#### Title:

### Clinical and immunological signatures of severe COVID-19 in previously healthy patients with clonal hematopoiesis

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#### 1 Abstract

2 Identifying additional risk factors for COVID-19 severity in numerous previously healthy patients without canonical clinical risk factors remains challenging. In this study, we 3 4 investigate whether clonal hematopoiesis of indeterminate potential (CHIP), a common agingrelated process that predisposes various inflammatory responses, may exert COVID-19 severity. 5 We examine the clinical impact of CHIP in 143 laboratory-confirmed COVID-19 patients. Both 6 7 stratified analyses and logistic regression including the interaction between canonical risk factors and CHIP show that CHIP is an independent risk factor for severe COVID-19, 8 9 especially in previously healthy patients. Analyses of 60,310 single-cell immune transcriptome 10 profiles identify distinct immunological signatures for CHIP (+) severe COVID-19 patients, 11 particularly in classical monocytes, with a marked increase in pro-inflammatory cytokine 12 responses and potent IFN-y mediated hyperinflammation signature. We further demonstrate 13 that the enhanced expression of CHIP (+) specific IFN- $\gamma$  response genes is attributed to the CHIP mutation-dependent epigenetic reprogramming of poised or bivalent *cis*-regulatory 14 elements. Our results highlight a unique immunopathogenic mechanism of CHIP in the 15 progression of severe COVID-19, which could be extended to elucidate how CHIP contributes 16 to a variety of human infectious diseases. 17

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#### 20 Main Text:

#### 21 Introduction

A pandemic of coronavirus disease-19 (COVID-19), an emerging infectious disease caused by 22 severe acute respiratory syndrome-coronavirus-2 (SARS-CoV-2), has been being a global 23 health threat of the century<sup>1,2</sup>. Epidemiologic data revealed that about 20% of patients 24 underwent severe or critical course<sup>3</sup>. Although many clinical risk factors for severe illness 25 26 including older age, comorbidities such as diabetes mellitus or hypertension, and morbid obesity have been found<sup>4,5</sup>, we could still only partly explain the development of severe 27 COVID-19. Indeed, there have been numerous cases of severe COVID-19 from previously 28 healthy adults<sup>6,7</sup>. 29

Clinical deteriorations such as acute respiratory distress syndrome or intensive care unit admission most commonly occur at around the 10<sup>th</sup> day of illness<sup>8,9</sup>, when the viral loads are declining after the early peak<sup>10,11</sup>. This temporal discrepancy suggests immunological phenomenon may play an important role in the progression of COVID-19. High levels of circulating pro-inflammatory cytokines<sup>12</sup>, aberrant hyperactivation of cytotoxic lymphocytes<sup>13</sup> or their infiltration in vital organs<sup>14</sup>, or dysregulated monocytes and macrophages<sup>15</sup> have been proposed as mechanisms for pathologic immune responses in severe COVID-19.

Clonal hematopoiesis of indeterminate potential (CHIP) refers to a population of immune cells with acquired gene mutations, but without fulfilling diagnostic criteria for a hematologic malignancy<sup>16</sup>. As a majority of the genes associated with CHIP including *DNMT3A*, *TET2*, and *ASXL1* are involved in epigenetic regulation, CHIP may have a wide range of effects on immune function through altered chromatin activities<sup>17</sup>. There is growing evidence supporting a role for the CHIP mutations in altered immune function through effector cells such as monocytes/macrophages and their dysregulated cytokine/chemokine expression,

which account for the increased risk of cardiovascular disease in individuals with CHIP<sup>18-21</sup>. 44 Since immunopathogenesis of such an adverse outcome of CHIP largely shares that of severe 45 COVID-19, we hypothesized that CHIP might contribute to the progression of COVID-19 with 46 its unique immune signature. Although recent reports describe the association between 47 acquired mutations in hematopoietic cells such as CH and severe COVID-19<sup>22,23</sup>, there has 48 been a controversy on the clinical impact of CHIP in COVID-19<sup>23-25</sup>. However, if there exists 49 a distinct CHIP-related clinical deterioration mechanism of COVID-19, tailored therapeutics 50 51 could be of help to salvage these patients.

In this study, to determine the clinical significance of CHIP in COVID-19 severity, 52 especially in previously healthy adults, we analyzed thorough clinical, radiological, and 53 54 laboratory characteristics of patients with COVID-19. In addition, we explored immune signatures using single-cell RNA expression data according to the presence of CHIP to suggest 55 56 how CHIP attributes to the immunologic responses in severe COVID-19. Lastly, since the majority of mutations in CHIP are related to epigenetic regulators of DNA methylation and 57 heterochromatin formation, we investigated CHIP mutation dependent dysregulated epigenetic 58 gene regulation mechanisms involved in CHIP-specific immunopathogenesis. 59

#### 60 **Results**

#### 61 Impact of CHIP on severe COVID-19 in previously healthy patients

A total of 143 laboratory-confirmed COVID-19 patients were analyzed in this study (Fig. 1a). 62 Among those, 34 patients had CHIP (23.8%, Supplementary Table 1). DNMT3A (13 variants) 63 was the most common mutated gene, followed by TET2 (7 variants) and ASXL1 (5 variants). 64 Clinical characteristics were retrospectively reviewed using electronic medical record (EMR) 65 66 systems of each institution. It included age, sex, body mass index, presence of comorbidities, details of oxygen and medical therapy, duration of hospital stay, and in-hospital mortality. 67 Serial laboratory findings including complete blood count with differential count and 68 69 chemistries were also collected. Cases with the highest ordinal scale 3 (need for supplemental oxygen therapy via nasal cannula) or more were classified as severe COVID-19, while others 70 were classified with mild ones<sup>3</sup>. 71

Baseline characteristics of these patients are shown in Supplementary Table 1. Median (interquartile range [IQR]) ages were 73 (61—81) and 65 (50—75) years in those with or without CHIP, respectively (Student's *t*-test, P < 0.001), as consistent with a common agingrelated property of CHIP. The presence of CHIP appears to contribute to COVID-19 severity as severe COVID-19 tended to be more frequent in patients with CHIP than those without, while the difference was statistically not significant (25/34, 73.5% vs. 65/109, 59.6%, Chisquared test, P = 0.143).

To precisely examine the clinical impact of CHIP in patients with COVID-19, we conducted a hierarchical clustering analysis for baseline characteristics and examined the distribution of CHIP among clusters (Fig. 1b). All continuous clinical information was transformed into a range of 0 to 1 using a logistic function, and comorbidity status was dichotomized into 0 and 1 for absence and presence (see Methods). Patients were grouped into

two main clusters, A and B. They mainly comprised severe and mild cases, respectively, since cluster A had significantly higher ordinal scores, peak serum C-reactive protein level, and peak chest X-ray score than cluster B (Unpaired t-test, P < 0.001) (Fig. 1c). Cluster A was subdivided into three clusters, A1, A2, and A3 with their own comorbidity status (Fig. 1d). Cluster A1 was characterized by the presence of hypertension, while cluster A3 was a DM-enriched group.

Interestingly, cluster A2 tended to have a higher rate of CHIP than the others in cluster A (Fisher's exact test, P = 0.074), while it had significantly lower BMI (median [IQR], 20.8 [17.8—23.1] vs. 23.0 [21.7—26.1]; Student's *t*-test, P = 0.005) and lower rate of DM (0/18, 0% vs. 22/51, 43.1%; Fisher's exact test, P = 0.001) or hypertension (0/18, 0% vs. 40/51, 78.4%; Fisher's exact test, P < 0.001) (Fig. 1d and Supplementary Table 2). However, age distribution was not statistically different (Fisher's exact test, P = 0.662).

The presence of a particular type of severe cases uniquely enriched by CHIP without
canonical risk factors such as DM, hypertension, and high BMI led us to hypothesize that CHIP
may contribute to severe COVID-19 in its own way. An additional hierarchical clustering with
DM, hypertension, and CHIP information in all severe patients (Ordinal scale >=3) also
supported our hypothesis since it showed that CHIP was clustered together (Extended Data Fig.
1).

To test the statistical significance of the impact of CHIP on COVID-19 severity in previously healthy patients, we stratified the entire patients by the presence of any of the canonical risk factors such as DM, hypertension, and BMI  $\geq$  30.0. When adjusted with age and gender, the risk of severe COVID-19 was significantly higher in CHIP (+) patients than in CHIP (-) ones in canonical risk factor-absent subgroup (adjusted odds ratio [95% confidence interval], 14.8 [1.3—164.1]; logistic regression P = 0.028; Table 1). Multivariate analysis

including the interaction between canonical risk factors and CHIP revealed that CHIP was an independent risk factor for severe COVID-19 (adjusted odds ratio [95% confidence interval], 10.7 [1.1-100.7], logistic regression P = 0.038, Table 2). The results of the patients clustering and the statistical evidence indicate that CHIP is an independent risk factor for severe COVID-19, especially in previously healthy patients.

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#### 113 Distinct immune signatures in CHIP (+) severe COVID-19

114 We next sought to identify distinct immune signatures for severe COVID-19 according to the presence of CHIP. To this end, a total of 60,310 high-quality single-cell transcriptome 115 profiles of peripheral blood mononuclear cells (PBMCs) generated by 10x Genomics single-116 cell RNA-seq (scRNA-seq) platform were integrated from healthy donors (n=4), severe 117 influenza (n=5), CHIP (-) mild COVID-19 (n=5), CHIP (-) severe COVID-19 (n=3), and 118 119 CHIP (+) severe COVID-19 (n=6) specimens (Supplementary Table 3 and 4, see Methods), with an average of 6,100 unique molecular identifies (UMIs), representing 1,400 genes. The 120 reproducibility and quality were ensured (Extended Data Fig. 2a-c)<sup>26</sup>. Based on t-distributed 121 122 stochastic neighbor embedding (t-SNE) of transcriptome profiles, 24 subgroups were derived. Assigning cell types with previously annotated marker genes (Extended Data Fig. 2d-e, see 123 Methods)<sup>26</sup>, we focused on 9 major immune cell types, including  $IgG^+ B$  cell,  $IgG^- B$  cell, 124 125 CD4<sup>+</sup> T cell, naïve CD4<sup>+</sup> T cell, CD8<sup>+</sup> T cell, CD8<sup>+</sup> memory T cell, natural killer (NK) T cell, classical monocyte, and non-classical monocyte in subsequent analyses (Fig. 2a). Non-126 immune cells such as platelets, red blood cells (RBCs), and uncategorized small cell 127 populations were excluded. Notably, the proportion of monocytes was markedly increased, 128 particularly in CHIP (+) severe COVID-19 patients (K-S test, P=3.49e-3) (Extended Data 129

130 Fig. 2f-g), consistent with the known impact of CHIP with increased myeloid cell

131 population<sup>27</sup>.

132 In terms of transcriptome profiles at the cell-type resolution, as expected, most immune cell types originating from COVID-19 were clustered together when compared to influenza 133 134 (Fig. 2b). Interestingly, those from severe COVID-19 were subdivided according to the presence of CHIP (Fig. 2b). To investigate relevant biological functions that establish such 135 unique host immune responses in CHIP (+) severe COVID-19, we identified up-regulated 136 genes specific to CHIP (+) severe COVID-19 compared to healthy normal control, influenza, 137 CHIP (-) mild COVID-19, and CHIP (-) severe COVID-19, respectively, using MAST 138 139 algorithm (Extended Data Fig. 3a)<sup>28</sup>. Regardless of both normal and disease control groups, tumor necrosis factor (TNF- $\alpha$ )/NF-kB and interferon-gamma (IFN- $\gamma$ ) responses were 140 commonly enriched in up-regulated genes in CHIP (+) severe COVID-19 (Extended Data Fig. 141 3b). A noticeable enrichment of CHIP (+) up-regulated genes was observed in classical 142 143 monocytes (Extended Data Fig. 3c).

To further investigate the unique immune signatures at the individual immune cell-144 type resolution, we conducted gene set enrichment analysis (GSEA) for differentially 145 expressed genes between CHIP (+) and CHIP (-) severe COVID-19. Based on cytokine-146 responsive gene sets originated from each cytokine treated cells (LINC L1000 ligand 147 perturbation analysis in Enrichr) (see Methods)<sup>29</sup>, strong IL-1 $\beta$  and TNF- $\alpha$  responses were 148 149 observed in both CHIP (+) and CHIP (-) severe COVID-19 compared to healthy normal control (Fig. 2c). However, direct comparison between CHIP (+) and CHIP (-) severe COVID-19 150 151 revealed that immune responses in classical monocytes were strongly skewed towards CHIP (+) patients (Fig. 2d), while other cell types such as T cells, B cells or non-classical monocytes 152 did not show such trend (Fig. 2e-g, Extended Data Fig. 4a-e). Taken together, CHIP (+) patients 153

under COVID-19 infection present unique host immune responses, particularly in classicalmonocytes.

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#### 157 Classical monocyte-mediated hyperinflammation in CHIP (+) severe COVID-19

To examine how the presence of CHIP attributes to the immunologic responses in classical 158 monocytes, we focused on analyzing 445 up- and 417 down-regulated CHIP (+) specific genes. 159 CHIP (+) up-regulated genes demonstrated enrichment with inflammation cytokine responses, 160 such as IL-1β compared to CHIP (-) (Mann-Whitney's U test, P=3.24e-2, IL-1β) (Fig. 3a). 161 Other COVID-19 representative interleukins such as IL-6, IL-10 and IL-15 were also elevated 162 in CHIP (+) severe COVID-19. (Fig. 3b)<sup>30</sup>. Notably, CHIP (+) up-regulated genes were 163 164 strongly related to both type I and II interferon (IFN) responses (Mann-Whitney's U test, P=1.08e-3, IFN- $\gamma$ ; P=3.97e-3, IFN- $\alpha$ ). We previously proposed that a group of genes involved 165 in type I IFN-induced TNF- $\alpha$  mediated hyperinflammation by abolishing the tolerance effects 166 of TNF- $\alpha$  (Class 1 gene in Park *et al.*<sup>31</sup>) in monocyte has a critical role in promoting 167 hyperinflammation of COVID-19<sup>26</sup>. Consistently, the CHIP (+) up-regulated genes presented 168 169 a modest enrichment with the Class I genes (Fig. 3c), partly explaining the hyperinflammation signature of CHIP (+). However, other inflammatory TLR-induced genes regardless of TNF- $\alpha$ 170 tolerization (Class II and III genes in Park et al.<sup>31</sup>) were extremely biased to CHIP (+) up-171 regulated genes, postulating the presence of additional classical monocyte driven responses 172 173 exacerbating the inflammation signatures in CHIP (+).

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175 IFN-γ mediated hyperinflammation in CHIP (+) severe COVID-19 revealed by a
176 pseudotime analysis

177 Intriguingly, IFN- $\gamma$  response was notably high in CHIP (+) up-regulated genes (Fig. 3a). As a high level of IFN-y has been reported as an indicator of severe COVID-198,32,33, we 178 hypothesized that IFN-y response could attribute to hyperinflammation signatures of classical 179 monocytes in CHIP (+) patients. We first determined the association between IFN- $\gamma$  response 180 and COVID-19 severity in CHIP (+) by conducting pseudotime analysis using the specimens 181 collected twice from one patient to exclude innate individual biases (Fig. 4a) (see Methods). 182 After ordering cells along with the trajectory analysis, we allocated the annotation of high and 183 184 low inflammation clusters based on inflammatory signatures termed in MsigDB Hallmark 2020 (Fig. 4b). We found that IFN- $\gamma$  response genes were significantly enriched in a high 185 inflammation group of CHIP (+), even more potent than that of CHIP (-) (Fig. 4c). 186

187 Recent mouse and scRNA-seq comparison studies have highlighted the immunopathogenic contribution of IFN-y in severe COVID-19 as demonstrated by IFN-y induced 188 inflammatory macrophage phenotype and synergistic effect of IFN- $\gamma$  and TNF- $\alpha^{34,35}$ . 189 Consistently, in our analysis, CHIP (+) specific genes were significantly enriched by pro-190 inflammatory M1-like macrophage-specific genes obtained from two independent studies<sup>36</sup> 191 <sup>37</sup>(Fig. 4d and Extended Data Fig. 5a) and associated with up-regulated genes by co-treatment 192 of TNF- $\alpha$  and IFN- $\gamma$  (Fig. 4e)<sup>35</sup>. Such enrichment suggests that CHIP (+) severe COVID-19 193 patients are representative cases that could be explained by previously discovered IFN-y 194 195 mediated disease exacerbating mechanism. For a treatment perspective, we noticed that spleen 196 tyrosine kinase (Syk) inhibitor, which is known to reduce the expressions of interferon-197 stimulated genes<sup>38</sup>, may be an effective molecule for the intervention of CHIP (+) up-regulated genes (Paired t-test, P=0.042) (Extended Data Fig. 5b). Taken together, IFN-y response is 198 199 thought to be a main source of the hyperinflammation immune signature in CHIP (+) severe COVID-19. 200

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#### 202 DNMT3A mutation-specific hypo-DMRs are linked to IFN-γ response genes

Next, we sought to identify mechanisms by which IFN- $\gamma$  response genes are up-regulated 203 204 explicitly in CHIP (+) COVID-19 patients. Considering mutations of multiple epigenetic 205 regulators such as DNMT3A, TET2, and ASXL1 in CHIP, we hypothesized that altered chromatin activity of *cis*-regulatory elements might exert CHIP-specific gene expression. To 206 207 test our hypothesis, we identified 2,348 differentially methylated regions (DMRs) in acute myeloid leukemia (AML) patients carrying DNMT3A mutations (see Methods) 208 (Supplementary Table 5)<sup>39</sup>. In support of our hypothesis, these DMRs were highly overlapped 209 with putative regulatory elements (Fisher's exact test, P < 0.001, Proximal to the promoter; 210 P<0.001, Distal regulatory element) (Fig. 5a) (see Methods). As exemplified in FOXO3 and 211 212 NFIL3, known IFN response genes, CHIP (+) up-regulated genes were also more closely located to the hypo-DMRs (Fig. 5b, Extended Data fig. 6). 213

214 As many *cis*-regulatory elements are known to target genes over large genomic distances<sup>40</sup>, we performed *in situ* Hi-C experiments on CD14<sup>++</sup>/CD16<sup>-</sup> classical monocytes of 215 two healthy donors to precisely annotate target genes of CHIP-dependent DMRs (see Methods). 216 217 With ~500M long-range chromatin interactions over 15kb genomic distance, we defined significant long-range chromatin contacts using covNorm in 10kb resolution (see Methods)<sup>41</sup>. 218 219 Using this information, as illustrated in *RBPJ* and *CXCL2* genes (Fig. 5c-d), we revealed that, 220 in total, around 33% of CHIP-specific up-regulated genes, denoted as 'linked genes', were associated with hypo-DMRs either in proximal (within 15kb) or long-range chromatin 221 interactions (over 15kb but less than 2Mb) (Fig. 5e). Notably, those linked genes were more 222 enriched by both type I and II IFN response genes compared to the remaining up-regulated 223 genes (Mann-Whitney's U test, P=2.50e-3, IFN- $\gamma$ ; P=3.97e-3, IFN- $\alpha$ ) (see Methods) (Fig. 5f). 224

Regarding high inflammation cluster in pseudotime analysis, we revealed that IFN- $\gamma$  response genes largely overlap by hypo-DMRs linked genes (Mann-Whitney's U test, *P* =1.08e-3, IFN- $\gamma$ ) (Fig. 5g). Our results strongly support that CHIP-dependent altered chromatin activities are associated with putative *cis*-regulatory elements of IFN- $\gamma$  response genes, which may establish unique gene expression profiles in CHIP patients during immune responses.

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#### 231 Activation of poised and bivalent *cis*-regulatory elements primes IFN-γ response genes

To further characterize CHIP-specific hypo-DMRs, we examined the enrichment of four 232 representative histone modification marks including histone H3 4th lysine mono-methylation 233 (H3K4me1), tri-methylation (H3K4me3), 27<sup>th</sup> lysine acetylation (H3K27ac), and tri-234 methylation (H3K27me3) of primary human classical monocyte<sup>42,43</sup>. When comparing DMRs 235 to randomly selected genomic regions, hypo-DMRs were mostly marked by H3K27me3 in the 236 primary human classical monocytes, while hyper-DMRs were enriched by H3K27ac as an 237 indicator of active regulatory elements (Fig. 6a-b). However, interestingly, a subset of hypo-238 239 DMRs, linking to CHIP (+) up-regulated genes, were also significantly co-occupied by H3K4me1 and H3K4me3 peaks compared to the unlinked hypo-DMRs (Fisher's exact test, 240 P<0.001, H3K4me1; P<0.001, H3K4me3; P =2.37e-2, H3K27ac) (Fig. 6c-d). Such co-241 242 exhibition of inactive and active chromatin signatures indicates that the regulatory elements of CHIP (+) up-regulated genes have shifted from poised or bivalent status to an active chromatin 243 state through the process of CHIP dependent hypo-DNA methylation. To test this possibility, 244 we annotated chromatin states of linked hypo-DMRs according to the combination of the 245 histone modification marks (see Methods). We found that promoter-distal hypo-DMRs were 246 significantly enriched by poised enhancer chromatin signatures (H3K4me1 without 247 H3K27me3) (Fisher's exact test, P < 0.001) (Fig. 6e). Similarly, promoter-proximal hypo-248

DMRs were enriched by bivalent promoters (H3K4me3 and H3K27me3) or active promoters (H3K4me3) (Fisher's exact test, P = 3.80e-3, Active promoter; P = 7.36e-2, Bivalent) (Fig. 6f). Thus, CHIP mutants appear to reprogram the epigenetic states including the loss of silent marker at poised enhancers or bivalent promoters, which prime the IFN associated immune response genes, thereby driving hyperinflammation and leading to the critical course of COVID-19 (Fig. 7).

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#### 257 Discussion

By analyzing thorough clinical, radiological, and laboratory characteristics, as well as the presence of CHIP, we showed that CHIP is a novel risk factor for severe COVID-19 in previously healthy population without canonical clinical risk factors. scRNA-seq analysis revealed a distinct IFN- $\gamma$  mediated immuno-pathogenic mechanism in CHIP (+) severe COVID-19 plausibly attributed by CHIP dependent chromatin reorganization. These results consistently indicate that CHIP may play a critical role in the progression of severe COVID-19, especially in previously healthy patients with its own immunologic pathway.

Exploration of an additional risk factor for severe COVID-19 is clinically valuable in 265 266 this pandemic to predict the progression of COVID-19 more accurately and to improve our 267 management strategy. Owing to its pro-inflammatory nature, CHIP may contribute to the progression of severe COVID-19. By analyzing more than 500 patients, Bolton et al. reported 268 that CHIP is significantly associated with severe COVID-19<sup>23</sup>, especially for patients carrying 269 non-putative driver mutations. There have been a few controversial reports, however, they 270 271 needed to be critically appraised because of methodological considerations. Duployez et al. showed a higher prevalence of CHIP in severe COVID-19 patients than age-matched 272 273 hematologic malignancy-free cohort, but they could not show that CHIP affects clinical outcome<sup>24</sup>. However, they could only analyze severe patients whose clinical outcomes might 274 hardly be differentiated by solely the presence of CHIP. In another study conducted by 275 Hameister et al. involving 102 hospitalized patients with COVID-19, the presence of CHIP 276 was not associated with severe COVID-19<sup>25</sup>. But the study lacked a stratified analysis or an 277 adjustment for possible interactions. By introducing a hierarchical clustering, followed by 278 thorough statistical examinations including interaction analysis, we could clearly show that 279 CHIP is an independent risk factor for severe COVID-19. 280

281 COVID-19 patients were reported to show heterogeneous symptoms ranging from asymptomatic to critical illness<sup>3,44</sup>. In line with it, many studies divided COVID-19 patients 282 into subgroups defined by immunological characteristics, for instance, patterns of sepsis<sup>45</sup>, 283 subpopulations of lymphocytes<sup>44</sup>, IFN responses in lung<sup>46</sup>, or carrying loss-of-function 284 variants<sup>47</sup>. Single-cell techniques have been vigorously applied in COVID-19 to dissect 285 underlying causes of the diverse immune responses<sup>33,48,49</sup> and to elaborately determine the 286 relationship between immune subtypes and clinical characteristics<sup>50,51</sup>. Despite those important 287 288 works, none of the single-cell study has characterized the immunological effects of CHIP in COVID-19 yet. In this regard, the current study uniquely demonstrated how CHIP-associated 289 somatic mutations in immune cells could actively establish a novel subgroup in COVID-19 290 291 patients. With single-cell immune transcriptome analysis, we could reveal that IFN-y related hyperinflammation is a hallmark of CHIP (+) severe COVID-19. Especially, there was an 292 enrichment of inflammatory signature in classical monocytes, which is compatible with recent 293 knowledge regarding the effect of CHIP on myeloid askew hematopoietic stem cell 294 differentiation<sup>27</sup>. From a cytokine perspective, IFN- $\gamma$  and its synergism with TNF- $\alpha$  were 295 296 thought to play a critical role in the pathogenesis of severe COVID-19 in CHIP (+) patients. This finding aligns with the previous report stating the role of IFN- $\gamma$  and/or TNF- $\alpha$  in 297 exacerbating chronic inflammatory disease by CHIP<sup>52</sup>. Our study also implies that not only 298 299 type I IFN response but also type II IFN response plays an important role in disease exacerbation in certain patients with severe COVID-19. Additional interesting immunological 300 finding reasonably explained with the CHIP biology is the up-regulation of genes related to 301 302 inflammatory macrophage in CHIP (+) severe COVID-19. CHIP is well known to drive 303 hyperinflammation in chronic disease mainly attributable to the altered function of monocyte and macrophage <sup>27</sup>. 304

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Recent studies have revealed the pathological effects of CHIP such as atherosclerosis

and malignancy<sup>18,53,54</sup> and characterized the effect of CHIP mutations on hematopoiesis and 306 immunological functions regarding epigenetic mechanisms<sup>55,56</sup>. However, there is still an 307 ambiguity in how physiological pathogenic characteristics are linked to the altered chromatin 308 activities by CHIP mutations in actual patient cohorts. In our study, such linkage is explained 309 310 as regulatory interactions between pathogenic genes and their *cis*-regulatory elements with the altered chromatin states, which are expected to be mediated by mutations in chromatin 311 regulators (Fig. 7). Although further investigation of other types of CHIP mutations such as 312 313 TET2 and ASXL1 are required to comprehensively characterize CHIP mutation-dependent epigenetic reprogramming, the pathogenesis of other CHIP-dependent diseases could be 314 elucidated by considering the similar mechanisms. 315

316 There are several limitations in the present study. First, sample sizes of either entire cohort or scRNA-seq-analyzed patients were limited. Second, the proportion of severe COVID-317 318 19 was high in the present study since it was conducted mainly in tertiary-care hospitals. Although we could show an apparent incline to severe COVID-19 in CHIP (+) patients and its 319 distinctive immune signature in this study, further validations in a larger prospective cohort 320 representing general COVID-19 patients are warranted. Third, scRNA-seq was performed with 321 PBMCs instead of lung fluid or infected lung tissues limiting our analysis in exploring systemic 322 323 inflammation as a result of COVID-19 pulmonary disease. Lastly, further studies are needed to reveal the exact epigenetic differences between mutant and wild type monocytes in CHIP 324 patients and the real time point when CHIP mutant monocytes stir hyperinflammation. 325

Lastly, in terms of therapeutic strategy, Syk inhibitors have been implicated in suppressing these pathogenic immune responses (Extended Data Fig. 5b) induced by CHIP. An *in vitro* study on Syk inhibitor fostamatinib suggested its therapeutic effect against COVID-19<sup>57</sup>, and we have pending results of a randomized placebo-controlled trial with the drug

(NCT04579393). As the therapeutic efficacy of Syk inhibitors could be more potent in CHIP
(+) patients, it is worth evaluating treatment outcomes involving Syk inhibitors according to
CHIP status.

In summary, despite such limitations, we successfully clarified that there is a distinct 333 CHIP-driven severe COVID-19 subgroup and elucidated its unique immunological mechanism. 334 Revealing the underlying epigenetic mechanism for the altered immune function that aligns 335 with well-known CHIP biology suggests the robustness of our findings. It appears that classical 336 monocytes in patients with CHIP (+) COVID-19 undergo distinct immune responses, thus 337 focusing on immunomodulation strategies according to the presence of CHIP is required. 338 Considering the shared pathogenic host immune response across infections, we postulate that 339 340 our findings might bring a better understanding of previously unexplained exacerbation of clinical conditions by various viruses. 341

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#### 351 Author Contribution

- 352 CKK, BC, YK, and IJ conceived the study. SP generated scRNA-seq data. AJL and YK
- 353 generated Hi-C data. CKK, BC, SK, SHY, DL, and SK performed data analysis. CKK, EC,
- JJ, PGC, WBP, ESK, HBK, NJK, MO, SK, HI, JK, YHL, JL, JYL, JHM, and K-HS
- 355 contributed to the collection of clinical information and samples. CKK, BC, YK, and IJ
- 356 contributed to data interpretation with assistant from SK and KK. CKK and BC prepared the
- 357 manuscript with assistance from YK and IJ. All authors read and commented on the
- 358 manuscript.
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#### 362 **References**

363	1.	World Health Organization. Novel Coronavirus (2019-nCoV) situation reports. (2020).
364	2.	Zhu, N., et al. A Novel Coronavirus from Patients with Pneumonia in China, 2019. N Engl J
365		Med <b>382</b> , 727-733 (2020).
366	3.	Wu, Z. & McGoogan, J.M. Characteristics of and Important Lessons From the Coronavirus
367		Disease 2019 (COVID-19) Outbreak in China: Summary of a Report of 72314 Cases From
368		the Chinese Center for Disease Control and Prevention. JAMA 323, 1239-1242 (2020).
369	4.	Cunningham, J.W., et al. Clinical Outcomes in Young US Adults Hospitalized With COVID-19.
370		JAMA Intern Med (2020).
371	5.	Williamson, E.J., et al. Factors associated with COVID-19-related death using OpenSAFELY.
372		<i>Nature</i> <b>584</b> , 430-436 (2020).
373	6.	Zhang, S.Y., Zhang, Q., Casanova, J.L., Su, H.C. & Team, C. Severe COVID-19 in the young and
374		healthy: monogenic inborn errors of immunity? Nat Rev Immunol 20, 455-456 (2020).
375	7.	Zhou, C., et al. Predictive factors of severe coronavirus disease 2019 in previously healthy
376		young adults: a single-center, retrospective study. <i>Respir Res</i> <b>21</b> , 157 (2020).
377	8.	Huang, C., et al. Clinical features of patients infected with 2019 novel coronavirus in Wuhan,
378		China. <i>Lancet</i> <b>395</b> , 497-506 (2020).
379	9.	Yang, X., et al. Clinical course and outcomes of critically ill patients with SARS-CoV-2
380		pneumonia in Wuhan, China: a single-centered, retrospective, observational study. Lancet
381		Respir Med (2020).
382	10.	Liu, Y., et al. Viral dynamics in mild and severe cases of COVID-19. Lancet Infect Dis (2020).
383	11.	Zou, L., et al. SARS-CoV-2 Viral Load in Upper Respiratory Specimens of Infected Patients.
384		N Engl J Med (2020).
385	12.	Mehta, P., et al. COVID-19: consider cytokine storm syndromes and immunosuppression.
386		<i>Lancet</i> <b>395</b> , 1033-1034 (2020).
387	13.	Kang, C.K., et al. Aberrant hyperactivation of cytotoxic T-cell as a potential determinant of
388		COVID-19 severity. Int J Infect Dis 97, 313-321 (2020).
389	14.	Xu, Z., et al. Pathological findings of COVID-19 associated with acute respiratory distress
390		syndrome. <i>Lancet Respir Med</i> <b>8</b> , 420-422 (2020).
391	15.	Merad, M. & Martin, J.C. Pathological inflammation in patients with COVID-19: a key role
392		for monocytes and macrophages. Nat Rev Immunol <b>20</b> , 355-362 (2020).
393	16.	Steensma, D.P., et al. Clonal hematopoiesis of indeterminate potential and its distinction
394		from myelodysplastic syndromes. <i>Blood</i> <b>126</b> , 9-16 (2015).
395	17.	Rodrigues, C.P., Shvedunova M., Akhtar A. Epigenetic Regulators as the Gatekeepers of
396		Hematopoiesis. Trends in Genetics 37(2021).
397	18.	Jaiswal, S., et al. Clonal Hematopoiesis and Risk of Atherosclerotic Cardiovascular Disease. N
398		Engl J Med <b>377</b> , 111-121 (2017).
399	19.	Sano, S., et al. CRISPR-Mediated Gene Editing to Assess the Roles of Tet2 and Dnmt3a in

400 Clonal Hematopoiesis and Cardiovascular Disease. *Circ Res* **123**, 335-341 (2018).

- 40120.Yura, Y., Sano, S. & Walsh, K. Clonal Hematopoiesis: A New Step Linking Inflammation to402Heart Failure. JACC Basic Transl Sci 5, 196-207 (2020).
- 403 21. Jaiswal, S. & Libby, P. Clonal haematopoiesis: connecting ageing and inflammation in
  404 cardiovascular disease. *Nat Rev Cardiol* **17**, 137-144 (2020).
- Zekavat, S.M., *et al.* Hematopoietic mosaic chromosomal alterations increase the risk for
  diverse types of infection. *Nat Med* 27, 1012-1024 (2021).
- 40723.Bolton, K.L., *et al.* Clonal hematopoiesis is associated with risk of severe Covid-19. *medRxiv*408(2020).
- 409 24. Duployez, N., *et al.* Clinico-Biological Features and Clonal Hematopoiesis in Patients with
  410 Severe COVID-19. *Cancers (Basel)* 12(2020).
- 411 25. Hameister, E., *et al.* Clonal Hematopoiesis in Hospitalized Elderly Patients With COVID-19.
  412 *Hemasphere* 4, e453 (2020).
- 413 26. Lee, J.S., *et al.* Immunophenotyping of COVID-19 and influenza highlights the role of type I
  414 interferons in development of severe COVID-19. *Sci Immunol* 5(2020).
- 415 27. Jaiswal, S. & Ebert, B.L. Clonal hematopoiesis in human aging and disease. *Science* **366**(2019).
- 416 28. Finak, G., *et al.* MAST: a flexible statistical framework for assessing transcriptional changes
  417 and characterizing heterogeneity in single-cell RNA sequencing data. *Genome Biol* 16, 278
  418 (2015).
- 419 29. Duan, Q., *et al.* LINCS Canvas Browser: interactive web app to query, browse and interrogate
  420 LINCS L1000 gene expression signatures. *Nucleic Acids Res* 42, W449-460 (2014).
- 421 30. Angioni, R., *et al.* Age-severity matched cytokine profiling reveals specific signatures in
  422 Covid-19 patients. *Cell Death Dis* **11**, 957 (2020).
- 423 31. Park, S.H., *et al.* Type I interferons and the cytokine TNF cooperatively reprogram the
  424 macrophage epigenome to promote inflammatory activation. *Nat Immunol* **18**, 1104-1116
  425 (2017).
- 426 32. Lucas, C., *et al.* Longitudinal analyses reveal immunological misfiring in severe COVID-19.
  427 *Nature* 584, 463-469 (2020).
- 428 33. Chua, R.L., *et al.* COVID-19 severity correlates with airway epithelium-immune cell
  429 interactions identified by single-cell analysis. *Nat Biotechnol* **38**, 970-979 (2020).
- 430 34. Karki, R., *et al.* Synergism of TNF-alpha and IFN-gamma Triggers Inflammatory Cell Death,
  431 Tissue Damage, and Mortality in SARS-CoV-2 Infection and Cytokine Shock Syndromes. *Cell*432 **184**, 149-168 e117 (2021).
- 433 35. Zhang, F., *et al.* IFN-gamma and TNF-alpha drive a CXCL10+ CCL2+ macrophage phenotype
  434 expanded in severe COVID-19 lungs and inflammatory diseases with tissue inflammation.
  435 *Genome Med* 13, 64 (2021).
- 436 36. Kang, K., *et al.* IFN-γ selectively suppresses a subset of TLR4-activated genes and enhancers
  437 to potentiate macrophage activation. *Nat Commun* **10**, 3320 (2019).
- 438 37. Carvalho K., R.E., Jansen C., Williams K., Dowey A., McGill C., Mortazavi A. Uncovering the

439		Gene Regulatory Networks Underlying Macrophage Polarization Through Comparative
440		Analysis of Bulk and Single-Cell Data. <i>bioRxiv</i> (2021).
441	38.	Liu, S., et al. Critical role of Syk-dependent STAT1 activation in innate antiviral immunity. Cell
442		<i>Rep</i> <b>34</b> , 108627 (2021).
443	39.	Li, S., et al. Distinct evolution and dynamics of epigenetic and genetic heterogeneity in acute
444		myeloid leukemia. <i>Nat Med</i> <b>22</b> , 792-799 (2016).
445	40.	Jung, I., et al. A compendium of promoter-centered long-range chromatin interactions in
446		the human genome. <i>Nat Genet</i> <b>51</b> , 1442-1449 (2019).
447	41.	Kim, K. & Jung, I. covNorm: An R package for coverage based normalization of Hi-C and
448		capture Hi-C data. <i>Comput Struct Biotechnol J</i> <b>19</b> , 3149-3159 (2021).
449	42.	Zhang, J., et al. An integrative ENCODE resource for cancer genomics. Nat Commun 11,
450		3696 (2020).
451	43.	Consortium, E.P. An integrated encyclopedia of DNA elements in the human genome. Nature
452		<b>489</b> , 57-74 (2012).
453	44.	Mathew, D., et al. Deep immune profiling of COVID-19 patients reveals distinct immunotypes
454		with therapeutic implications. Science 369(2020).
455	45.	Giamarellos-Bourboulis, E.J., et al. Complex Immune Dysregulation in COVID-19 Patients with
456		Severe Respiratory Failure. Cell Host Microbe 27, 992-1000 e1003 (2020).
457	46.	Nienhold, R., et al. Two distinct immunopathological profiles in autopsy lungs of COVID-19.
458		<i>Nat Commun</i> <b>11</b> , 5086 (2020).
459	47.	Zhang, Q., et al. Inborn errors of type I IFN immunity in patients with life-threatening COVID-
460		19. <i>Science</i> <b>370</b> (2020).
461	48.	Liao, M., et al. Single-cell landscape of bronchoalveolar immune cells in patients with COVID-
462		19. <i>Nat Med</i> <b>26</b> , 842-844 (2020).
463	49.	Wilk, A.J., et al. A single-cell atlas of the peripheral immune response in patients with severe
464		COVID-19. <i>Nat Med</i> <b>26</b> , 1070-1076 (2020).
465	50.	Ren, X., et al. COVID-19 immune features revealed by a large-scale single-cell transcriptome
466		atlas. <i>Cell</i> <b>184</b> , 1895-1913 e1819 (2021).
467	51.	Stephenson, E., et al. Single-cell multi-omics analysis of the immune response in COVID-19.
468		<i>Nat Med</i> <b>27</b> , 904-916 (2021).
469	52.	Zhang, C.R.C., et al. Inflammatory cytokines promote clonal hematopoiesis with specific
470		mutations in ulcerative colitis patients. Exp Hematol 80, 36-41 e33 (2019).
471	53.	Jaiswal, S., et al. Age-related clonal hematopoiesis associated with adverse outcomes. N Engl
472		<i>J Med</i> <b>371</b> , 2488-2498 (2014).
473	54.	Libby, P., et al. Clonal Hematopoiesis: Crossroads of Aging, Cardiovascular Disease, and
474		Cancer: JACC Review Topic of the Week. J Am Coll Cardiol 74, 567-577 (2019).
475	55.	Izzo, F., et al. DNA methylation disruption reshapes the hematopoietic differentiation
476		landscape. <i>Nat Genet</i> <b>52</b> , 378-387 (2020).
477	56.	Zhang, Q., et al. Tet2 is required to resolve inflammation by recruiting Hdac2 to specifically

478 repress IL-6. *Nature* **525**, 389-393 (2015).

479 57. Strich, J.R., *et al.* Fostamatinib Inhibits Neutrophils Extracellular Traps Induced by COVID-19
480 Patient Plasma: A Potential Therapeutic. *J Infect Dis* 223, 981-984 (2021).

481

#### 482 Figure Legends

### 483 Figure 1. Hierarchical clustering analysis for clinical characteristics of severe COVID484 19

**a**, Overview of study design. **b**, A heatmap shows the hierarchical clustering result of clinical 485 486 characteristics. On the top, three different bars represent clusters and the presence of CHIP mutations for each patient. The first bar represents two main clusters of patients (n=69 for 487 cluster A and n=74 for cluster B). The second bar represents five sub-clusters of patients 488 (n=32 for A1, n=18 for A2, n=19 for A3, n=47 for B1, and n=26 for B2). The third bar 489 represents the presence of CHIP. c, Boxplots showing clinical characteristics between cluster 490 A (orange) and B (green). For the boxplots, the box represents the interquartile range (IQR) 491 and the whiskers correspond to the highest and lowest points within  $1.5 \times IQR$ . Statistical 492 significance was examined with unpaired t-test (\* < p-value 0.05, \*\* < p-value 0.01, and \*\*\* 493 < p-value 0.001). d, Barplots showing fractions of patients with comorbidities or CHIP for 494 cluster A1, A2, and A3. HTN stands for hypertension. DM stands for diabetes mellitus. 495 496

#### 497 Figure 2. Single-cell transcriptome analyses of COVID-19 according to CHIP status

a, Scatter plots of integrated scRNA-seq data represented with a t-SNE method. Left, immunes 498 cells are presented according to the presence of CHIP. Others group indicates CHIP (-) COVID-499 500 19 mild, influenza, and healthy normal control groups. Right, nine immune cell types were plotted by a t-SNE method. **b**, A PCA analysis with transcriptome profiles according to the 501 502 immune cell types and disease groups. Colors and shapes represent the respective disease groups or cell types. c, A scatter plot showing combined scores of LINCS L1000 Ligand 503 Perturbations up gene ontology library between CHIP (+) severe COVID-19 and CHIP (-) 504 severe COVID-19 compared to the healthy normal control. Identity lines are presented on 505 diagonal. Square of correlation of combined scores is shown together. d-g, Scatter plots 506

showing combined scores same gene ontology library in Fig. 2c for differentially expressed genes between CHIP (+) and CHIP (-) severe COVID-19 in classical monocyte (d), CD4+ T cell (e), non-classical monocyte (f), and IgG + B cell (g). The horizontal axis, up-regulated genes in CHIP (+); Vertical axis, up-regulated genes in CHIP (-). Identity lines are presented on diagonal. The color indicates types of perturbed ligand.

512

#### 513 Figure 3. CHIP specific immune signatures in classical monocytes

514 a, Barplots showing combined scores of DEGs in classical monocytes between CHIP (+) and CHIP (-) severe COVID-19 for same gene ontology library in Fig. 2c-g. The color indicates 515 up-regulated genes in CHIP (+) (green) and CHIP (-) (blue). Each point indicates one ligand 516 perturbation term in the library, in total 6 different types of ligands: IFN- $\alpha$  (n=5), IL-1 $\beta$  (n=6), 517 518 IFN- $\gamma$  (n=6), IL-17 (n=2), IL-6 (n=2), TNF- $\alpha$  (n=6). The mean and standard error of the mean (s.e.m) of each gene set are shown together. One-sided Mann-Whitney's U test was performed 519 (\*: P<0.05, \*\*: P<0.01). **b**, Barplots showing combined scores of same gene sets in Fig. 3a for 520 521 Ligand Perturbations from GEO up gene ontology library. The color indicates up-regulated 522 genes of CHIP (+) (pink) and CHIP (-) (yellow). c, Gene set enrichment analysis (GSEA) on the same DEGs used in Fig. 3a-b for three classes of TLR induced genes<sup>31</sup>. Each plot shows 523 524 the distribution of enrichment of distinct class genes along with the list of the DEGs pre-ranked with log-fold changes based on the CHIP (-) severe COVID-19. The color under the plot 525 indicates patient groups of up-regulated genes. Red, up-regulated in CHIP (+) severe COVID-526 19. Blue, up-regulated in CHIP (-) severe COVID-19. Normalized enrichment scores (NES) 527 and FDR are shown together. Top, Class I genes. Middle, Class II genes. Bottom, Class III 528 529 genes.

530

#### 531 Figure 4. Pseudotime analyses of severe COVID-19 with CHIP in classical monocytes

a-c, Pseudotime analyses for CHIP (+) or CHIP (-) severe COVID-19 patients. a, Cells are 532 aligned according to the pseudotime axis calculated by Monocle2. The color indicates a type 533 of cluster. Top, CHIP (+) patient. Bottom, CHIP (-) patient. b, Heatmaps representing the 534 expression level of marker genes for the ordered cells. The list of genes is the representative 535 gene set of each cluster. Barplots showing combined scores of each cluster for inflammatory 536 response term in MsigDB Hallmark 2020. c, Scatter plots of combined scores of marker genes 537 538 of inflammation clusters for LINCS L1000 Ligand Perturbations up gene ontology library. The horizontal axis, high inflammation cluster; the vertical axis, low inflammation cluster. Identity 539 lines are presented on diagonal. Colors indicate types of perturbed ligand for IFN- $\alpha$  (n=5), IL-540  $1\beta$  (n=6), IFN-  $\gamma$  (n=6), IL-17 (n=2), IL-6 (n=2), TNF- $\alpha$  (n=6). Shapes represent the presence 541 or absence of CHIP. d, e, GSEA plots for marker genes of inflammation clusters in CHIP (+) 542 and CHIP (-), respectively. Genes are ordered based on log-fold changes between high 543 inflammation cluster and low inflammation cluster. Normalized enrichment scores (NES) and 544 FDR are presented for DEGs between M1-like (LPS-IFN-γ stimulated) and M0 macrophage 545 (untreated)  $^{36}$ (d) and DEGs between TNF- $\alpha$ -IFN- $\gamma$  co-treatment and untreated condition  $^{35}$  (e), 546 547 respectively. LPS indicates Lipopolysaccharide.

548

#### 549 Figure 5. Regulatory potential of CHIP-specific hypo-DMRs in IFN response genes

a, Stacked bar plots showing the proportion of annotated hypo- and hyper-DMRs. In DMR,

551 Proximal to the promoter, n=1124; Distal regulatory element, n=423; others, n=801. In

- random for DMR, Proximal to promoter, n=314; Distal regulatory element, n=81; others,
- 553 n=1953. **b**, Examples of CHIP (+) up-regulated genes are presented with hypo-DMRs and
- multiple histone modification signatures for *FOXO3* (right) and *NFIL3* (left). **c**, Examples of

555 analysis of Hi-C data. Whole interaction map of chromosome 4 in 40kb resolution. The color indicates normalized chromatin contact frequencies. Two example regions containing CHIP 556 (+) severe COVID-19 up-regulated genes in classical monocytes (region 1 and region 2) are 557 highlighted by yellow dashed lines. d, Hi-C contact maps (heatmap) for region 1 (RBPJ) and 558 region 2 (CXCL2) are shown together with significant long-range chromatin interactions with 559 the promoter regions (arcs on the below of the heatmap) and distribution of hypo-DMRs and 560 histone modifications signals. e, A pie chart showing proportions of hypo-DMR linked up-561 562 regulated genes in CHIP (+) severe COVID-19 classical monocytes. The color indicates the types of linkage between hypo-DMRs and up-regulated genes. f, g, Barplots of relative 563 combined scores to TNF- $\alpha$  of genes linked to hypo-DMRs and others for same gene ontology 564 565 library in Fig. 2c-g. Colors indicate types of perturbed ligands. Each point indicates one ligand perturbation term. The mean and standard error of the mean (s.e.m) of each gene set 566 are presented in barplot. One-sided Mann-Whitney's U test was performed (n.s: non-567 significant, \*\*: P < 0.01). Up-regulated genes in CHIP (+) compared to CHIP (-) (f) and 568 marker gens of high inflammation cluster compared to low inflammation cluster of CHIP (+) 569 570 patient in Fig. 4 (g).

571

### 572 Figure 6. Chromatic states of hypo-DMRs linking to CHIP specifically up-regulated 573 genes

**a, b,** CHIP-seq signal distribution (a for H3K27ac and b for H3K27me3) of 20k upstream and downstream surrounding of hypo-DMRs (n=1,693), hyper-DMRs (n=655) and randomly selected regions. Each randomly selected regions have the same distribution of chromosome number and length of hypo- and hyper-DMR, respectively. Top, average ChIP-seq signal distributions. Bottom, heatmaps of CHIP-seq signals of the corresponding regions. **c, d,** CHIP-

seq signal distribution for CHIP (+) up-regulated genes linked (n=209) and unliked (n=1484) hypo-DMRs for H3K4me1 (c) and H3K4me3 (d). Top, average profiles of CHIP-seq signals for linked and unlinked hypo-DMRs. Bottom, heatmaps of CHIP-seq signals of the corresponding regions. e, f, Stacked barplots of the linked and unlinked hypo-DMRs with annotation of chromatin states. For statistical significance, one-sided Fisher's exact test was performed between linked and unlinked for promoter-distal (e) or -proximal (f) hypo-DMRs.

585

### Figure 7. A proposed model for the pathogenesis of severe COVID-19 in patients with CHIP

A schematic overview shows the progression of disease exacerbation in terms of gene regulation, cellular level, and clinical/immunological signatures under CHIP (+) severe COVID-19.

### 591 Extended Data Figure 1. A heatmap showing hierarchical clustering of severe COVID-19 592 patients with comorbidities and CHIP.

The first bar represents two clusters, cyan for non-CHIP enriched (n=65), and orange for CHIP enriched one (n=25). The second bar represents five distinct types of sub-clusters, namely, red, for without comorbidity (n=19), orange for DM (n=9), green for HTN (n=26), purple for CHIP (n=13), and blue for complex (n=23). The color in the heatmap represents the presence of CHIP.

597

# 598 Extended Data Figure 2. Quality-control and cell-type annotation of single-cell RNA-seq 599 results

a, b, Scatter plots showing CHIP (+) patients' immune cells according to the UMI count and 600 other features. Percentage of the mitochondrial genes (a) and the number of detected genes (b). 601 602 c, Scatter plot of log 10-transformed count data between individual patients. R represents Pearson's correlation coefficient values. d, t-SNE clusters of integrated single-cell data. e, Each 603 cell type marker gene expression on t-SNE plot. f, Stacked barplots show cell-type proportions 604 of each patient group. g, Boxplots showing the ratio of the proportion of classical monocytes. 605 (left) All pairs within CHIP (+) patients (n=30). (right) all pairs between CHIP (+) and CHIP 606 (-) (n=18). The box represents the interquartile range (IQR) and the whiskers correspond to the 607 highest and lowest points within 1.5 × IQR. Two-sided Kolmogorov-Smirnov test were 608 performed (\*\* < p-value 0.01). 609

610

# Extended Data Figure 3. Analyses of differently expressed genes between CHIP (+) severe COVID-19 and other groups

613 a, Chow-ruskey venn diagram of the up-regulated genes in CHIP (+) severe COVID-19

614 compared to other disease groups. The color of the border in diagrams represents five immune cell types. Monocyte (red), classical monocyte and non-classical monocyte; natural killer T 615 616 cells (orange); CD4<sup>+</sup> T cell (green), CD4<sup>+</sup> T cell and CD4<sup>+</sup> naïve T cell; CD8<sup>+</sup> T cell (blue), CD8<sup>+</sup> T cell and CD8<sup>+</sup> memory T cells; B cell (purple), IgG<sup>+</sup> B cell and IgG<sup>-</sup> B cell. **b**, Barplots 617 showing combined scores for gene ontology terms in MsigDB Hallmark 2020 with up-618 regulated genes in CHIP(+) severe COVID-19. Top six terms were presented. The color 619 indicates normal or disease controls. c, Ratio of cell-type specific CHIP (+) severe COVID-19 620 up-regulated genes compared to total up-regulated genes for comparison with other disease 621 groups. The mean and standard error of the mean (s.e.m) of each gene set are presented in 622 barplots. The color indicates the type of disease group for comparison. 623

624

### Extended Data Figure 4. Enriched immune signatures in CHIP (+) and CHIP (-) severe COVID-19 up-regulated genes compared to healthy normal control

a-e, Scatter plots showing combined scores of differentially expressed genes (DEGs) in
selected cell types between severe COVID-19 patient groups for same gene ontology library in
Fig. 2c. The horizontal axis, up-regulated genes in CHIP (+) patients; the vertical axis, upregulated genes in CHIP (-) patients. Identity lines are presented on diagonal. The color
indicates types of perturbed ligand in database terms. a, CD8+ T cell. b, CD8+ memory T cell.
c, IgG- B cell. d, CD4+ naive T cell. e, Natural killer T cell.

633

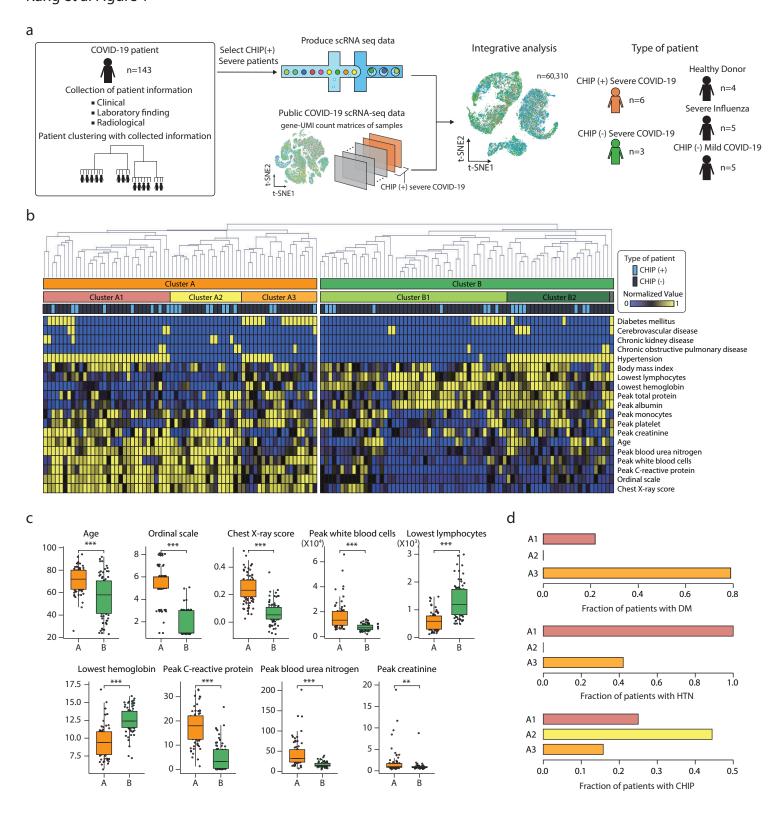
# Extended Data Figure 5. An inflammatory macrophage signature in CHIP (+) classical monocytes in severe COVID-19

636 a, GSEA plots for marker genes of inflammation clusters in CHIP (+) and CHIP (-), respectively. Genes are ordered based on log-fold changes between high inflammation cluster and low 637 inflammation cluster. Normalized enrichment scores (NES) and FDR are presented for DEGs 638 between M1-like and M0 macrophage<sup>37</sup>. **b**, the effect of SYK inhibitor to suppress CHIP (+) 639 up-regulated genes. Comparison between combined scores of marker genes of high 640 inflammation cluster for Kinase Perturbations from GEO down gene ontology library for 641 inhibitors or knock out of SYK kinase terms. One-sided Paired t-test was performed (\*: P< 642 643 0.05).

644

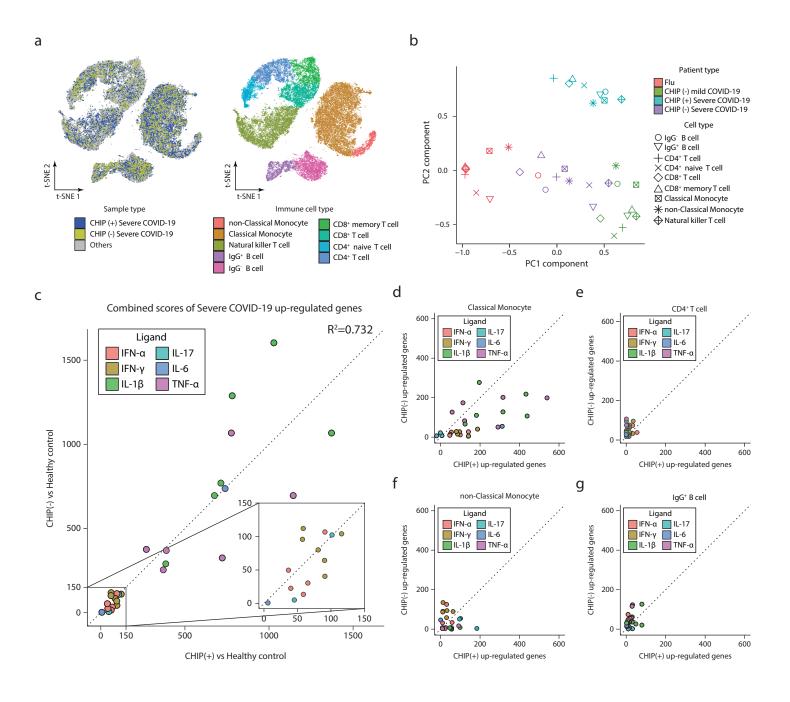
### Extended Data Figure 6. The distribution of the nearest distance between differently expressed gene promoters and DMRs

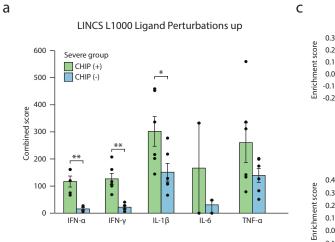
647 Boxplots of the nearest distance between differentially expressed genes (right: CHIP (+) upregulated genes, left: CHIP (-) up-regulated genes) and DMRs. Hypo-DMRs were randomly 648 649 selected to have the same sample size as hyper-DMRs. The box represents the interquartile 650 range (IQR) and the whiskers correspond to the highest and lowest points within  $1.5 \times IQR$ . The color indicates the types of DMRs. Distance is represented as the log scale, with a 10kb 651 resolution. For statistical significance test, two-sided Kolmogorov-Smirnov test were 652 653 performed between hypo- and hyper-methylated regions (P<0.001, CHIP (+); P=3.46e-3, CHIP 654 (-)).



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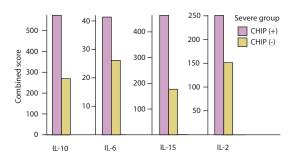
Kang et al Figure 2

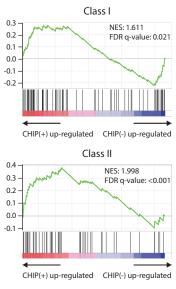




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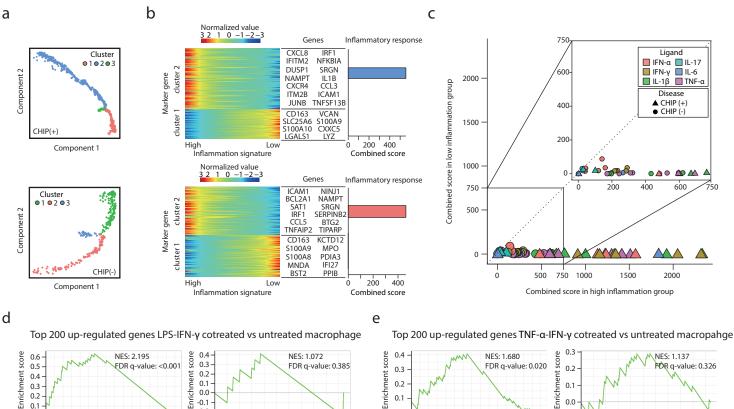


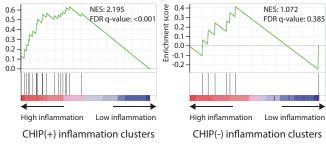


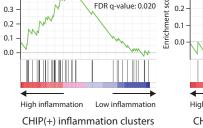
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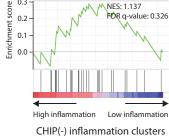
CHIP(+) up-regulated CHIP(-) up-regulated

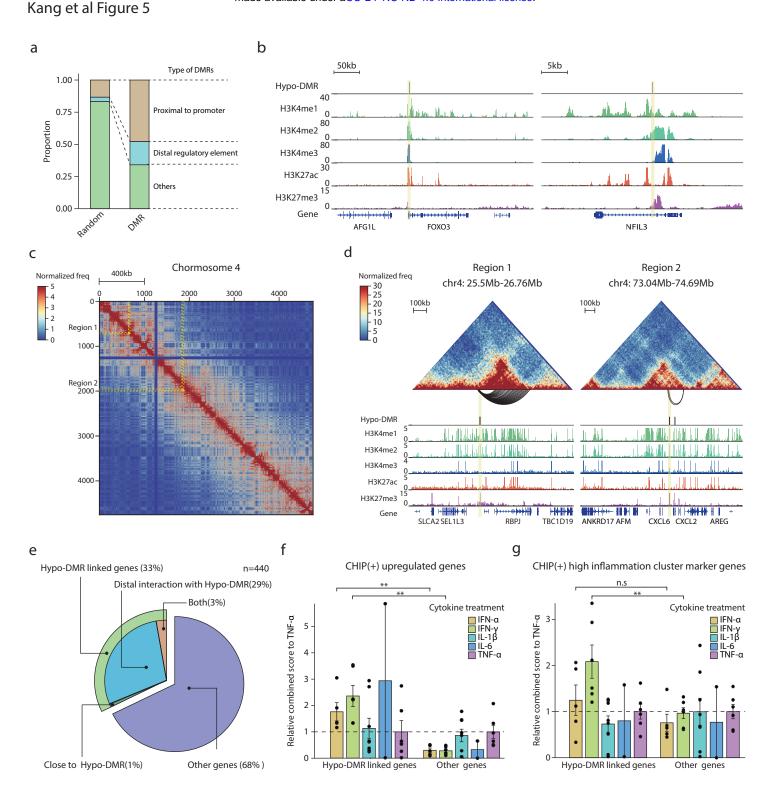
#### Kang et al Figure 4



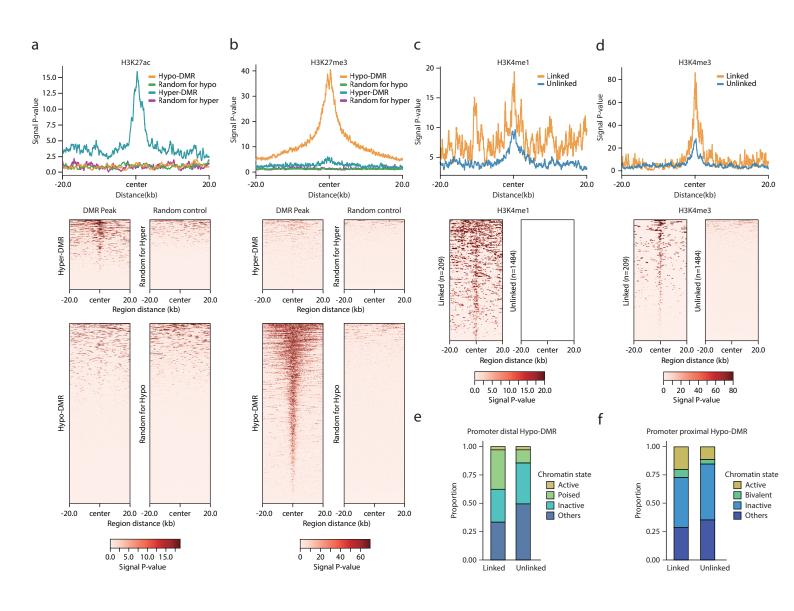




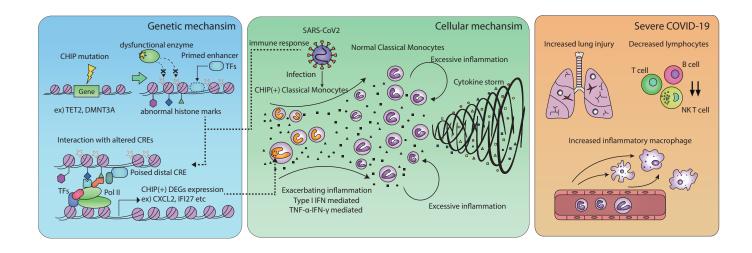


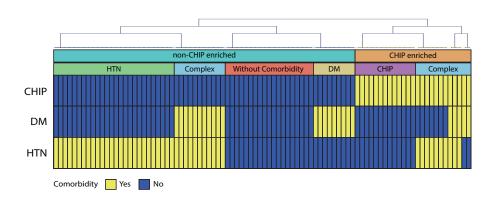


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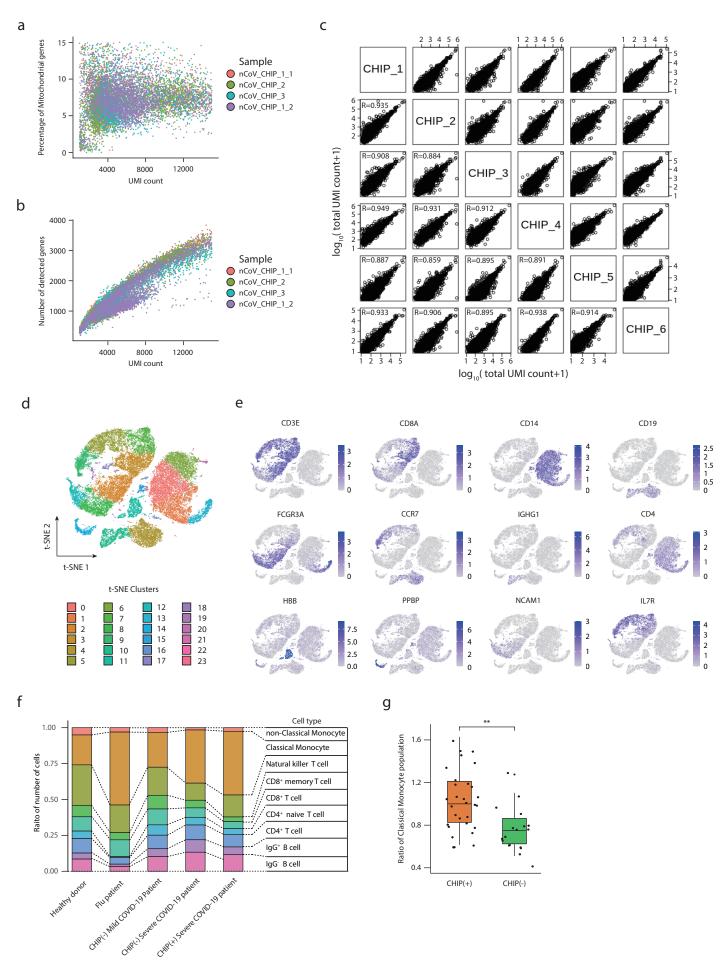


#### Kang et al Figure 7

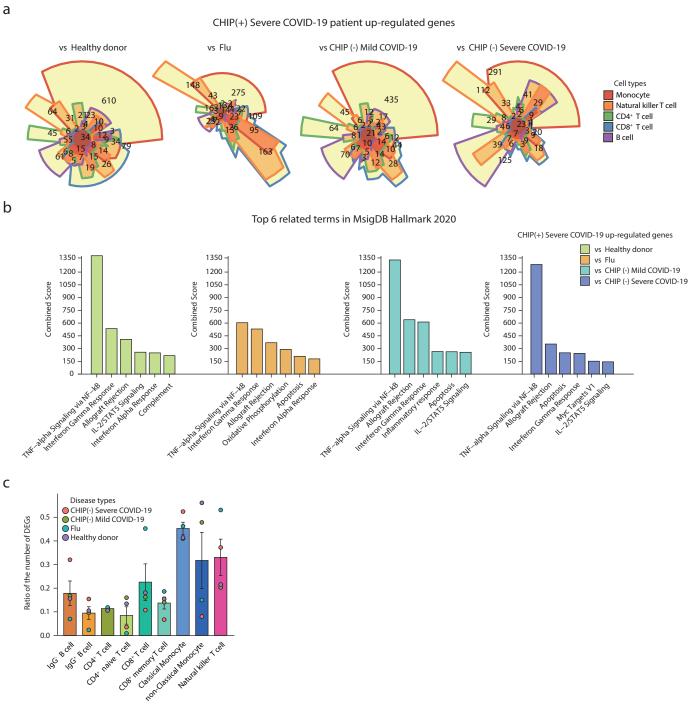




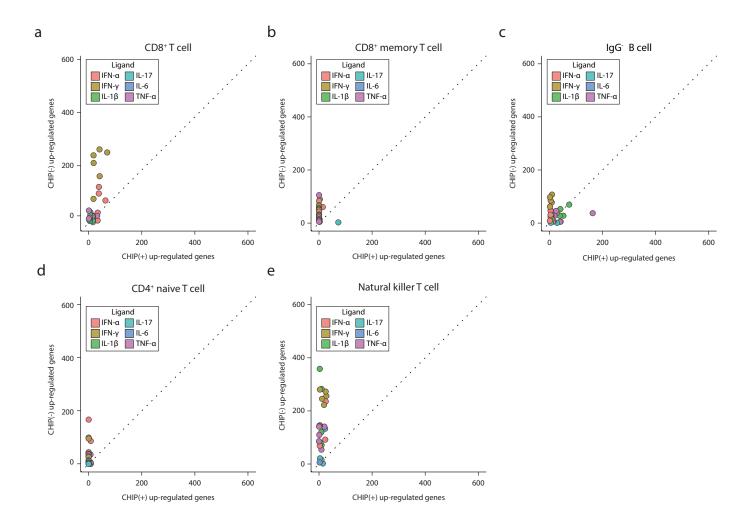
Kang et al Extended Data Fig 2



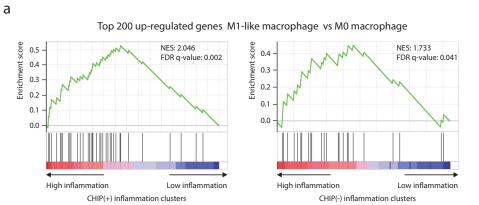
#### Kang et al Extended Data Fig 3



#### Kang et al Extended Data Fig 4

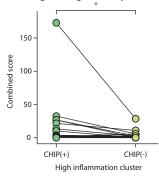


#### Kang et al Extended Data Fig 5

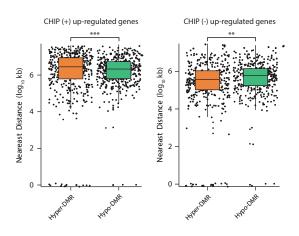


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Downregulated genes of syk inhibition



#### Kang et al Extended Data Fig 6



- 655 Tables
- Table 1. Age and gender-adjusted odds ratio of the presence of CHIP for severe COVID-
- 657 19 in canonical risk factors-stratified subgroups
- **Table 2. Final multivariate model for independent risk factors for severe COVID-19**
- 659 including interaction term between CHIP and canonical risk factors
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- 661 Supplementary Tables
- 662 Supplementary Table 1. Baseline characteristics of COVID-19 patients in this study
- 663 according to the presence or absence of clonal hematopoiesis of indeterminate potential
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#### Table 1. Age and gender-adjusted odds ratio of the presence of CHIP for severe COVID-

#### 677 **19 in canonical risk factors-stratified subgroups**

		Severe C	Severe COVID-19		
		CHIP (+)	CHIP (-)	aOR (95% CI)	Р
Canonical risk factor present		13/21 (61.9%)	47/68 (69.1%)	0.4 (0.1—1.4)	0.159
Canonic	al risk factor absent	12/13 (92.3%)	18/41 (43.9%)	14.8 (1.3—164.1)	0.023
Total		25/34 (73.5%)	65/109 (59.6%)	1.1 (0.4—2.8)	0.829
678	CHIP, clonal hematop	poiesis with indetermina	te potential; aOR, adj	usted odds ratio; CI,	
679	confidence interval				
680	Canonical risk factors	were BMI ≥ 30.0, diabe	tes mellitus, and hyperte	ension	
000			ines merinas, and nypera		
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#### 691 Table 2. Final multivariate model for independent risk factors for severe COVID-19

#### 692 including interaction term between CHIP and canonical risk factors

	aOR	Р
Age, per one year	1.1 (1.0—1.1)	< 0.001
Male gender	2.0 (0.9-4.5)	0.075
CHIP	10.7 (1.1—100.7)	0.038
Canonical risk factors	2.0 (0.8-5.0)	0.120
CHIP * conventional risk factors	0.0 (0.0-0.5)	0.012

693 CHIP, clonal hematopoiesis with indeterminate potential; aOR, adjusted odds ratio

694 Canonical risk factors were BMI  $\geq$  30.0, diabetes mellitus, and hypertension.

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