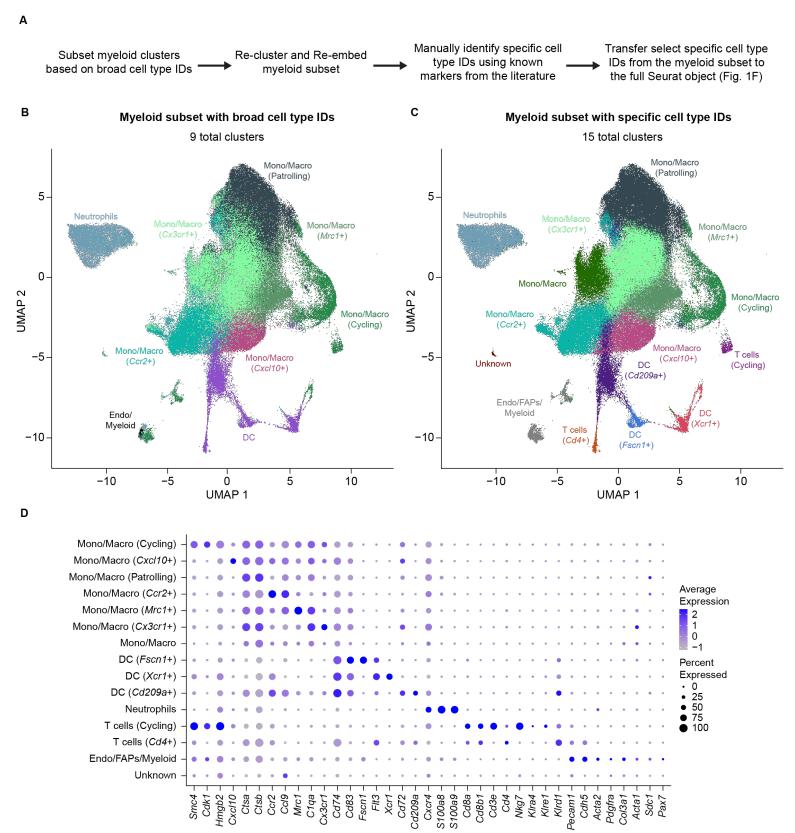




1113 Figure 5: Aging-associated accumulation of senescent-like cells at critical transitory 1114 myogenic cell states. (A) Scatter plot of the normalized cartesian coordinate Cell Cycle Scores 1115 and the One-way FBR senescence score in all MuSCs and progenitors. Cells colored in red coexpress Cdkn2a and Cdkn1a. All other cells in gray. The vertical line is the G1 cutoff, and the 1116 horizontal line is where 50% of the cells above this line co-express Cdkn2a and Cdkn1a. (B) 1117 Receiver Operator Characteristic (ROC) curves based on the co-expression of Cdkn2a and 1118 Cdkn1a in the MuSCs and progenitors (all ages and days post-injury (dpi)) in G1 and non-G1 (S, 1119 G2, and M) when using the One-way FBR senescence score. Area under the curve is reported 1120 for each ROC curve. (C-D) Dot plots of the fraction of cells that co-express Cdkn2a and Cdkn1a 1121 1122 (C) and the fraction of One-way FBR senescence score-high cells (D) in each dpi and pseudotime-1123 based myogenic cell state bin. The size of the circle is the percent of cells in each pseudotime-1124 based myogenic cell state bin for each age and dpi combination. (E-G) Scatter plot of the fraction of MuSCs 1 (E), MuSCs 2-6 (F), and all MPCs (G) at 3.5 dpi that co-express Cdkn2a and Cdkn1a 1125 1126 by age. Points are the fraction for each sample (n = 2-4) and the horizontal line is the median for 1127 each age group. Significance was evaluated using the Student's t-test. (H-J) Scatter plot of the fraction of MuSCs 1 (H), MuSCs 2-6 (I), and all MPCs (J) at 3.5 dpi that are One-way FBR 1128 1129 senescence score high by age. Points are the fraction for each sample (n = 2-4) and the horizontal 1130 line is the median for each age group. Significance was evaluated using the Student's t-test.



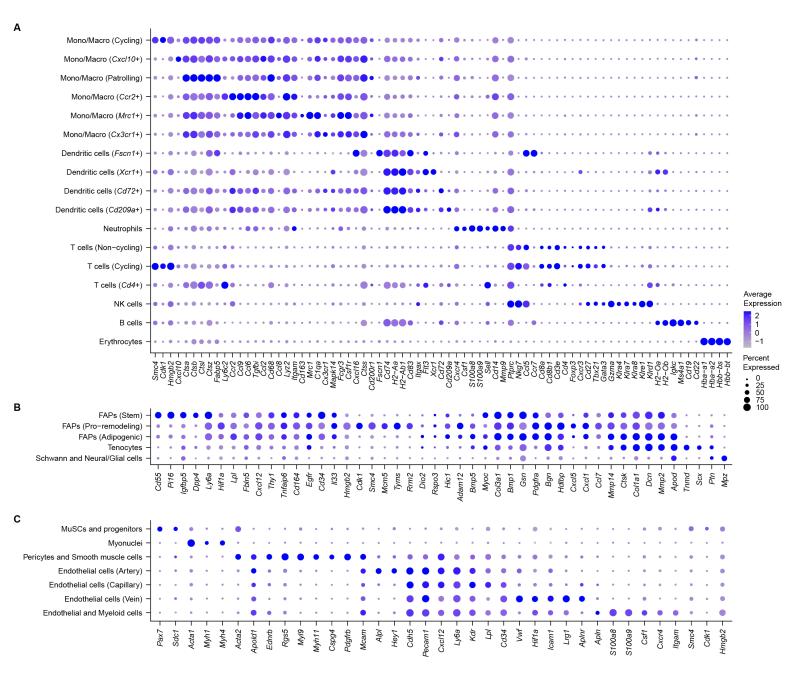
1132 Supplemental Figure 1: Evaluating sample guality. (A-C) Quality control workflow and 1133 resulting UMAPs with cells colored by manually assigned cell type IDs based on the expression 1134 of hallmark skeletal muscle genes. Prior to any guality-control there were 365,710 cells and 24 cell types were identified, including 6 low-quality (LQ) clusters (A). After ambient RNA removal 1135 1136 with SoupX, 23 cell types were identified, including 5 LQ clusters (B). After ambient RNA removal 1137 with SoupX and removal of LQ cells based on the number of genes and UMIs and the percent of 1138 mitochondrial reads, there were 286,273 cells and 24 cell types were identified, including two doublet clusters (C). (D) This is the same UMAP as in (B), but the cells are colored by quality 1139 status. Cells that had <200 genes, <750 UMIs, and >25% mitochondrial reads are considered LQ. 1140 1141 All other cells are considered high-quality (HQ). (E) This is the same UMAP as in (C), but the cells are colored by doublet status as determined by DoubletFinder using an estimated doublet rate of 1142 5%. (F) For every cell type cluster in (C), the fraction of singlets and doublets was calculated. (G-1143 I) Violin plots of the number of genes (G), the number of UMIs (H), and the percent of 1144 1145 mitochondrial reads (I) in each sample.



1146

1147 Supplemental Figure 2: Identifying additional immune cell types when focusing on just the

1148 myeloid cells. (A) Workflow to clarify the myeloid cell types. The 9 myeloid clusters based on 1149 broad cell type IDs were subset from the final dataset, re-clustered, and re-embedded. More specific cell type IDs were manually assigned using genes known to mark myeloid cell types. 1150 1151 Some of these more specific cell type IDs from the myeloid subset were transferred back to the 1152 final dataset (Figure 1F) based on the cell barcodes. (B-C) UMAPs of the myeloid subset after 1153 re-embedding, the cells are colored by the broad cell type IDs originally identified in the final dataset (B). After re-clustering, re-embedding, and re-annotating based on known immune cell 1154 markers, the cells are colored by the more specific cell type IDs (C). If the same cell type is in (B) 1155 and (C), it has the same color designation in both UMAPs. (D) Dot plot showing the expression 1156 frequency and magnitude of genes used to manually assign the more specific cell type IDs as 1157 1158 shown in (**C**).



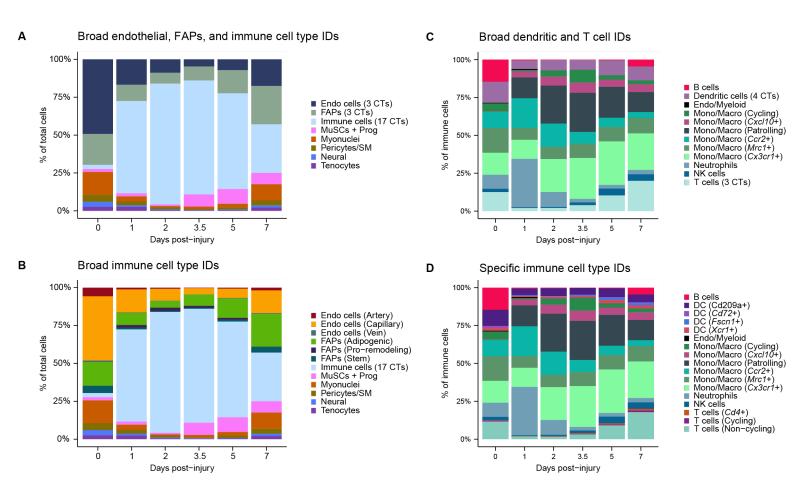
1159 Supplemental Figure 3: Identifying cell types in skeletal muscle during homeostasis and

1160 regeneration. (A-C) Dot plots showing the expression frequency and magnitude of genes used

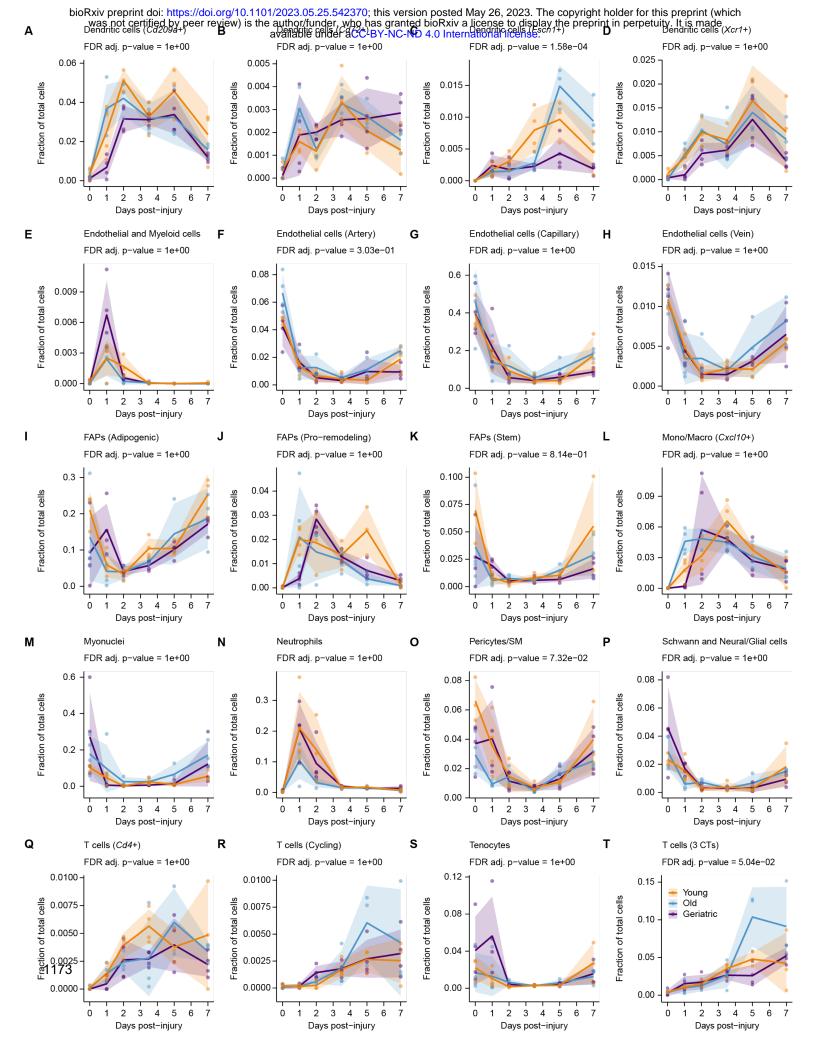
to manually assign cell type IDs, including the more specific immune cell type IDs. We identified

1162 17 immune cell clusters (A), 5 FAPs, Tenocytes, and Neural cell clusters (B), and 7 myogenic,

1163 pericyte/skeletal muscle, and endothelial cell clusters (**C**).

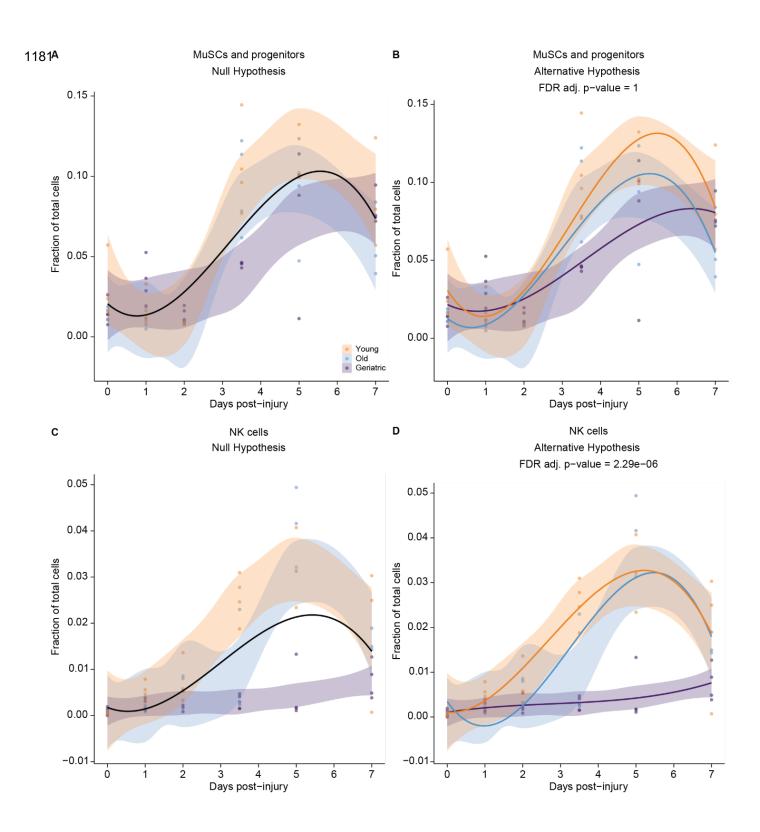


Supplemental Figure 4: Determining the cell type composition in each day post injury. (A-1164 1165 B) Stacked bar plots of the percent of each cell type found at a given day post injury (dpi). The three endothelial populations were combined into "Endo (3 CTs)", the three FAPs populations 1166 were combined into "FAPs (3 CTs)", and the 17 immune populations were combined into "Immune 1167 cells (17 CTs)" (A). Only the 17 immune populations are combined into "Immune cells (17 CTs)" 1168 (this plot is the same as in Figure 2K) (B). (C-D) Stacked bar plots of the percent of each immune 1169 cell type out of all immune cells at a given dpi. The four dendritic cell populations were combined 1170 1171 into "Dendritic cells (4 CTs)" and the three T cell populations were combined into "T cells (3 CTs)" 1172 (C). All individual immune cell type IDs (D).



1174 Supplemental Figure 5: Cell type dynamics (those that are not in main Figure 2). (A-T) Line

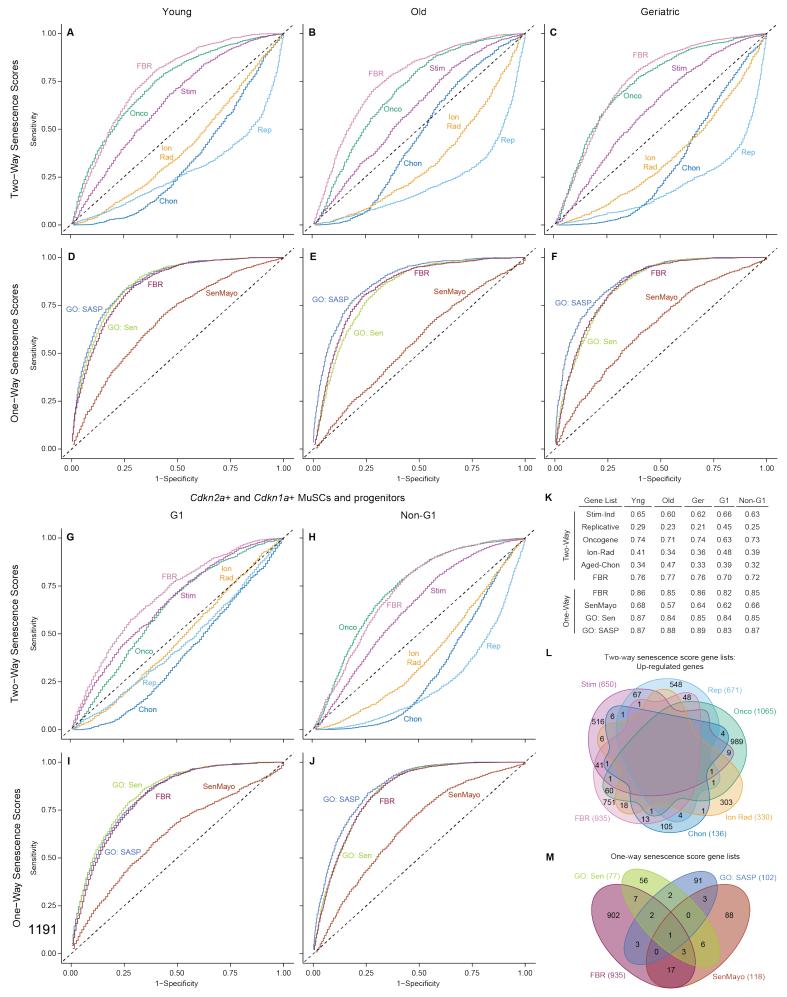
- 1175 plots for the remaining cell types not shown in **Figure 2** showing cell type relative abundance as
- 1176 a fraction of total cells from 0-7 days post injury (dpi). For each sample, the number of cells of the
- 1177 reported type was divided by the total number of cells (excluding erythrocytes). Points are each
- sample (n = 3-4). Ribbon is the standard deviation. Statistical significance of age-specific cell type
- 1179 dynamics was evaluated using non-linear modeling and FDR-corrected p-values are reported
- 1180 (see **Supplementary Figure 6**).



1182

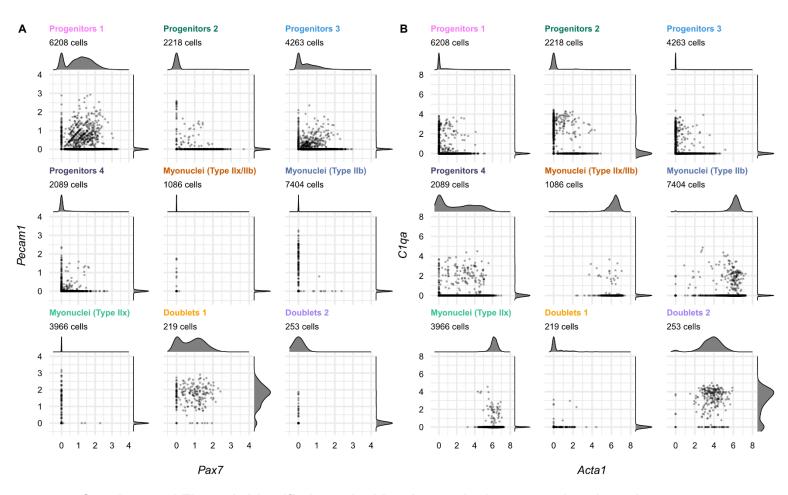
1183	Supplemental Figure 6: Cell type dynamics non-linear modeling. (A-B) Plots of the fraction
1184	of MuSCs and progenitors from 0-7 days post injury (dpi) by age. For each sample, the number
1185	of cells was divided by the total number of cells (excluding erythrocytes). The points are the
1186	fraction for each sample (n = 3-4) and the ribbon is the confidence interval. The black line is the
1187	non-linear model independent of age (A) and the three colored lines are the non-linear model
1188	dependent on age (B). Whether there was a significant difference in the non-linear models
1189	independent of and dependent on age was determined using a likelihood ratio test (ANOVA) and
1190	the p-values were corrected with FDR. (C-D) Same as in (A-B) but with NK cells.

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1192 Supplemental Figure 7: Evaluation of accuracy of senescence scoring methods. (A-F)

- 1193 Receiver Operator Characteristic (ROC) curves based on the co-expression of Cdkn2a and
- 1194 *Cdkn1a* for the six Two-way senescence scores (**A-C**) and the four One-way senescence scores
- 1195 (**D-F**) split into young (**A**, **D**), old (**B**, **E**), and geriatric (**C**, **F**) MuSCs and progenitors. (**G-J**) ROC
- 1196 curves based on the co-expression of *Cdkn2a* and *Cdkn1a* for the six Two-way senescence
- scores (**G-H**) and the four One-way senescence scores (**I-J**) split into G1 (**G**, **I**) and non-G1 (S,
- 1198 G2, and M) (H, J) MuSCs and progenitors. (K) Table of the area under the curve (AUC) for each
- 1199 ROC curve. (L-M) Venn diagrams of the unique and shared up-regulated genes found in the Two-
- 1200 way senescence scores (L) and the One-way senescence scores (M).

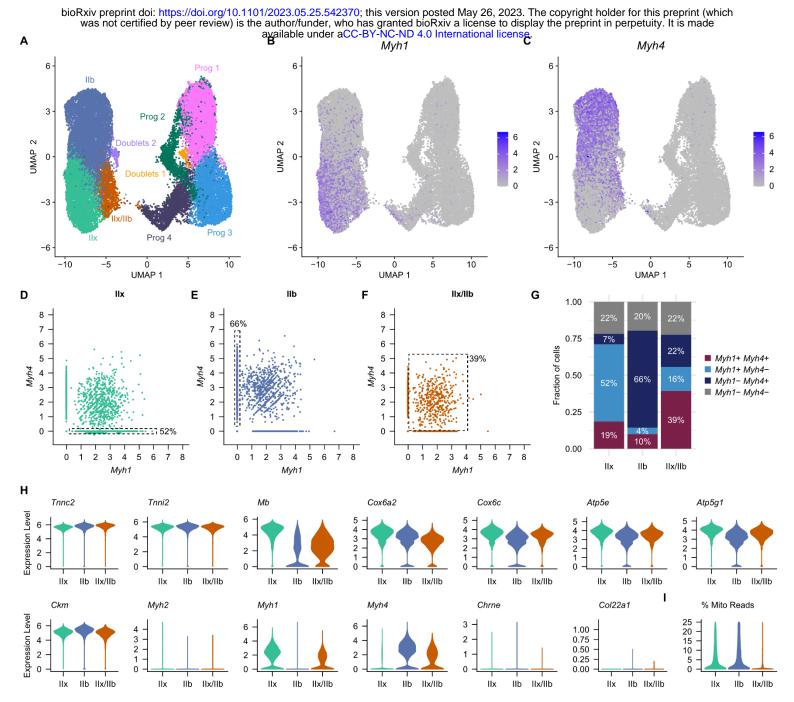


1201 Supplemental Figure 8: Identified two doublet clusters in the myogenic subset that were

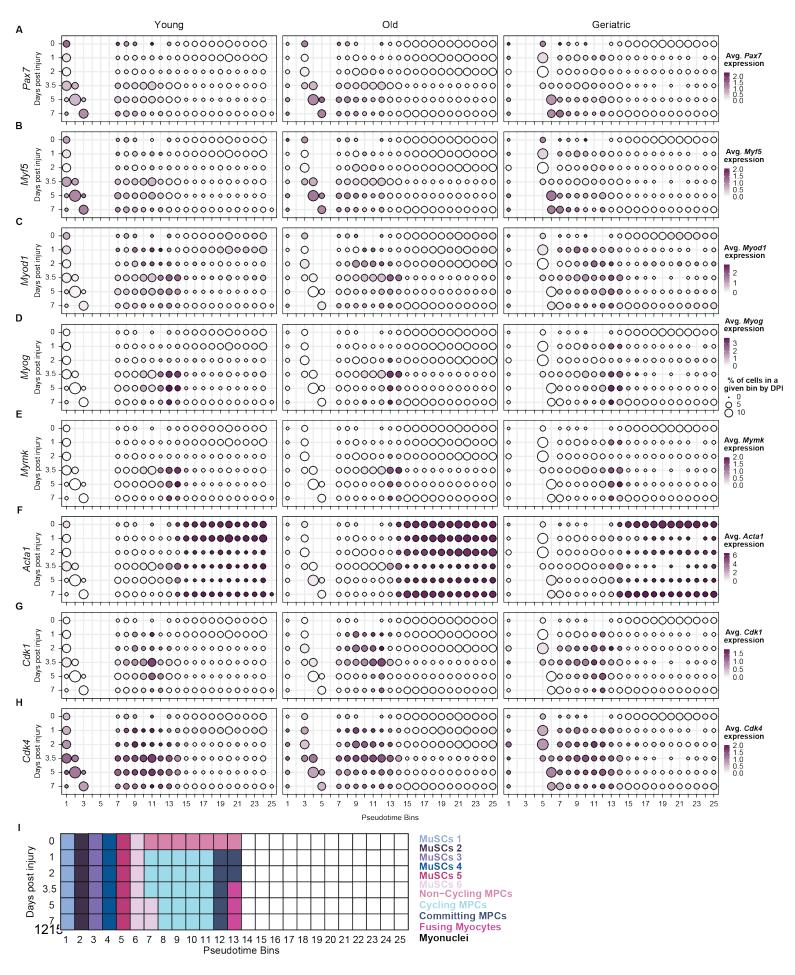
1202 not identified by DoubletFinder. (A-B) Scatter plots of the log-normalized expression levels of

1203 Pax7 and Pecam1 (A) and Acta1 and C1qa (B) by broad myogenic IDs as defined in Figure 4A.

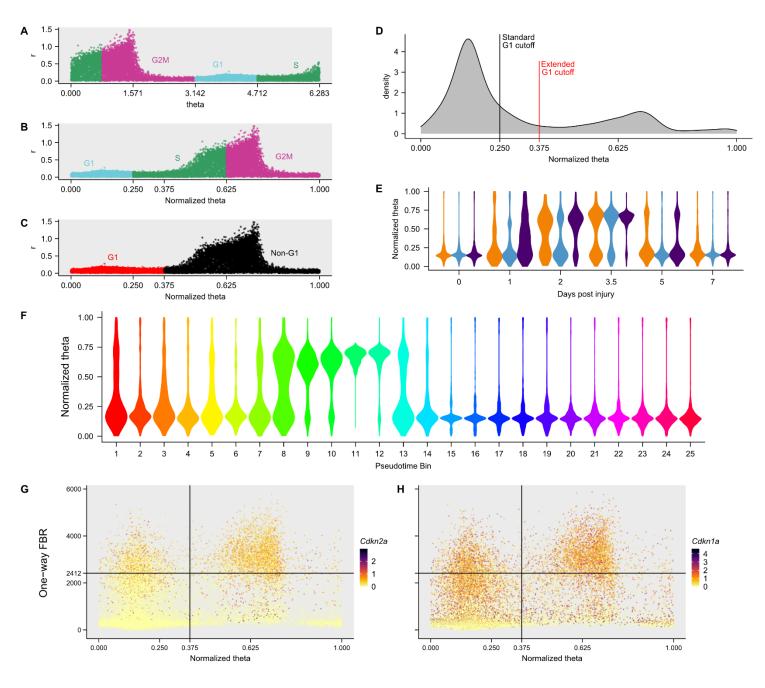
1204 A density curve is plotted on each axis.



1205 Supplemental Figure 9: Identifying a transitional myonuclei state. (A-C) Same UMAP of the 1206 myogenic subset as in Figure 4A colored by broad myogenic IDs (A) and colored by the lognormalized expression of Myh1 (B) and Myh4 (C). (D-F) Scatter plots of the log-normalized 1207 expression levels of Myh1 and Myh4 in the myonuclei clusters Type IIx (D), Type IIb (E), and Type 1208 IIx/IIb (F). The dotted-line boxes highlight the cells that express the marker(s) that should be 1209 expressed in each myonuclei cluster. (G) Stacked bar plot of the fraction of cells within each 1210 1211 myonuclei cluster that express a combination of Myh1 and Myh4. (H) Violin plots of the log-1212 normalized expression levels of markers of high metabolic rate (Tnnc2, Tnni2, Mb, Cox6a2, 1213 Cox6c, Atp5e, Atp5g1) and myonuclei (Ckm, Myh2, Myh1, Myh4, Chrne, Col22a1) in each 1214 myonuclei cluster. (I) Violin plot of the percent of mitochondrial reads in each myonuclei cluster.



- Supplemental Figure 10: Myogenic subset pseudotime analysis. (A-H) Dot Plots of the
 average log-normalized expression of *Pax7* (A), *Myf5* (B), *Myod1* (C), *Myog* (D), *Mymk* (E), *Acta1*(F), *Cdk1* (G), and *Cdk4* (H) in each day post injury (dpi) and pseudotime bin. The size of the
 circle is the percent of cells in each pseudotime bin for each age and dpi combination. (I)
 Schematic of newly assigned myogenic IDs (referred to as 'pseudotime-based myogenic cell state
- bin') based on the expression of known myogenic markers in each dpi and pseudotime bin.



1222

1223 Supplemental Figure 11: Cell cycle workflow. (A-C) The polar coordinates in Figure 4D were 1224 converted to cartesian coordinates (A) and rescaled to fit in a range from 0 to 1 (this plot is the 1225 same as in Figure 4E) (B). The cells are colored by the predicted cell cycle phase based on the two scores (A-B) and G1 status (C). (D) Distribution of MuSCs and progenitors across the 1226 1227 normalized theta values. The black line represents the standard Seurat G1 cutoff (normalized 1228 theta = 0.25), and the red line represents our extended G1 cutoff (normalized theta = 0.375). (E) 1229 Violin plot of the distribution of the normalized theta values in MuSCs and progenitors split by age and days post injury (dpi). (F) Violin plot of the distribution of the normalized theta values in 1230 MuSCs and progenitors split by pseudotime bin. (G-H) Scatter plot of the normalized theta values 1231 1232 and the One-way FBR senescence score in MuSCs and progenitors. The cells are colored by lognormalized Cdkn2a expression (G) and by Cdkn1a expression (H). The vertical line is the 1233 1234 extended G1 cutoff, and the horizontal line is where 50% of the cells above this line co-express 1235 Cdkn2a and Cdkn1a.

Cell Types	0	1	2	3.5	5	7 dpi
Endo cells (3 CTs)	49.2	16.8	8.9	4.7	7.2	17.6
FAPs (3 CTs)	20.4	10.7	7.2	9.3	15.2	25.3
Immune cells (17 CTs)	2.7	60.9	79.7	75.2	63.2	32.1
MuSCs + Prog	2.0	2.1	1.1	8.1	9.7	7.5
Myonuclei	15.1	3.3	0.9	1.5	2.5	10.6
Pericytes/SM	4.6	2.5	1.2	0.6	1.3	3.3
Neural	3.4	1.1	0.5	0.3	0.4	1.5
Tenocytes	2.6	2.5	0.5	0.3	0.5	2.1

в

		% of Total Cells				
Cell Types	0	1	2	3.5	5	7 dpi
Endo cells (Artery)	5.7	1.2	0.8	0.4	0.6	1.8
Endo cells (Capillary)	42.4	15.2	7.9	4.2	6.2	15.1
Endo cells (Vein)	1.1	0.4	0.2	0.2	0.3	0.7
FAPs (Adipogenic)	15.6	7.9	4.4	7.3	12.8	21.4
FAPs (Pro-remodeling)	0.0	1.8	2.2	1.3	1.3	0.2
FAPs (Stem)	4.8	1.0	0.7	0.6	1.2	3.8
Immune cells (17 CTs)	2.7	60.9	79.7	75.2	63.2	32.1
MuSCs + Prog	2.0	2.1	1.1	8.1	9.7	7.5
Myonuclei	15.1	3.3	0.9	1.5	2.5	10.6
Pericytes/SM	4.6	2.5	1.2	0.6	1.3	3.3
Neural	3.4	1.1	0.5	0.3	0.4	1.5
Tenocytes	2.6	2.5	0.5	0.3	0.5	2.1

С

	% of Immune Cells					
Cell Types	0	1	2	3.5	5	7 dpi
B cells	14.6	0.6	0.4	0.3	0.5	4.6
Dendritic cells (4 CTs)	13.9	5.6	6.8	6.5	9.9	9.2
Endo/Myeloid	0.5	0.7	0.1	0.0	0.0	0.0
Mono/Macro (Cycling)	5.3	0.8	4.1	8.4	2.9	2.6
Mono/Macro (Cxcl10+)	0.3	4.0	5.9	6.8	4.7	5.0
Mono/Macro (Patrolling)	0.0	13.7	24.9	25.7	20.3	13.2
Mono/Macro (<i>Ccr2</i> +)	10.8	19.7	15.4	8.0	6.2	4.0
Mono/Macro (<i>Mrc1</i> +)	16.3	7.8	8.1	9.3	9.5	10.2
Mono/Macro (<i>Cx3cr1</i> +)	14.5	12.6	21.7	26.9	28.7	24.1
Neutrophils	9.3	32.0	9.7	2.4	2.4	2.9
NK cells	2.3	0.6	0.8	1.7	4.5	4.3
T cells (3 CTs)	12.5	1.9	2.1	3.9	10.3	20.0

D

		% of Immune Cells				
Cell Types	0	1	2	3.5	5	7 dpi
B cells	14.6	0.6	0.4	0.3	0.5	4.6
DC (<i>Cd209a</i> +)	10.6	4.3	5.2	4.5	5.8	5.1
DC (Cd72+)	1.1	0.4	0.2	0.4	0.4	0.6
DC (Fscn1+)	0.0	0.3	0.3	0.6	1.5	1.5
DC (<i>Xcr1</i> +)	2.1	0.7	1.1	1.1	2.2	2.1
Endo/Myeloid	0.5	0.7	0.1	0.0	0.0	0.0
Mono/Macro (Cycling)	5.3	0.8	4.1	8.4	2.9	2.6
Mono/Macro (Cxcl10+)	0.3	4.0	5.9	6.8	4.7	5.0
Mono/Macro (Patrolling)	0.0	13.7	24.9	25.7	20.3	13.2
Mono/Macro (Ccr2+)	10.8	19.7	15.4	8.0	6.2	4.0
Mono/Macro (<i>Mrc1</i> +)	16.3	7.8	8.1	9.3	9.5	10.2
Mono/Macro (Cx3cr1+)	14.5	12.6	21.7	26.9	28.7	24.1
Neutrophils	9.3	32.0	9.7	2.4	2.4	2.9
NK cells	2.3	0.6	0.8	1.7	4.5	4.3
T cells (Cd4+)	0.3	0.2	0.4	0.5	0.7	1.0
T cells (Cycling)	0.6	0.0	0.1	0.3	0.6	1.1
T cells (Non-cycling)	11.6	1.7	1.6	3.1	9.0	17.8

1237 Supplementary Table 1: Determining the cell type composition in each day post injury. (A-

- 1238 B) Percent of each cell type found at a given day post injury (dpi). The three endothelial
- 1239 populations were combined into "Endo (3 CTs)", the three FAPs populations were combined into
- 1240 "FAPs (3 CTs)", and the 17 immune populations were combined into "Immune cells (17 CTs)" (**A**).
- 1241 Only the 17 immune populations are combined into "Immune cells (17 CTs)" (**B**). (**C-D**) Percent
- 1242 of each immune cell type out of all immune cells at a given dpi. The four dendritic cell populations
- 1243 were combined into "Dendritic cells (4 CTs)" and the three T cell populations were combined into
- 1244 "T cells (3 CTs)" (**C**). All individual immune cell type IDs (**D**).

	Equation used in		FDR-corrected	
Cell Type	non-linear modeling	p-value	p-value	
B cells	Quadratic	1.45E-03	4.06E-02	
Dendritic cells (Cd209a+)	Quadratic	4.65E-02	1.00E+00	
Dendritic cells (Cd72+)	Quadratic	3.60E-01	1.00E+00	
Dendritic cells (Xcr1+)	Quadratic	2.02E-01	1.00E+00	
Endothelial and Myeloid cells	Quadratic	7.66E-01	1.00E+00	
Endothelial cells (Capillary)	Quadratic	7.27E-01	1.00E+00	
FAPs (Adipogenic)	Quadratic	4.25E-01	1.00E+00	
FAPs (Stem)	Quadratic	2.91E-02	8.14E-01	
Mono/Macro (<i>Cxcl10</i> +)	Quadratic	8.30E-01	1.00E+00	
Myonuclei	Quadratic	1.76E-01	1.00E+00	
Pericytes/SM	Quadratic	2.62E-03	7.32E-02	
Schwann and Neural/Glial cells	Quadratic	1.06E-01	1.00E+00	
T cells (Cd4+)	Quadratic	3.36E-01	1.00E+00	
T cells (Cycling)	Quadratic	4.37E-01	1.00E+00	
T cells (Non-cycling)	Quadratic	7.06E-04	1.98E-02	
Tenocytes	Quadratic	3.86E-02	1.00E+00	
Dendritic cells (<i>Fscn1</i> +)	Cubic	5.65E-06	1.58E-04	
Endothelial cells (Artery)	Cubic	1.08E-02	3.03E-01	
Endothelial cells (Vein)	Cubic	7.71E-01	1.00E+00	
FAPs (Pro-remodeling)	Cubic	5.06E-01	1.00E+00	
Mono/Macro (<i>Mrc1</i> +)	Cubic	1.26E-08	3.52E-07	
Mono/Macro (<i>Cx3cr1</i> +)	Cubic	1.92E-04	5.37E-03	
MuSCs and progenitors	Cubic	4.10E-02	1.00E+00	
NK cells	Cubic	8.17E-08	2.29E-06	
Mono/Macro (Cycling)	Quartic	2.66E-05	7.46E-04	
Mono/Macro (Patrolling)	Quartic	6.71E-06	1.88E-04	
Mono/Macro (Ccr2+)	Quartic	1.00E-02	2.81E-01	
Neutrophils	Quartic	9.47E-02	1.00E+00	

Supplementary Table 2: Cell type dynamics statistics summary. For all cell types, listed the
equation type used in the non-linear modeling, the unadjusted p-value, and the FDR adjusted pvalue. The adjusted p-values that are significant (<0.05) are in red.

1248 EXTENDED DATA FILES

1249

1250 Extended Data File 1: Summary of single-cell RNA-sequencing samples in this study.

1251

1252 Extended Data File 2: Lists of senescence gene signatures used in this study.