Multi-omics Reveals Immune Response and Metabolic Profiles during High-Altitude Mountaineering

Jianhua Yin[1,2,9], Jingzhi Lv[1,3,9], Shichen Yang[3,4,9], Yang Wang[3,4,9], Zhuoli Huang[1,3], Xue Wang[4], Guixue Hou[5], Wenwen Zhou[1], Ying Liu[1,3,4], Weikai Wang[1,3], Xiumei Lin[3,4], Yunting Huang[6], Yuhui Zheng[1,3], Chen Wei[1,3], Yue Yuan[1,4], Yaling Huang[1,4], Chang Liu[1,4], Haoran Tao[5], Huanhuan Liu[1], Ruquan Liu[1], Yan Zhang[1], Guodan Zeng[1], Peng Gao[2,5], Longqi Liu[1,2,3,4], Jun Cao[5,*], Chuanyu Liu[1,2,4,*], Xin Jin[1,2,7,*], Jian Wang[1,8*]

[1]BGI Research, Shenzhen 518103, China

[2]Shanxi Medical University - BGI Collaborative Center for Future Medicine, Shanxi Medical University, Taiyuan 030001, China

[3]College of Life Sciences, University of Chinese Academy of Sciences, Beijing 100049, China

[4]BGI Research, Hangzhou 310030, China

[5]BGI, Shenzhen 518083, China

[6]China National GeneBank, BGI Research, Shenzhen 518120, China

[7]School of Medicine, South China University of Technology, Guangzhou 510006, China

[8]James D. Watson Institute of Genome Sciences, Hangzhou 310058, China

[9]These authors contributed equally

*Correspondence: caojun@genomics.cn (J.C.); liuchuanyu@genomics.cn (C.L.); jinxin@genomics.cn (X.J.); wangjian@genomics.cn (J.W.)

SUMMARY

The physiological perturbations induced by high-altitude exposure in mountain climbers,

manifesting as metabolic and immunologic deviations, have been previously reported but are not

fully understood. In this study, we obtained longitudinal multi-omic profiles of blood samples for

healthy mountain climbers during two mountaineering stages (acclimatization and extreme

altitude mountaineering). Our integrative assay included metabolomics and lipidomics profiling of

plasma coupled with single-cell transcriptomic analysis of 375,722 immune cells. Longitudinal

analysis revealed dynamic immune response profiles, during the acclimatization period,

characterized by the downregulation of inflammatory responses in monocytes and classical

dendritic cells (cDCs) and an increase in the proportion of cytotoxic CD8$^+$ T cells with enhanced

immune effector processes. In contrast, during extreme altitude mountaineering, the activation of

inflammatory responses and impairment of T cell effector function were observed, concomitant

with an increased cellular response to hypoxia and oxidative stress pathways. Furthermore, we

found upregulated glycolysis and antioxidant gene expression during extreme altitude

mountaineering, which was primarily orchestrated by *HIF1A* and *NFE2L2*, while decreased

expression of these genes was observed in dysregulated plasmacytoid dendritic cells (pDCs).

Finally, high-resolution plasma metabolic analysis revealed significant alterations in the

metabolism of climbers, involving enhanced glutamine and fatty acid metabolism.

INTRODUCTION

High-altitude mountaineering, with the main objective of reaching a summit, is a challenging and potentially dangerous activity. Increased accessibility to high mountains has led to the growing popularity of mountaineering[1]. Mountain climbers are confronted with harsh environmental conditions upon exposure to high altitudes, among which the most crucial variable is hypoxia owing to the progressive decline in barometric pressure with increasing altitude[2]. Several physiological responses are initiated in climbers to adapt to reduced oxygen availability, such as enhanced ventilatory response, increased cardiac output, and improved tissue oxygen extraction[3]. The combination of hypoxia and intense physical activity may impose greater physiological and metabolic demands on mountain climbers[4]. Notably, mountain climbers are susceptible to a range of health issues, including altitude illness[3], body mass loss[5], immune dysfunction and increased vulnerability to infections[6]. Among them, immunological and metabolic outcomes are key mediators, but the underlying mechanisms remain incompletely characterized.

Moderate exercise is beneficial for immune function, while an excessive duration and intensity of exercise may lead to immunological impairment[7, 8]; therefore, it is crucial to understand the immune outcomes of different types of exercise. Previous studies have reported that low oxygen availability at high altitudes has a significant impact on the abundance and function of immune cells; specifically, it leads to the downregulated expression of innate immune-related genes[9], a reduction in the proportion of plasmacytoid dendritic cells (pDCs)[10], and a decrease in $CD3^+$ T lymphocytes[11]. Importantly, exercise at high altitudes may intensify the extent of hypoxia, further impeding immune function[4] and elevating the levels of inflammation and oxidative stress[12-14]. Notably, exercise has the potential to reprogram immune cell metabolism through alterations in oxygen availability, the regulation of cellular energy sensors, and the accumulation of immunometabolic regulators[4, 15]. Previous studies have assessed the metabolic activity of immune cells during high-altitude exercise by assessing metabolism-related parameters, including reactive oxygen species (ROS), mitochondrial activity, and intracellular calcium ions[16, 17]. These metabolic changes may subsequently impact the immune cell state and cell fate[18]. However, the underlying mechanism of the immune response to high-altitude mountaineering remains elusive. In addition, in a previous study, participants who ascended to high altitudes

exhibited substantial alterations in plasma metabolic molecules[19]. A comprehensive

characterization of both immune cells and plasma analytes from mountain climbers is needed to

fully understand the dynamic alterations in the immune response and plasma metabolites.

The emergence of single-cell RNA sequencing (scRNA-seq) has facilitated an in-depth

dissection of immune response changes driven by exercise and has been applied to exercise

immunology[20]. To elucidate the immune response and metabolic alterations during high-altitude

mountaineering, we performed multi-omics profiling, including targeted metabolomics and

lipidomics of plasma, as well as single-cell transcriptome analysis of circulating immune cells, on

each sample from eleven mountain climbers (Figure 1A). In this study, our longitudinal analysis

revealed dynamic immune responses at different stages of high-altitude mountaineering. In

particular, we identified a crucial immune adaptive response mediated by the transcription factors

(TFs) *HIF1A* and *NFE2L2* during extreme altitude mountaineering. Furthermore, substantial

alterations in plasma metabolites, including increased glutamine metabolism and fatty acid

metabolism, were also observed during high-altitude mountaineering. Overall, the results from this

study improve our understanding of the dynamic immune and metabolic landscapes elicited by

high-altitude mountaineering.

RESULTS

Effects of high altitude on physiological parameters in mountain climbers

This study was conducted during an expedition to the Muztagh Ata peak (7546 m) with the aim of

investigating the dynamic physiological, metabolic, and immune responses of mountain climbers

at high altitudes. Eleven climbers (8 males, 3 females) with a mean age of 37.4 ± 11.4 years and a

mean body mass index (BMI) of 23.60 ± 3.16 kg/m^2 were recruited (Table S1). After reaching

1289 m on D1, the mountaineering experimental plan consisted of two stages: the period of

acclimatization (D2-D8) and then the period of extreme altitude mountaineering (D9-D16) (Table

S1). A total of 10 physiological phenotypic indexes, including blood oxygen saturation (SpO$_2$),

heart rate (HR), Lake Louise score (LLS), body composition, and routine blood and ultrasensitive

C-reactive protein (CRP) tests, were assessed for eleven climbers (Figure 1A). Furthermore, 55

peripheral blood samples were collected longitudinally at five different time points of

mountaineering: D1 (altitude, 1289 m; SpO_2, 95%), performed in low altitudes as a baseline

control; D4 (altitude, 4400 m; SpO_2, 82%) and D9 (altitude, 5500 m; SpO_2, 72%), performed

following acclimatization to high altitudes of 4400 m and 5500 m; and D11 (altitude, 3200 m) and

D16 (altitude, 1289 m), performed after reaching extreme altitudes of 6300 m and 7546 m (Table

S1).

We first analyzed the variations in SpO_2 and HR during different stages of high-altitude

mountaineering. Overall, we observed a progressive decrease in the SpO_2 of climbers with

increasing altitude and a compensatory increase in the HR from 72 to 105 min^{-1}, with high

consistency among climbers (Figure 1B and S1A). When the mountain climbers were exposed to

extreme altitudes of 6,300 m and 6,900 m, the SpO_2 decreased to 72% and 69%, respectively.

However, in comparison to the initial exposure at 4400 m on D3, we observed a significant

increase in SpO_2 from 86% to 93% on D11 following acclimatization, accompanied by a notable

decrease in HR from 94 min^{-1} to 71 min^{-1}; such trends were also observed upon re-exposure to an

altitude of 5,500 m (Figure S1B). These data indicated that the mountain climbers may have

acclimatized to the reduced oxygen levels at very high altitudes (3,500-5,500 m) following the

acclimatization period (D2-D8). Next, we compared the changes in body composition

characteristics, including BMI, body fat percentage (BFP%), muscle mass (MM, kg) and fat mass

(FM, kg), and no significant changes were observed in these parameters (Figure S1C). In addition,

routine blood tests and CRP analysis were performed before (D1) and after (D16) the

mountaineering expedition (Figure 1A). The results showed a significant increase in the numbers

of neutrophils (NEUT) and monocytes (MONO) on D16 compared with those at baseline (D1)

(Figure 1C). Moreover, we detected a significant increase in the level of CRP (Figure 1C), a

marker of the inflammatory response, consistent with previous reports that long and arduous

trekking at high altitudes leads to an increase in the inflammatory response[5]. Notably, the

proportion of lymphocytes significantly decreased on D16 (Figure S2). In general, the

mountaineering expedition induced dynamic changes in multiple physiological phenotypes, which

initially confirmed the hypoxic state of mountain climbers at high altitudes and further reflected

the impact of high-altitude mountaineering on immune responses.

Multi-omics profiling of plasma and peripheral immune cells in mountain climbers

Whole blood samples were collected from eleven healthy volunteers at five different time points during mountaineering. Subsequently, the blood samples were separated: the upper plasma was subjected to metabolomic and lipidomic analyses, and the isolated immune cells were subjected to scRNA-seq analysis (Figure 1A). We analyzed the plasma metabolome and lipidome to obtain a global view of the body's metabolic status, and targeted analysis was performed via ultra-performance liquid chromatography-tandem mass spectrometry (UPLC-MS/MS). After data preprocessing, a total of 309 metabolites and 717 complex lipids were measured per sample, and the list containing all the metabolic analytes can be found in Table S2 and S3. Then, our focus shifted toward metabolites and lipids that were significantly affected by high-altitude mountaineering. The variable importance in projection (VIP) score was used to estimate the differentially abundant metabolites and lipids with the greatest variation in the data; ultimately, 348 significantly changed analytes were selected. Extensive perturbations of these molecules were observed at different time points (Figure 1D). Overall, the preliminary findings indicated that the metabolism of climbers underwent substantial alterations.

We next performed a single-cell transcriptomics analysis of circulating immune cells obtained from mountain climbers to comprehensively characterize the alterations in the immune response induced by mountaineering. After quality control, a total of 375,722 single cells were obtained with an average of 1,083 genes per cell (Figure S3A). The number of cells in each sample ranged from 48,686 to 100,271, and the number of cells at each time point ranged from 12,853 to 55,231 (Figure S3B). Then, uniform manifold approximation and projection (UMAP) for dimensionality reduction was employed, and we manually annotated cells based on the expression of classical markers (Figure S4A). In total, 15 major cell types were identified, namely, naive CD4$^+$ T cells, memory CD4$^+$ T cells, naive CD8$^+$ T cells, cytotoxic CD8$^+$ T cells, mucosal-associated invariant T (MAIT) cells, natural killer (NK) cells, proliferating T cells, naive B cells, memory B cells, plasma B cells, CD14$^+$ monocytes, CD16$^+$ monocytes, classical dendritic cells (cDCs), pDCs and platelets (Figure 1E). Next, we calculated changes in the relative proportions of these major cell subpopulations among the circulating immune cells at each time point. The proportion of naive CD4$^+$ T cells decreased significantly on D4, accompanied by a sustained increase in the proportion

of memory CD4$^+$ T cells on D11 and D16 (Figure 1F). In contrast, the abundance of NK cells

initially exhibited a significant increase on D4, followed by a gradual decrease (Figure 1F).

Several subpopulations also exhibited notable reductions at later time points, including the

proportion of CD14$^+$ monocytes on D11 and the proportions of cytotoxic CD8$^+$ T cells and pDCs

on D16 (Figure 1F, S4B-S4D). These results indicated that the composition of circulating immune

cells in mountain climbers significantly changed during high-altitude mountaineering.

Altered inflammatory response in monocytes and DCs

Previous studies have demonstrated that high-altitude mountaineering induces an increase in the

inflammatory response[12]. Considering the critical roles played by myeloid cells in inflammation,

we initially investigated their transcriptional alterations during mountaineering. All monocytes

and DCs were subclustered (n=33,577) and classified into nine subpopulations based on the

expression of classical marker genes, including three CD14$^+$ monocyte (CD14$^+$ Mono) subgroups:

FCN1$^+$ CD14$^+$ Monos, CCL3$^+$ CD14$^+$ Monos and IFN$^+$ CD14$^+$ Monos; three CD16$^+$ monocyte

(CD16$^+$ Mono) subgroups: IFN$^+$ CD16$^+$ Monos, CD16$^+$ Monos and C1$^+$ CD16$^+$ Monos; and three

DC subgroups: cDC1s, cDC2s and pDCs (Figure 2A and 2B). Remarkable alterations in the

relative proportions of these subgroups were observed: CCL3$^+$ CD14$^+$ Monos significantly

decreased on D4 and D9, followed by a subsequent recovery and significant expansion on D16,

and FCN1$^+$ CD14$^+$ Monos significantly decreased on D11 and D16 (Figure 2C). The proportion of

CD16$^+$ Monos significantly increased on D4 and D9, followed by a decreasing trend. Furthermore,

the proportion of cDC2s significantly increased on D11, while the proportion of pDCs

significantly decreased on D16 (Figure 2C, S5A and S5B).

To gain insight into the functional changes in different monocyte and DC subgroups during

mountaineering, we performed differentially expressed genes (DEGs) analysis (D1 was used as

the control group) (Table S4). Gene Ontology (GO) enrichment analysis of these DEGs revealed

significant enrichment in pathways related to innate immunity, cytokine production, cellular

chemotaxis, hypoxia and the inflammatory response in CCL3$^+$ CD14$^+$ Monos, FCN1$^+$ CD14$^+$

Monos, CD16$^+$ Monos and cDC2s (Figure S5C). We also performed pathway score analysis to

investigate the dynamic changes in key pathways in each myeloid cell subgroup during

mountaineering. The expression of genes involved in the innate immune response, inflammatory

response, NF-κB signaling and hypoxia pathway was downregulated on D4 and D9, followed by

significant upregulation on D11 and D16 in most myeloid cell subgroups, except for pDCs (Figure

2D). The expression of *S100A8* and *S100A9* in CCL3$^+$ CD14$^+$ Monos was significantly

upregulated on D4 and then downregulated (Figure 2E). *S100A8* and *S100A9* have been identified

as important endogenous damage-associated molecular pattern (DAMP) molecules, which are

early amplifiers of the innate immune response to danger signals[21]. Additionally, the expression

of multiple genes involved in inflammation were significantly downregulated on D4 and D9 but

upregulated on D11 and D16 in CCL3$^+$ CD14$^+$ Monos, CD16$^+$ Monos, cDC2s and FCN1$^+$ CD14$^+$

Monos, including cytokine-related genes (*TNF*, *CCL3* and *CCL4*); central transcription factors of

inflammatory response NF-κB subunits (*NFκB1* and *REL*); and inflammasome activation-

associated genes (*NLRP3* and *IL1B*) (Figure 2E and S5D). The activation of the NLRP3

inflammasome is triggered by a variety of upstream signals, including mitochondrial dysfunction,

metabolic changes and ROS[22]. These observations suggested that high-altitude mountaineering

induced dynamic changes in inflammatory responses.

Next, we analyzed the dynamic changes in TF regulon activity in monocytes and DCs at

different stages using single-cell regulatory network inference and clustering (SCENIC)[23]. The

regulon activities of multiple TFs, such as inflammation and stress-related TFs (*FOS*, *JUN*, *JUNB*,

FOSB, *CEBPD*, *BHLHE40*, *NFκB1*, *NFκB2* and *RELB*), decreased on D4 and D9 but increased on

D11 and D16 (Figure 2F). A positive correlation between the hypoxia score and inflammatory

response score was observed (Figure 2G), suggesting that hypoxia may be a key factor in

regulating and activating inflammatory responses during mountaineering. Notably, the expression

levels of genes related to the hypoxia pathway and *HIF1A* were significantly increased on D11

and D16 (Figure 2D and 2H). Hypoxia induces the upregulation of *HIF1A* expression, leading to

the activation of HIF signaling and increased transcription of *NF-κB,* which serves as a

downstream target of HIF[24], consistent with previous studies showing that *HIF1A* is essential

for regulating the inflammatory response in myeloid cells[25].

Dysregulation of pDCs in mountain climbers

The proportion of pDCs in mountain climbers exhibited a striking reduction on D16 (Figure 2C). pDCs can produce type I interferons (IFNs), secrete cytokines and chemokines, and capture and present antigens, thereby playing an important role in immunity to infections[26]. We investigated the changes in the molecular features of pDCs during high-altitude mountaineering, and DEGs and pathway enrichment analysis revealed that the downregulated DEGs were enriched mainly in the following pathways: 'viral process', 'antigen processing and presentation', 'response to unfolded protein', and 'oxidative phosphorylation' (Figure S6A). The downregulated DEGs during mountaineering mainly included the IFN-α regulatory genes *IRF4* and *IRF7*, antigen presentation-related human leukocyte antigen (HLA) class II genes (*CD74*, *HLA-DRB5*, *HLA-DRB1*, *HLA-DRA*, *HLA-DQB1*, *HLA-DRP1* and *HLA-DPA1*), and the chemokine receptors *CXCR3* and *CXCR4* (Figure S6B). *CXCR3* and *CXCR4* play essential roles in the migration of pDCs from peripheral blood to infection sites[26]. In addition, we found that multiple DEGs related to protein secretion, such as S*EC61B*, *LMAN2*, *SSR3*, and *PDIA6*, were markedly downregulated (Figure S6B). Therefore, the observed reduction in the proportion of pDCs accompanied by the decrease in the expression level of key genes suggested that pDCs may experience functional impairment during high-altitude mountaineering.

Next, we explored the changes in the regulon activity of TFs in pDCs using SCENIC. The regulon activities of multiple TFs, such as inflammation- and stress-related TFs (*JUND*, *FOS* and *KLF6*), the IFN-related TF *IRF7* and the unfolded protein response (UPR)-related TFs *XBP1* and *ATF4*, began to decrease on D9 (Figure S6C). *IRF7* is a major transcriptional regulator of the production of type I IFNs in pDCs. *XBP1* is essential for pDC development and survival, and a lack of *XBP1* markedly reduces the size of the pDC compartment[27]. It was speculated that hypoxia may be a negative regulator of pDCs, which is consistent with previous studies showing that the proportion of pDCs significantly decreased under hypoxic conditions[10, 28]. Marked downregulation of the hypoxia pathway was detected in pDCs during mountaineering (Figure 2D). In particular, compared with other monocytes and cDCs, pDCs showed lower expression of *HIF1A* on D11 and D16 (Figure 2H), and in vitro studies have shown the essential role of *HIF1A* in type I IFN production by DCs[29]. Taken together, our findings indicate that mountain climbers

may experience pDC dysregulation.

Dynamic characterization of T and NK cell subsets during high-altitude mountaineering

T cell- and NK-cell-mediated immunity is one of the core immune functions, and we explored

their functional changes during mountaineering. All CD8[+] T, CD4[+] T and NK cells were

subclustered and classified into 20 subpopulations based on the expression of classical marker

genes, including nine subgroups of CD8[+] T cells and nonclassical T cells (n=135,616): naive CD8[+]

T cells, CD8[+] effector memory T cells (CD8[+] Tems), CD8[+] central memory T cells (CD8[+] Tcms),

cytotoxic CD8[+] T cells, terminal effector-like CD8[+] T cells (TE-like CD8[+] T cells), $\gamma\delta$T cells,

MAIT cells, proliferating T cells and NK-like T cells (Figure 3A and 3B); six CD4[+] T cell

subgroups (n=79,847): naive CD4[+] T cells, IFN[+] CD4[+] T cells, CD4[+] central memory T cells

(CD4[+] Tcms), T helper 2 cells (Th2 cells), Th17-like T cells and CD4[+] regulatory T cells (Tregs)

(Figure S7A and S7B); and five NK cell subgroups (n=69,673): CD56[+] NK cells, active CD16[+]

NK cells, CD16[+] NK cells, ZEB2[+] NK cells and type 1 innate lymphoid cells (ILC1s) (Figure S7C

and S7D). The abundances of the T and NK cell subgroups exhibited significant alterations during

different periods of mountaineering (Figure 3C and S8A-S8D). The proportion of Tregs, the major

suppressors of immune responses, was significantly increased on D9 (Figure 3C), and Tregs play

crucial roles in the functional homeostasis of the immune system[30]. The proportion of naive

CD4[+] T cells decreased on D11, and that of Th2 cells increased on D11 (Figure 3C and S8D).

Pathway analysis revealed that the T cell activation pathway was markedly activated in naive

CD4[+] T and Th2 cells on D11 and D16 (Figure S7E). These results suggested that Th2 cells may

be activated during extreme altitude mountaineering.

Notably, the proportions of cytotoxic CD8[+] T, $\gamma\delta$T and CD16[+] NK cells exhibited similar

variation trends: the proportion of cytotoxic CD8[+] T cells increased on D4 but maintained a

decreasing trend afterward and decreased to a minimum on D16 (Figure 3C). To investigate the

dynamic changes in the functionality of these T and NK cells during different mountaineering

stages, we identified DEGs (Table S5) and performed pathway analysis (Figure 3D). Overall, the

pathway scores related to cytotoxicity, T cell activation, the immune effector process and the T

cell receptor signaling pathway increased on D4 but significantly decreased on D11 and D16

(Figure 3D). Notably, the expression levels of cytotoxic genes (*GZMA*, *GZMK*, *GZMH* and *NKG7*)

were also significantly reduced in cytotoxic CD8$^+$ T, γδT and CD16$^+$ NK cells on D11 and D16

(Figure 3E). Furthermore, the expression of *KLRD1*, which mediates inhibitory receptor signaling

in T and NK cells, was significantly downregulated on D11 and D16 in cytotoxic CD8$^+$ T, γδT and

CD16$^+$ NK cells (Figure 3F). Previous reports demonstrated that the deficiency of CD94 encoded

by *KLRD1* resulted in susceptibility to lethal viral disease[31]. The expression of the chemokine

receptor *CX3CR1*, which is expressed on cytotoxic T cells and NK cells and is thought to

participate in T cell migration and immune memory formation[32], was significantly upregulated

on D4 and D9 and downregulated on D11 and D16 in cytotoxic CD8$^+$ T, γδT and CD16$^+$ NK cells

(Figure 3F). The expression of *CD160*, an activating receptor expressed by NK cells and a

functional regulator of cytokine production by NK cells[33, 34], was significantly downregulated

in CD16$^+$ NK cells on D11 and D16 (Figure 3F). We also observed significant upregulation of the

expression of the immunoregulatory gene *TGFB1* in cytotoxic CD8$^+$ T cells and γδT cells on D11

and D16 (Figure 3F); this gene inhibits the differentiation and activation of T cells[35]. Overall,

we observed enhanced phenotypes of cytotoxic CD8$^+$ T, γδT and CD16$^+$ NK cells on D4 during

the period of acclimatization. However, on D11 and D16 during extreme altitude mountaineering,

these cell populations exhibited altered phenotypes characterized by the downregulated expression

of effector process-associated genes and the upregulated expression of the immunosuppressive

molecule *TGFB1*.

Additionally, we identified activated CD8$^+$ Tems that exhibited increased expression levels of

activation-associated transcripts such as *CD69*, *CXCR4* and *JUN* (Figure 3B). Notably, the

proportion of CD8$^+$ Tems was significantly increased on D11 and D16 (Figure 3C). An elevated

proportion of CD8$^+$ CD69$^+$ T cells has been previously reported following high-altitude trekking

and is considered a beneficial response to immune perturbation[17]. To further investigate the

transcriptional changes in CD8$^+$ Tems during mountaineering, DEG and pathway analyses were

performed. The pathway scores associated with T cell activation and cytotoxicity were increased

on D4 but were significantly decreased on D11 in CD8$^+$ Tems (Figure 3D). The expression of

CD69, a classical marker of T cell activation, was significantly increased on D9 and D11 (Figure

3F). Along with the potential activation of CD8+ Tems, the expression of the cytotoxic serine

protease *GZMB*, the antigen presentation-related HLA II class molecule *HLA-DRB5* and the *NF-*

κB subunit *REL* was significantly upregulated on D11 and D16 in CD8[+] Tems (Figure 3E and 3F).

Next, we analyzed the changes in TF regulon activity in CD8[+] T and NK cells at different stages

using SCENIC. The regulon activities of a set of TFs associated with inflammation and stress,

including *JUN*, *REL*, *ATF3*, *ATF5* and *BHLHE40*, were obviously decreased on D4 and D9 but

enhanced on D11 and D16 (Figure 3G). Notably, the regulon activities of *TBX21* and *EOMES*

increased on D4 and then obviously decreased, especially on D16 (Figure 3G and 3H). *TBX21* and

EOMES are highly expressed in CD8[+] T and NK cells[36] and regulate the expression of

downstream genes, such as *GZMA*, *CCL5*, *NKG7*, *CD160* and *SPON2* (Figure S7F). The regulon

activities of *TBX21* and *EOMES* may be suppressed during extreme altitude mountaineering. In

general, these results suggested that mountain climbers may experience impaired functionality in

cytotoxic CD8[+] T, γδT and CD16[+] NK cells on D11 and D16.

Enhanced unfolded protein response in plasma B cells during high-altitude mountaineering

B cells play an important role in humoral immunity. We subclustered 54,546 B cells and

annotated them into eight subgroups based on the expression of classical marker genes, including

six B-cell subsets (naive B cells, IFN[+] B cells, activated B cells, memory B cells, FCRL3[+] B cells

and SOX5[+] B cells) and two plasma cell subsets (plasma B cells and proliferating plasma B cells)

(Figure 4A and 4B). Then, we analyzed the compositional changes in different stages and

observed a significant reduction in the proportion of naive B cells on D4, accompanied by a

significant increase in activated B cells. The plasma B cells and other B cell subgroups did not

exhibit statistically significant changes (Figure 4C, S9A and S9B). To reveal the functional

changes in B cells in mountain climbers, we performed DEG analysis (Table S6). The expression

of HLA class II genes (*HLA-DRB5* and *HLA-DQA2*) in activated B cells significantly increased

during mountaineering, indicating an augmentation of B cell-mediated antigen presentation

capabilities (Figure 4D). In addition to the marked increase in the expression level of *CD69*, we

also discovered a significant upregulation of *CD83* on D11 and D16 (Figure 4D), which is

important for B cell activation[37].

To further investigate the functional changes in plasma B cells during mountaineering, DEG

analysis was performed (Table S6). Pathway enrichment analysis revealed that the upregulated

DEGs were mainly enriched in pathways related to protein folding and the UPR (Figure 4E). The

UPR pathway is an essential component of plasma B cell differentiation, and plasma B cells

employ a specialized UPR dependent on the IRE1-XBP1 axis for protein synthesis[38]. The

expression of *ERN1* (also known as IRE1), a major sensor of the UPR, was significantly

upregulated on D11 and D16 (Figure 4F). The expression of *XBP1* significantly increased on D9

and D11 (Figure 4F). Additionally, we observed prominently upregulated expression of protein

secretion-related genes (*LMAN1*, *HSPA5*, *SSR3* and *PDIA4*) and the immunoglobulin genes

IGHA1 and *JCHAIN* (Figure 4F). The activation of the UPR in plasma B cells potentially

contributes to the enhancement of the antibody secretion response in mountain climbers, which is

consistent with the reported increase in immunoglobulin levels at high altitudes[39].

The development of plasma B cells requires the involvement of specific TFs. We also identified

XBP1 in plasma B cells using SCENIC, and the regulon activity of *XBP1* was upregulated on D9

and D11 (Figure 4G). As a critical member of the UPR, *XBP1* regulates the terminal

differentiation of B cells into plasma B cells[40] and controls downstream genes involved in

protein synthesis (Figure S9C). Hypoxia can induce *XBP1* mRNA expression and activate its

mRNA splicing[41], and a positive correlation between the hypoxia score and the expression of

XBP1 was observed in plasma B cells (Figure 4H). Taken together, these results demonstrated that

high-altitude mountaineering induced the activation of the UPR in plasma B cells, which may

contribute to the enhancement of humoral immunity in mountain climbers.

Metabolic reprogramming of circulating immune cells in mountain climbers

Pathway enrichment analysis revealed a reduction in the levels of oxidative phosphorylation in

CCL3+ CD14+ Monos and pDCs during mountaineering (Figure S5C and S6A). Considering the

profound impact of metabolic programs on immune cell function[18], an analysis of metabolic

features centered on oxidative phosphorylation and the glycolysis pathway across different cell

types was performed. The expression level of oxidative phosphorylation increased on D4 but

decreased significantly on D9, D11 and D16, especially in monocytes (Figure 5A and 5B). In

contrast, the expression level of glycolysis decreased on D4 and D9 but significantly increased on

D11 and D16 (Figure 5A). This change was consistent with the observed variation in the hypoxia

pathway, which was initially suppressed and subsequently activated (Figure 2D and S10A). A

positive correlation between the hypoxia score and glycolysis score was observed in different

immune cell subgroups (Figure S11A and S11B), suggesting that hypoxia may be a key factor in

regulating the metabolic program of immune cells during mountaineering. The expression of

mitochondrial electron transport chain (ETC) subunits was downregulated. For instance, the

expression of *ATP5F1E* (ATP synthase complex) was significantly downregulated during

mountaineering in CCL3[+] CD14[+] Monos, FCN1[+] CD14[+] Monos, C1[+] CD16[+] Monos and cDC2s

(Figure 5C). Decreased expression levels of *COX4I1*, *COX7A2*, *COX5B* and *COX7C* (complex IV)

were observed in IFN[+] CD16[+] Monos (Figure 5D). It was evident that the activity of the

mitochondrial ETC decreased under high-altitude hypoxic conditions. HIF is widely recognized as

the primary regulator of metabolic adaptation to hypoxia and can drive a switch from oxidative to

glycolytic metabolism during hypoxia[42]. Interestingly, significantly upregulated *HIF1A*

expression was observed on D11 and D16 in most subgroups, except for pDCs (Figure 2H and

S10A). Moreover, the expression of *LDHA* (lactate dehydrogenase A) and *GAPDH*

(glyceraldehyde 3-phosphate dehydrogenase) was significantly elevated during mountaineering in

CD8[+] Tems and plasma B cells, respectively (Figure 5E). *LDHA* encodes a key enzyme in

glycolysis that facilitates the conversion of pyruvate to lactate. *GAPDH* is an essential component

of glycolysis that catalyzes the conversion of glyceraldehyde-3-phosphate to 1,3-

bisphosphoglycerate[43]. We also observed upregulated expression of the glucose transporter

SLC2A3 on D11 and D16(Figure 5E); this gene facilitates cellular glucose uptake to support the

glycolytic pathway[44]. Taken together, these observations suggested that the circulating immune

cells of mountain climbers may undergo metabolic reprogramming.

Cell energy sensors also play important roles in the metabolic regulation of immune cells[15].

AMP-activated protein kinase (AMPK) serves as the main regulator of intracellular energy

homeostasis and can be activated by various stimuli, including cellular stress and physical

activity[45]. The activity of the AMPK-related pathway 'CAMKK AMPK Signaling Cascade'

was significantly increased on D4 and D9, particularly in monocytes; however, it decreased on

D11 and D16 (Figure 5F and S10B). The expression of the AMPK subunits *PRKAB1* and

PRKAB2, as well as the upstream kinase *CAMMK2*, was upregulated on D4 and D9 in CCL3[+]

CD14[+] Monos, FCN1[+] CD14[+] Monos, cytotoxic CD8[+] T cells and γδT cells (Figure S10C). In

addition, the expression level of *PRKAA1* was also significantly upregulated on D4 and D9 in

cytotoxic CD8[+] T cells (Figure S10C). *PRKAA1* is crucial for the proliferation and differentiation

of cytotoxic T lymphocytes[46]. Activation of the AMPK pathway can not only promote the

metabolic adaptation of immune cells but also exert a wide variety of immunoregulatory

effects[47]. For example, the AMPK pathway exerts inhibitory effects on the inflammatory

response of macrophages and DCs while promoting T cell effector function[48, 49]. In our study,

we observed that during the period of acclimation, when the AMPK-related pathway was activated,

the inflammatory response in monocytes and cDC2s was suppressed, and the immune effector

process of cytotoxic CD8[+] T cells was upregulated (Figure 5G). In contrast, the activity of the

AMPK-related pathway decreased during extreme altitude mountaineering, whereas the activity of

the hypoxia pathway increased, accompanied by the activation of inflammatory responses in

monocytes and cDC2s and a decrease in the immune effector process in cytotoxic CD8[+] T cells

(Figure 5G). Overall, our findings suggested that the dynamic activation of the AMPK and

hypoxia pathways induced by high-altitude mountaineering may play crucial roles in regulating

the metabolism and function of immune cells.

The defense of circulating immune cells against oxidative stress in mountain climbers

Previous findings have indicated that exercise at high altitudes increases the generation of

ROS[17]. When ROS production exceeds the load capacity of the antioxidant system, it can lead

to oxidative stress. The pathway scores for 'Cellular Response to Reactive Oxygen Species' and

'Cellular Response to Oxidative Stress' were calculated for each immune subgroup, and we found

that the scores decreased on D4 and D9 and then increased on D11 and D16 in most subgroups, in

addition to pDCs and several B cell subgroups (Figure 6A). A positive correlation between the

hypoxia score and oxidative stress score was observed for circulating immune cells (Figure 6B).

These findings indicated that circulating immune cells manifested distinct reactions to oxidative

stress during high-altitude mountaineering.

450  Moreover, cells are equipped with an antioxidant system that scavenges excess ROS to reduce

451 oxidative damage[50]. We next calculated the pathway scores for 'Cellular Oxidant Detoxification'

452 in different immune subsets and observed increased scores in T and NK cells on D4, whereas the

453 scores were generally lower in most subgroups on D9, D11 and D16 (Figure 6A). Notably, the

454 oxidative detoxification scores were greater on D11 and D16 in monocytes and plasma B cells

455 (Figure 6A). The expression of multiple antioxidant genes in different mountaineering stages,

456 including *SOD2*, *NFE2L2*, *SOD1*, *GPX4* and *TXNRD1*, was significantly upregulated on D11 and

457 D16 (Figure 6C). Among them, *SOD2* and *NFE2L2* levels were significantly increased in

458 monocytes and DCs but not in pDCs (Figure 6D). The SOD2 enzyme is specifically localized to

459 the mitochondrial matrix at the main site of superoxide production and catalyzes the reaction of

460 superoxide to less reactive hydrogen peroxide[51]. *NFE2L2* (also known as *NRF2*) serves as a

461 central regulator that responds to oxidative stress by controlling a battery of defensive genes

462 encoding antioxidant and detoxification enzymes[52]. In addition, we observed that the expression

463 of *PRDX4* and *TXN* was significantly elevated in plasma B cells during mountaineering (Figure

464 4F). In contrast, markedly decreased expression of *SOD1*, *TXN*, *PRDX5* and *PRDX6* was observed

465 in pDCs (Figure S6B). *TXN* and *PRDXs* are major members of the thioredoxin system, which is

466 one of the central antioxidant systems and plays a vital role in maintaining the intracellular ROS

467 balance[53]. In particular, *PRDX4*, a typical endoplasmic reticulum (ER)-resident antioxidant that

468 scavenges excess H_2O_2, is essential for the correct folding of proteins[54]. Generally, when the

469 level of oxidative stress increased on D11 and D16, monocytes and plasma B cells exhibited

470 enhanced oxidative detoxification ability, while pDCs and most T and NK cells exhibited

471 decreased oxidative detoxification ability. These results highlighted the importance of the

472 enhanced antioxidant capacity of circulating immune cells to defend against elevated oxidative

473 stress and further maintain their immune functions.

475 **Plasma metabolic changes in mountain climbers**

476 Metabolic reprogramming in immune cells is observed during mountaineering, and metabolic

477 changes in immune cells may be localized, but if they occur across multiple cells or tissues, such

478 changes can result in systemic metabolic alterations[18]. To explore the plasma metabolic

479 alterations in mountain climbers during mountaineering, we conducted VIP and c-means

clustering analysis. According to the VIP scores, the levels of some metabolites, including 3-methyloxindole, N-acetyl-L-aspartic acid, asparagine, glycine and palmitoylcarnitine, increased during mountaineering, while the levels of other metabolites, such as glucose and piperine, decreased (Figure 7A). Four change patterns were identified in different periods of mountaineering: cluster 1 contained analytes whose levels were sharply decreased on D4 and D9, followed by analytes whose levels were increased on D11 and decreased on D16; cluster 4 exhibited the opposite trend (Figure 7B); the analytes in cluster 2 exhibited a sharp decrease on D4 and subsequently remained at a low level; and the analytes in cluster 3 showed a pattern of a gradually decreasing trend (Figure 7B). The differentially abundant metabolites were mainly distributed in cluster 1 and cluster 4, whereas differential lipids exhibited a predominant distribution in cluster 2 and cluster 3 (Figure 7B).

The analytes in cluster 1 were mainly enriched in serine and glycine metabolism, representative metabolites that included glycine, serine and methionine (Figure 7C and S12A). The levels of serine and glycine decreased on D4 and D9, followed by an increase on D11 and D16 (Figure 7D). The concentration of plasma glycine is regulated by glucagon, which stimulates the degradation of glycine, and glucagon deficiency elevates the level of glycine[55]. Furthermore, intense physical activity may result in increased muscle protein breakdown and the subsequent release of amino acids into the bloodstream[56], potentially resulting in increased glycine levels. The increased availability of glycine can be utilized for the synthesis of serine and glutathione. The role of glutathione as a vital antioxidant lies in its ability to reduce cellular damage induced by oxidative stress[57]. The analytes in cluster 2 were not enriched in metabolic pathways, and those in cluster 3 were mainly involved in tryptophan metabolism (Figure S12B).

The analytes in cluster 4 were enriched in glutamine metabolism, and representative metabolites included glutamine, N-acetyl-L-aspartic acid, alanine and gamma-aminobutyric acid (GABA) (Figure 7C, 7D and S12A). Glutamine is the most abundant circulating amino acid in plasma, as it is a carbon source second only to glucose, which can generate 2-oxoglutarate through glutaminolysis[58]. Consistently, the levels of citrate cycle (TCA cycle)-related substances, including 2-oxoglutarate and isocitric acid, increased during mountaineering (Figure S12C). It has

been suggested that mountain climbers may rely on glutamine as an important anaplerotic

substrate to complete the TCA cycle during mountaineering, consistent with previous studies

showing that high altitude-exposed individuals presented increased plasma glutamine[59].

Importantly, glutamine can actively improve immune function, and glutamine supplementation

may reduce the incidence of infections reported by marathon runners[60]. In addition, GABA, a

neurotransmitter, has a variety of biological functions, including antifatigue and immune

regulation activities[61].

Analytes in cluster 4 were also involved the metabolism of selenocompounds, from which

selenomethionine (Se-Met) (Figure 7C and S12C), a natural organic selenium, is a key metabolite.

As the main source of selenium in humans, Se-Met has been shown to have important antioxidant

properties involving the formation of antioxidant enzymes[62]. Se-Met increased on D4 and D9

but significantly decreased on D11 (Figure 7E). The decreased level of Se-Met may be related to

the increased oxidative stress response observed in immune cells, as a significant positive

correlation between selenocompound metabolism and oxidative stress in circulating immune cells

was observed (Figure 7F). Intriguingly, we observed a similar variation trend in omega-3

polyunsaturated fatty acids (n-3 PUFAs), alpha-linolenic acid, docosahexaenoic acid,

docosapentaenoic acid and eicosapentaenoic acid (Figure 7E). PUFAs are vulnerable to ROS

attack due to their structural instability, resulting in a marked increase in the end-product

malondialdehyde (MDA), which is a biomarker of oxidative stress[63].

In addition, fatty acid oxidation may be activated on D11 and D16, as reflected by the

accumulation of acylcarnitines and medium- to long-chain fatty acids (Figure S12D).

Acylcarnitine is an intermediate product of fatty acid oxidation, and the heart is considered the

main contributor to the increased abundance of long-chain acylcarnitines in plasma[64], such as

palmitoylcarnitine and stearoylcarnitine (Figure S12D). These changes were concomitant with the

accumulation of 3-hydroxybutyric acid, the main ketone body in the blood (Figure S12E). Ketone

bodies are predominantly produced from fatty acid β-oxidation-derived acetyl-CoA in the liver

and serve as key contributors to energy metabolism in the context of energy-depleted states[65].

These observations suggested that the utilization of fatty acids might be enhanced during extreme

altitude mountaineering.

Clusters 2 and 3 mainly contained complex lipids, such as triacylglycerol (TAG),

lysophosphatidylcholine (LPC), phosphatidylethanolamine (PE), phosphatidylcholine (PC),

phosphatidylinositol (PI), lysophosphatidylethanolamine (LPE), ceramide (CER) and

sphingomyelin (SM) (Figure 7B and 7G). The role of lipids is critical for cell

structure, intracellular and extracellular signaling and energy storage. The levels of TAG, LPC, PE

and PC decreased significantly during mountaineering (Figure 7H). TAG molecules represent the

major form of fatty acid storage within cells, and in the plasma, prolonged exercise has been

reported to accelerate plasma TAG clearance[66]. LPC can activate a variety of signaling

pathways in monocytes/macrophages through G protein-coupled receptors and Toll-like receptors,

further increasing the production of proinflammatory cytokines, whose downregulated expression

is considered associated with worse health status[67]. PE and PC are the most abundant

phospholipids in mammalian cell membranes and play crucial roles in regulating lipid metabolism

and maintaining membrane protein stability[68]. The progressive decrease in plasma PE levels

during mountaineering may be regarded as a potentially positive change[69]. The levels of PI and

LPE were significantly decreased on D4 and D9 and then gradually recovered, while the levels of

CER and SM were significantly decreased on D4 and D9 (Figure 7H). CER is the precursor of

most SM. The plasma concentration of SM is altered in various metabolic disorders, serving as a

valuable indicator for prognosis and diagnosis[70]. Overall, the observed decrease in lipid levels

may reflect lipid metabolism disorders during mountaineering.

DISCUSSION

Extreme adventure sports, such as high-altitude mountaineering, have become increasingly

popular. High-altitude mountaineering involves exposure to a hypobaric hypoxic environment,

leading to a series of physiological, metabolic and immunological changes. Circulating immune

cells, including monocytes, DCs, T cells, NK cells and B cells, function as "sentinel tissue" to

monitor the body's response[71]. Previous studies have proposed peripheral blood lymphocytes as

biosensors for whole-body responses to high altitudes[16]. However, few studies have

investigated the response profiles of circulating immune cells during mountaineering. We

identified and characterized the immune response and metabolic changes during high-altitude mountaineering. Importantly, the mountaineering plan consisted of two stages (the first being the period of acclimatization, and the second being the period of extreme altitude mountaineering). Sampling at multiple time points enabled a more comprehensive understanding of the immune response alterations and adaptation characteristics of mountain climbers in different periods.

Research in the field of exercise immunology has demonstrated that physical activity can induce significant alterations in the immune response, contingent upon exercise intensity, duration, and type[72]. Moderate-intensity exercise is acknowledged to confer a multitude of immunological benefits, including augmented immunosurveillance, diminished systemic inflammation levels, and heightened lymphocyte concentrations, whereas prolonged or high-intensity exercise is associated with immune dysfunction, elevated inflammation levels and heightened susceptibility to infectious disease[7, 8]. Our analysis revealed that high-altitude mountaineering induced intricate and dynamic immune alterations in mountain climbers. Climbers exhibited distinct immune alterations in the two stages of mountaineering. During the acclimation period, for myeloid cells, we observed the significant suppression of the inflammatory response in monocytes and cDCs. The immunosuppressive phenotype of $CCL3^+$ $CD14^+$ Monos was subsequently characterized by notable the upregulation of *S100A8* and *S100A9* expression and marked downregulation of the expression of multiple inflammatory genes on D4 and D9. The upregulation of *S100A8* expression has been documented in individuals acutely exposed to high altitudes[73]. For lymphocytes, the proportions of cytotoxic $CD8^+$ T, γδT and $CD16^+$ NK cells were significantly increased on D4, and the expression of effector process-related genes was significantly upregulated on D4. Notably, AMPK-associated pathways were also activated on D4 and D9 in monocytes, cDC2s, cytotoxic $CD8^+$ T cells and γδT cells.

As one of the central regulators of cellular metabolism, AMPK plays a critical role in orchestrating cellular metabolic reprogramming. Under conditions of low energy availability, AMPK phosphorylates downstream targets to enhance adenosine triphosphate (ATP) production while reducing ATP consumption[45]. Previous studies have demonstrated that exercise-induced activation of AMPK can confer a wide range of health benefits, making it an attractive target for

the treatment of immune-related diseases[47, 74]. In myeloid cells, AMPK exerts inhibitory

effects on inflammatory responses[48], highlighting the intricate interplay between inflammation

and AMPK signaling. In T cells, AMPK plays a pivotal role in regulating T cell-mediated

adaptive immunity[49]. This finding aligned with our observation that during the acclimation

period, when the AMPK-related pathway was activated, there was a concomitant suppression of

the inflammatory response in monocytes and cDCs and an increase in effector process scores for

cytotoxic CD8$^+$ T cells.

During extreme high-altitude mountaineering, monocyte- and cDC-mediated inflammatory

responses were significantly activated on D11 and D16, with increased expression of *IL1B*, *TNF*

and *NFκB1*, in line with the observed increase in CRP levels during trekking in the Himalayas[5].

Proinflammatory *IL1B* expression has been reported to be correlated with worsening symptoms of

acute mountain sickness (AMS)[75], and the exacerbation of the inflammatory response in high-

altitude hypoxic environments may contribute to the pathogenesis of diseases, such as chronic

obstructive pulmonary disease or chronic obstructive sleep apnea[76]. Compared to those on D1,

the proportions of cytotoxic CD8$^+$ T, γδT and CD16$^+$ NK cells on D16 were significantly lower,

accompanied by the downregulated expression of genes associated with immune effects, including

GZMA, *GZMK*, *GZMH*, *NKG7*, *KLRD1*, *CD160* and *CX3CR1*. These findings are consistent with

the observed decrease in the percentage of cytotoxic T cells following a marathon[20]. The

impairment of T cell-mediated function at extreme altitudes might disrupt immune homeostasis

and increase the risk of infectious disease. These observations may be attributed to the increased

intensity of physical activity during extreme altitude mountaineering (D11 and D16), which could

further exacerbate the degree of hypoxia. Importantly, the activity of the hypoxia pathway was

significantly activated on D11 and D16 in most immune cells.

The effect of hypoxia on the inflammatory response has been widely reported in studies of

high-altitude environments[24]. On the one hand, hypoxia-induced *HIF1A* can upregulate the

expression of *NF-κB*; on the other hand, hypoxia promotes the release of *NF-κB* and its

translocation to the nucleus by activating the IKKβ pathway, further upregulating the transcription

of inflammatory genes[77]. Among T and NK cells, the upregulation of the immunoregulatory

gene *TGFB1* was observed in cytotoxic CD8[+] T and γδT cells on D11 and D16. Hypoxia-induced

TGFB1 may exert inhibitory effects on the expression of *TBX21* and *EOMES* in T cells[35, 78].

Similarly, *TGFB1* also downregulated the expression of *TBX21* in NK cells[79]. Within plasma B

cells, hypoxia may promote the activity of *XBP1*[41], which controls the downstream genes

involved in protein synthesis. Notably, the activity of the hypoxia pathway and the expression of

*HIF1*A were significantly increased in most cell types during extreme altitude mountaineering,

while decreased hypoxia scores and low *HIF1A* expression were observed in functionally

impaired cells, such as pDCs, confirming the key role of hypoxia in regulating the immune

response of mountain climbers.

Furthermore, another intriguing finding in our study is the adaptation characteristics of

circulating immune cells during extreme altitude mountaineering. Considering the exposure to

high-altitude hypoxic conditions coupled with intense physical activity, the energy and metabolic

homeostasis of mountain climbers may be challenged substantially. We observed a decrease in

oxidative phosphorylation activity and an increase in glycolytic activity on D11 and D16 in most

immune cells. Previous studies have reported that climbers experience attenuated mitochondrial

function after exposure to high altitudes[16, 80]; these findings imply that the functionality of

mitochondria might be constrained under high-altitude conditions. Notably, the expression of the

glycolysis-related genes *LDHA*, *GAPDH* and *SLC2A3* was significantly enhanced on D11 and

D16 in CD8[+] Tems and plasma B cells. HIF is known to play an important role in hypoxia-induced

reprogramming, and increased *HIF1A* expression was observed on D11 and D16 in most immune

cells. Moreover, we observed increased pathway activity in most subgroups in response to ROS

and oxidative stress on D11 and D16, which was consistent with previous studies showing that

exercise at high altitudes increased the levels of oxidative stress[13]. In the context of increased

oxidative stress on D11 and D16, monocytes and plasma B cells showed increased expression of

antioxidant-related genes (*NFE2L2*, *SOD2*, *PRDX4* and *TXN*) on D11 and D16. *NFE2L2* is the

major transcription regulator in the cellular response to oxidative stress[52]. An increase in SOD

activity is considered a crucial adaptive mechanism for coping with hypoxic conditions at high

altitudes to reduce oxidative damage[81].

Finally, the high-resolution analysis of plasma analytes revealed numerous molecules affected

by high-altitude mountaineering, and these metabolic processes were involved in energy

metabolism (amino acid and fatty acid metabolism) and oxidative stress (selenocompound

metabolism), suggesting the crucial involvement of metabolites in metabolic adaptation in

climbers. In high-altitude hypoxic environments, mountain climbers are in a low-sugar state,

which may improve their energy supply by promoting glutamine metabolism and fatty acid

metabolism. Interplay among metabolism, oxidative stress and immunity was observed, reflected

in selenocompound metabolism, and a positive correlation between selenocompound metabolism

and oxidative stress was also observed in circulating immune cells.

In conclusion, the results of our study provide a multi-omics profile of the response to high-

altitude mountaineering. We used a single-cell transcriptome to analyze the circulating immune

profile of climbers, revealed distinct immune responses during two stages of mountaineering, and

explored the adaptive characteristics of circulating immune cells during extreme altitude

mountaineering. The enhanced expression of glycolysis and antioxidant genes was shown to play

a crucial role in supporting the functionality of immune cells. Conversely, decreased expression of

those genes was observed in pDCs with impaired immune function. Furthermore, the energy status

of mountain climbers can potentially be promoted through the enhancement of glutamine

metabolism and fatty acid metabolism.

Data availability

The scRNA-seq data generated by this study were deposited at the China National GeneBank

(CNGB) Sequence Archive (https://db.cngb.org/cnsa/) under accession nos. Other relevant data

are available from the corresponding author upon reasonable request.

Code availability

R codes and other custom scripts are available upon reasonable request.

Acknowledgements

We sincerely thank the eleven mountain climbers who enthusiastically participated in this

mountaineering expedition. This work was supported by the Guangzhou Basic and Applied Basic

Research Program (202201010189) and the National Key R&D Program of China

(2022YFC3400400). We would also like to acknowledge the support from the Chinese National

Gene Bank.

Author contributions

Experimental strategy and design: J.W., X.J., C.Y.L., J.C., L.Q.L., J.H.Y.

Laboratory experiments: Y.W., X.M.L., Y.T.H., Y.Y., Y.L.H., C.L., G.X.H., H.R.T., H.H.L., Y.Z.,

G.D.Z.

Statistical analyses: S.C.Y., J.Z.L., Z.L.H., X.W., Y.L., W.K.W., Y.H.Z., C.W.

Manuscript writing: J.H.Y., J.Z.L., S.C.Y.

Manuscript editing: J.H.Y., J.Z.L., W.W.Z., R.Q.L.,

All authors critically revised the manuscript for important intellectual content and gave final

approval for the version to be published. All authors agree to be accountable for all aspects of the

work in ensuring that questions related to the accuracy or integrity of any part of the work are

appropriately investigated and resolved.

METHODS

Sample collection and ethics statement

This study was performed during an expedition to summit the Muztagh Ata peak (7,546 m), and

eleven healthy volunteers residing at low altitudes (< 300 m) were recruited to participate in the

expedition. None of the individuals had known chronic diseases, such as cardiovascular or

respiratory system disorders. During mountaineering, we monitored the dynamic changes in 10

physiological parameters (e.g., routine blood tests, SpO_2, HR, LLS and body composition) of

climbers using professional equipment. To investigate alterations in metabolism and the immune

response during high-altitude mountaineering, 55 blood samples were collected from climbers at

five distinct time points. The research protocol received approval from BGI's institutional review

board of bioethics and biosafety, and written informed consent was obtained from each individual

participating in the mountaineering expedition.

Protocol for the mountaineering expedition

For the mountaineering itinerary, participants reached 1,289 m on the first day (D1), and the

mountaineering expedition was divided into two phases: an initial acclimatization period (D2-D8)

followed by an extreme altitude mountaineering period (D9-D15). The participants embarked on a

trek to reach 3,200 m and subsequently arrived at the base camp (4,400 m) on D3. From there,

acclimatization to high altitudes was carried out at the base camp. During this period, the

participants ascended to Camp 1 (5,500 m) on D5, followed by a two-day rest at base camp before

proceeding to Camp 2 (6,300 m) on D9. Finally, the participants undertook a four-day consecutive

ascent from base camp to the summit (7,546 m). Before reaching the summit, five out of the

eleven individuals utilized supplemental oxygen for a duration of time on D15. On D16, the

participants returned 1,289 m. During the expedition, 55 blood samples at five different time

points (D1, D4, D9, D11 and D16) were collected. Fasting blood samples for each participant

were collected at 9:00 a.m.; the fifth sampling was performed before dinner due to itinerary

constraints. No medications (including acetazolamide) were taken by the participants during the

expedition. According to the LLS, none of the eleven participants suffered from severe acute

mountain sickness. For additional details, see Supplementary Table 1.

Plasma and peripheral blood mononuclear cells (PBMCs) separation

Plasma and PBMC isolation were conducted with the following protocols. The whole blood of the mountain climbers was collected in 5mL EDTA anticoagulant tubes. Briefly, 5 mL of whole blood was centrifuged at 940×g for 10 min, after which the upper plasma layer was transferred to a 15-mL centrifuge tube, collected after centrifugation at 2,600×g for 10 min, aliquoted, and stored at -80 °C. The lower immune cells were diluted with 1x phosphate-buffered saline (PBS) supplemented with 2% bovine serum albumin (BSA) and transferred to SepMate™–50 tubes. After centrifugation at 1200×g for 10 min, the PBMC layer was poured into a new centrifuge tube. The cells were washed twice with 3 mL of 1× PBS containing 2% fetal bovine serum (FBS) and centrifuged at 300×g for 8 min. The supernatant was discarded, and the PBMC pellet was resuspended in FBS supplemented with 10% dimethylsulfoxide (DMSO). Afterwards, the frozen tubes were transported on dry ice to be stored in liquid nitrogen at the end of the expedition.

Preparation of single-cell suspensions

To thaw the frozen PBMCs, the cells were placed in a 37 °C water bath for 2 min, after which the cells were gently poured into a 15-mL centrifuge tube. The thawed cells were resuspended in 10 mL of preheated 1× PBS supplemented with 10% FBS at 37 °C and mixed gently. After centrifugation at 500×g for 5 min at room temperature, the supernatant was removed, and the cell pellet was resuspended in 2 mL of PBS supplemented with 0.04% BSA. The cells were strained through a 40-μm cell strainer, and the filtered cells were collected and then resuspended at a concentration of 800-1,500 cells/μL. The cell suspensions were maintained on ice for sequencing.

Sequencing library construction

The sequencing libraries were constructed according to the instructions of the DNA Nanoball (DNB) elab C4 scRNA Preparation Kit (MGI). The prepared single-cell suspension, the barcode mRNA capture beads, and the droplet generation oil were loaded into the corresponding reservoirs on a microfluidic chip for droplet generation. The cells were lysed, and the released mRNA was captured and barcoded in the droplets. Following reverse transcription, complementary DNA (cDNA) was generated and amplified. The amplified cDNA was quantified using a BioAnalyzer High Sensitivity Chip (Agilent) and subsequently fragmented to 400-600 bp with NEBNext

dsDNA Fragmentase. The cDNA and oligo library construction steps were performed as follows.

The libraries were made of DNBs and sequenced on an ultrahigh-throughput DNBSEQ-T1

sequencer at the CNGB. cDNA libraries were generated using the following read lengths: 41-bp

read 1 (containing a 20-bp cell barcode and a 10-bp unique molecular identifier (UMI)), 100-bp

read 2, and a 10-bp sample index. The following oligo libraries were used: 26-bp read 1, 42-bp

read 2, and 10-bp sample index.

Single-cell RNA-seq data processing

Sequencing data were processed using the Open Source Pipeline (https://github.com/MGI-tech-

bioinformatics/DNBelab_C_Series_HT_scRNA-analysis-software). First, bead barcodes and UMI

sequences were extracted using the parsing function in PISA (https://github.com/MGI-tech-

bioinformatics/DNBelab_C_Series_HT_scRNA-analysis-software/software/PISA).   Reads with

incorrect barcodes were excluded based on the use of a barcode whitelist. The scRNA-seq data

were then aligned to the GRCh38 (hg38) reference genome using STAR[82]. Finally, gene

expression levels in cells were assessed using PISA, and gene-cell matrices were created for each

library.

Then, we used the R package Seurat (version 4.4.0) to apply preliminary counts to downstream

data analysis, including quality control, normalization, feature selection, dimensionality reduction,

unsupervised clustering, and visualization[83]. First, cells with more than 10% mitochondrial

genes, more than 1% erythrocyte genes, and less than 200 or more than 6,000 genes were

excluded. Then, for each library, DoubletFinder (version 2.0.3) was used to remove doublets[84].

The top 5% of cells most similar to the "pseudo-doublet" were excluded. Finally, genes expressed

in fewer than three cells, as well as mitochondrial genes, noncoding RNA genes, and ribosomal

genes were filtered. In addition, a portion of the cells were clustered together by red blood cells

contamination with highly expressed red blood cell genes, and we removed the red blood cell

clusters to eliminate the effect on clustering. Subsequently, the "NormalizeData" function was

used to convert the data into logarithmic space, and the "FindVariableGene" function was used to

find the top 2,000 variable genes in the dataset. Then, "ScaleData" was used to remove unwanted

variations due to differences in sequencing depth. The first 20 principal components (PCs) were

computed using RunPCA. Finally, Harmony (version 1.1.0) was used to correct for batch effects

of different library.

Unsupervised clustering and subclustering

The Louvain algorithm was used as a modular optimization technique to set the granularity of the

clusters at a resolution of 0.75. The nonlinear dimensionality reduction technique "UMAP" was

used to visualize the clusters in two-dimensional space. Cellular identity was determined by

identifying differentially expressed genes (DEGs) for each cluster using the "FindALLMarkers"

function with default parameters and comparing those genes to known cell type-specific genes.

The clusters were annotated based on typical marker expression, and 15 cell subpopulations were

identified. After scaling, myeloid, $CD4^+$ T, $CD8^+$ T, NK, and B cell clusters were extracted as

separate Seurat objects; the principal components were identified, each subset was clustered at a

unique resolution using the Louvain algorithm, and the clusters were annotated based on

dimensionality and gene expression associated with the phenotypes of the typical subsets

described above.

DEGs and GO enrichment analysis

To search for DEGs in each cell subgroup during mountaineering, we used the "FindMarkers"

function (Seurat). For each cell subgroup, we computed the fold change in mean gene expression

levels between D1 and subsequent time points, and the p value was calculated utilizing the

Wilcoxon rank sum test. To annotate the functions of these DEGs, we performed GO pathway

enrichment analysis by using the clusterProfiler package (version 4.10.0) in R (OrgDb =

org.Hs.eg.db, pvalueCutoff = 0.05, qvalueCutoff = 0.05, pAdjustMethod = "BH") to enrich the

DEGs in GO terms[85]. For DEG details, see Supplementary Tables 4, 5 and 6.

Module scores for feature gene set expression

To assess the dynamic changes in biological processes mediated by immune cell subsets, we

employed the "AddModuleScore" (Seurat) function to assess the scores for the gene sets. Briefly,

the score for each cell was defined as the average expression of the featured gene set minus the

average expression of the corresponding control feature gene set. The referenced gene sets are

listed in Supplementary Table 7 and were collected from the Molecular Signatures Database

(MSigDB)[86]. The Wilcoxon rank-sum test was used to evaluate the statistical significance of

differences between D1 and subsequent time points.

Gene regulatory network analysis based on SCENIC

To predict the potential transcriptional regulatory networks in different immune cell subgroups,

we used pySCENIC (version 0.12.1). Initially, we employed GRNBoost to infer all potential

targets of transcription factors. Subsequently, the output coexpression module was utilized in

conjunction with the cisTarget database to identify putative regulators. The regulon areas under

the curve per cell (AUCell) module of pySCENIC was used to analyze regulator activity, and

active regulators were identified using the default thresholds[23]. The differentially expressed

regulators were identified using the R package limma (version 3.50.0) with the following

parameters: adjusted $p \leqslant 0.05$ and $|\text{logFoldChange}| \geqslant 0.4$. For regulator details, see

Supplementary Table 8.

Target metabolite quantification by HM Meta Assays

The HM Meta Assay (BGI, Shenzhen, China) was utilized for quantifying metabolites. This assay

covers a wide range of chemical classes, including bile acids, amino acids, fatty acids, carboxylic

acids, hydroxyl acids, phenolic acids and indoles, by measuring 700 compounds. Calibration

curves were generated using serial dilutions of metabolite standards. In 96-well plates, 20-μL

aliquots of either standards or plasma samples were mixed with 120 μL of internal standard

solution (methanol-diluted metabolite internal standards). The plates were then stored at -20 °C

for 20 min, followed by centrifugation at $4,000 \times g$ and 4 °C for 30 min. The supernatants (30 μL)

were transferred to new plates for derivatization with freshly prepared reagents (10 μL), which

included a mixture of 200 mM 3-NPH in 75% aqueous methanol and 96 mM EDC-6% pyridine in

methanol. Derivatization took place at 30 °C for one hour. Prior to LC–MS analysis, the samples

were diluted with ice-cold 50% methanol and then transferred to new plates containing 135 μL of

the supernatant.

A Waters ACQUITY UPLC instrument coupled to a SCIEX QTRAP 6500 PLUS mass

spectrometer equipped with an ESI source controlled by Analyst software was used for UPLC-

MRM analysis. Chromatographic separation was performed on a Waters ACQUITY BEH C18

column (1.7 μm particle size; dimensions: 100 mm × 2.1 mm). Both positive and negative ion

modes were employed during instrument operation. Ultimately, HMQUANT software (BGI,

Shenzhen, China) was used for the absolute quantification of metabolites.

Target lipid quantification by HM lipid assays

Lipid measurement was conducted using the HM Lipid Assay (BGI, Shenzhen, China). This assay

covers a wide range of lipid subclasses and quantifies 1600 lipid molecules, including 18 lipid

classes: SM, CER, cholesterol ester (CE), monoacylglycerol (MAG), diacylglycerol (DAG), TAG,

lysophosphatidic acid (LPA), phosphatidic acid (PA), LPC, PC, LPE, PE,

lysophosphatidylinositol (LPI), PI, lysophosphatidylglycerol (LPG), phosphatidylglycerol (PG),

lysophosphatidylserine (LPS) and phosphatidylserine (PS). Calibration curves were generated

using serial dilutions of lipid standards. In 96-well plates, aliquots of either standards or plasma

samples were mixed with internal standard solution (precooled isopropanol with SPLASH internal

standards, avanti) (20 μL each). The plates were then stored at -20 °C for 20 min before being

centrifuged at 4,000 × g and 4 °C for 30 min. Supernatants containing lipids were transferred to

new plates for LC-MS analysis in negative mode, while a portion of the supernatants was diluted

into methanol for LC-MS analysis in positive mode.

UPLC-MS/MS analysis was performed on a Waters ACQUITY UPLC coupled to a SCIEX

QTRAP5500 PLUS mass spectrometer equipped with an ESI source controlled by Analyst

software. Chromatographic separation was performed on a Waters ACQUITY CSH C18 column

(1.7 μm, 100 mm × 2.1 mm). SM, CE, Cer, TAG, DAG, and MAG were quantified in positive

mode, whereas the phospholipids and lysophospholipids were quantified in negative mode

utilizing the scheduled MRM settings. HMQUANT software (BGI, Shenzhen, China)

incorporating isotope correction via the LICAR package was used for absolute lipid quantification.

To ensure the accuracy of the analytical results, we discarded lipids detected in less than 2/3 of

the samples, and missing values were estimated using the lower limit from the corresponding

lipid[87].

Screening for differential plasma metabolites and lipids

903 To identify differential plasma metabolites and lipids, we first calculated VIP scores using PLS-

904 DA in the R package MetaboAnalystR (version 4.0)[88]. We analyzed metabolites with VIP

905 scores $\geqslant$ 1 as differentially abundant metabolites and lipids for downstream data analysis. For

906 details on the metabolites and lipids, see Supplementary Tables 2 and 3.

Fuzzy c-means clustering

909 Fuzzy c-means clustering was performed using the R package Mfuzz (version 2.62.0)[89]. We

910 selected the screened differentially abundant metabolites and lipids for clustering.

Plasma metabolite pathway analysis

913 We performed pathway enrichment analysis of the metabolites obtained from fuzzy c-means

914 clustering by group separately using the pathway analysis module in the MetaboAnalystR package.

915 For bubble plots, we selected metabolic pathways with p values $\leqslant$ 0.05 and impacts $\geqslant$ 0.1[90].

Linear mixed model

Since the assumption of independence cannot be met for repeated measurements, zone group data,

and spatially correlated data, the above data are often analyzed using linear mixed-effects models

(e.g., correlation analysis)[91]. The following model was implemented:

$$Y \sim X + (X \mid \text{Random Effects})$$

Mixed linear models include both fixed and random effects, where fixed effects are the

variables under study and random effects are the influences that we wish to control for, which are

referred to as "Groups" in this paper. The mixed linear model was generated using the R package

statistical function lme4 (version 1.1-35.1). We tested the difference between the fixed-effects

model and the model with fixed effects removed through ANOVA to determine whether the linear

correlation between the fixed effects was significant.

Quantification and statistical analysis

Statistical analysis was performed using R (version 4.3.1). The Wilcoxon rank-sum test was used

in this study. Multiple comparison adjustments were performed using the Benjamini-Hochberg

method. $^*p < 0.05$, $^{**}p < 0.01$, $^{***}p < 0.001$.

 FIGURE LEGENDS

Figure 1. Overview of the multi-omics profiling of metabolic molecules and immune

responses in mountain climbers.

(A) Flowchart depicting the overall mountaineering design, sample collection and multi-omics

data analysis. All the data were collected from 11 healthy mountain climbers. The figures were

created with Adobe Illustrator 2023 and BioRender.com.

(B) Effects of high altitude on heart rate (HR) and blood saturation (SpO_2) during mountaineering.

Red represents HR, blue represents SpO_2, and the black dotted line represents altitude. M was

measured in the morning, and E was measured in the evening.

(C) Violin plots showing significant changes in selected routine blood parameters and C-reactive

protein (CRP) levels before (D1) and after (D16) the mountaineering expedition. The two-sided p

values from the paired Wilcoxon rank-sum test are shown, [*]$p < 0.05$, [**]$p < 0.01$, [***]$p < 0.001$.

(D) Bar plots showing changes in the numbers of significantly differentially abundant metabolites

and complex lipids during mountaineering.

(E) Uniform manifold approximation and projection (UMAP) plot showing 15 cell types among

375,722 circulating immune cells. Cells are colored according to different cell subtypes.

(F) Boxplots showing the relative proportion changes in selected subsets during mountaineering

(day 1, day 4, day 7, day 11 and day 16, n = 11); sample points from the same mountain climber

are connected with the same color. The two-sided p values from the paired Wilcoxon rank-sum

test are shown, [*]$p < 0.05$, [**]$p < 0.01$, [***]$p < 0.001$.

Figure 2. Dynamic changes in the inflammatory response in monocytes and DCs.

(A) UMAP plot showing nine myeloid cell subsets.

(B) Dot plots depicting the percentages and average expression levels of the canonical genes in

nine subsets of myeloid cells.

(C) Boxplots showing the changes in the relative proportions of selected myeloid cell subsets

before and during mountaineering (day 1, day 4, day 7, day 11 and day 16, n = 11); sample points

from the same mountain climber are connected with the same color. The two-sided p values from

the paired Wilcoxon rank-sum test are shown, [*]$p < 0.05$, [**]$p < 0.01$, [***]$p < 0.001$.

(D) Heatmap showing the scaled expression of genes in important biological pathways mediated

by myeloid cells across different time points. The two-sided p values from the Wilcoxon rank-sum

test are shown, [*]$p < 0.05$, [**]$p < 0.01$, [***]$p < 0.001$.

(E) Violin plots showing dynamic changes in the expression of selected differentially expressed

genes (DEGs) in CCL3$^+$ CD14$^+$ Monos, cDC2s and CD16$^+$ Monos ($|\log_2FC| \geqslant 0.7$, adjusted $p <$

0.05). [*]$p < 0.05$, [**]$p < 0.01$, [***]$p < 0.001$.

(F) Heatmap showing the regulon areas under the curve per cell (AUCell) scores for myeloid cells

across the five time points, calculated using the SCENIC algorithm.

(G) Correlation analysis between hypoxia scores and inflammatory response scores for each

climber at all five time points (linear mixed model).

(H) Dot plots showing the scaled expression and percentages of *HIF1A* in myeloid cell subsets

across different time points. The two-sided p values from the Wilcoxon rank-sum test are shown,

[*]$p < 0.05$, [**]$p < 0.01$, [***]$p < 0.001$.

1002

Figure 3. Dynamic changes in the functional status of T and NK cells in mountain climbers.

(A) UMAP plot showing nine subsets of CD8$^+$ T cells and other cells.

(B) Dot plots depicting the percentages and average expression of the canonical genes in nine

subsets of CD8$^+$ T cells and other cells.

(C) Boxplots showing the relative proportions of selected T and NK cell subsets during

mountaineering (day 1, day 4, day 7, day 11 and day 16, n = 11); sample points from the same

mountain climber are connected with the same color. The two-sided p values from the paired

Wilcoxon rank-sum test are shown, [*]$p < 0.05$, [**]$p < 0.01$, [***]$p < 0.001$.

(D) Heatmap showing the scaled scores for important immune-related pathways in cytotoxic CD8$^+$

T, γδT, CD16$^+$ NK and CD8$^+$ Tem cells at different time points. The two-sided p values from the

Wilcoxon rank-sum test are shown, [*]$p < 0.05$, [**]$p < 0.01$, [***]$p < 0.001$.

(E) Heatmap showing the expression levels of cytotoxicity-related genes in cytotoxic CD8$^+$ T, γδT,

CD16$^+$ NK and CD8$^+$ Tem cells at different time points. The two-sided p values from the

Wilcoxon rank-sum test are shown, [*]$p < 0.05$, [**]$p < 0.01$, [***]$p < 0.001$.

(F) Violin plots showing dynamic changes in the expression of selected DEGs in cytotoxic CD8$^+$

T, γδT, CD16$^+$ NK and CD8$^+$ Tem cells ($|\log_2FC| \geqslant 0.7$, adjusted $p < 0.05$). [*]$p < 0.05$, [**]$p < 0.01$,

[***]$p < 0.001$.

(G) Heatmap showing the regulon AUCell scores for CD8$^+$ T cells across the five time points,

calculated using the SCENIC algorithm.

(H) UMAP plots showing the regulon activities of *EOMES* and *TBX21* on D4 and D16 in CD8$^+$ T

cells, color-coded by AUCell score.

1024

Figure 4. Activation of the unfolded protein response in plasma B cells during

mountaineering.

(A) UMAP plot showing eight B cell subsets.

(B) Dot plots depicting the percentages and average expression levels of the canonical genes in

eight subsets of B cells.

(C) Boxplots showing the relative proportions of selected B cell subsets during mountaineering

(day 1, day, day 7, day 11 and day 16, n = 11); sample points from the same mountain climber are

connected with the same color. The two-sided *p* values from the paired Wilcoxon rank-sum test

are shown, $^*p < 0.05$, $^{**}p < 0.01$, $^{***}p < 0.001$.

(D) Violin plots showing dynamic changes in the expression of selected DEGs in activated B

cells($|\log_2 FC| \geqslant 0.7$, adjusted $p < 0.05$). $^*p < 0.05$, $^{**}p < 0.01$, $^{***}p < 0.001$.

(E) The fifteen enriched biological processes according to Gene Ontology (GO) analysis of the

upregulated DEGs in plasma B cells. Dot color indicates the statistical significance of the

enrichment, and dot size represents the gene ratio annotated to each term.

(F) Heatmap illustrating scaled expression values of selected DEGs across time points in plasma B

cells ($|\log_2 FC| \geqslant 0.7$, adjusted $p < 0.05$). $^*p < 0.05$, $^{**}p < 0.01$, $^{***}p < 0.001$.

(G) Heatmap showing the regulon AUCell scores from plasma B cells across different time points,

calculated using the SCENIC algorithm.

(H) Correlation analysis between hypoxia scores and *XBP1* expression levels in plasma B cells for

each climber all five time points (linear mixed model).

1045

1046   **Figure 5. Metabolic profile of circulating immune cells during mountaineering.**

1047   (A) Heatmap showing the scaled scores for oxidative phosphorylation and glycolysis pathways

1048   across different time points in selected cell subsets. The two-sided *p* values from the Wilcoxon

1049   rank-sum test are shown, $^*p < 0.05$, $^{**}p < 0.01$, $^{***}p < 0.001$.

(B) Heatmap showing the average expression of selected genes from oxidative phosphorylation pathways in myeloid cells across different time points.

(C) Violin plots showing dynamic changes in the expression of *ATP5F1E* in CCL3$^+$ CD14$^+$ Monos, FCN1$^+$ CD14$^+$ Monos, C1$^+$ CD16$^+$ Monos and cDC2s ($|\log_2 FC| \geqslant 0.7$, adjusted $p < 0.05$). $^*p < 0.05$, $^{**}p < 0.01$, $^{***}p < 0.001$.

(D) Violin plots showing dynamic changes in the expression of *COX4I1*, *COX7A2*, *COX5B* and *COX7C* in IFN$^+$ CD16$^+$ Monos ($|\log_2 FC| \geqslant 0.7$, adjusted $p < 0.05$). $^*p < 0.05$, $^{**}p < 0.01$, $^{***}p < 0.001$.

(E) Violin plots showing dynamic changes in the expression of glycolysis-related genes in plasma B cells and CD8$^+$ Tems ($|\log_2 FC| \geqslant 0.7$, adjusted $p < 0.05$). $^*p < 0.05$, $^{**}p < 0.01$, $^{***}p < 0.001$.

(F) Dynamic changes in AMPK-related pathways ('CAMKK AMPK Signaling Cascade') during high-altitude mountaineering in different immune cell subsets. Stage 1 is the acclimatization period, and stage 2 is the extreme altitude mountaineering period. Dots represent the mean $\log_2$-fold change relative to baseline (D1).

(G) The biological processes that significantly changed during high-altitude mountaineering in FCN1$^+$ CD14$^+$ Monos, CD16$^+$ Monos, cDC2s and cytotoxic CD8$^+$ T cells included the AMPK signaling, inflammatory response, hypoxia and immune effector process pathways. Dots represent the mean $\log_2$-fold change relative to baseline (D1).

Figure 6. Oxidative stress response of circulating immune cells during mountaineering.

(A) Heatmap showing the scaled scores for reactive oxygen species, oxidative stress and oxidant detoxification-related pathways across different time points. The two-sided p values from the Wilcoxon rank-sum test are shown, $^*p < 0.05$, $^{**}p < 0.01$, $^{***}p < 0.001$.

(B) Correlation analysis between hypoxia scores and oxidative stress scores for each climber at all five time points (linear mixed model).

(C) Heatmap showing the scaled expression of selected genes from cellular oxidant detoxification pathways in circulating immune cells across different time points. The two-sided p values from the Wilcoxon rank-sum test are shown, $^*p < 0.05$, $^{**}p < 0.01$, $^{***}p < 0.001$.

(D) Dot plots showing the scaled average expression levels and percentages of *SOD2* and *NFE2L2* in selected immune cell subsets at different time points. The two-sided p values from the

1080 Wilcoxon rank-sum test are shown, $^*p < 0.05$, $^{**}p < 0.01$, $^{***}p < 0.001$.

1081

Figure 7. Time series analysis of plasma metabolomics and lipidomic data during high-

altitude mountaineering.

(A) Variable importance in projection (VIP) scores showing the top 15 differentially abundant

metabolites for each sampling point. The heatmap on the right displays the scaled value of the

metabolite at each time point.

(B) Clustering of differentially abundant metabolites and lipids. The circular plots on the right

show the percentage of differentially abundant metabolites and lipids for each cluster.

(C) Pathway enrichment analysis of metabolites from cluster 1 and cluster 4. The red horizontal

dashed line indicates the threshold of statistical significance for the y-axis calculated by the

hypergeometric test ($p < 0.05$). The red vertical dashed lines indicate pathway impact values $\geqslant$

0.1.

(D) The dynamic changes in key metabolites in the enrichment pathways of cluster 1 and cluster 4.

Dots represent the mean $\log_2$-fold change relative to D1, and horizontal bars represent the standard

error of the mean (SEM).

(E) Dynamic changes in oxidative stress-related metabolites during mountaineering. The dots

represent the mean $\log_2$-fold change relative to day 1, and the bars represent the standard error of

the mean (SEM).

(F) Correlation analysis between oxidative stress scores and selenocompound metabolism scores

for each climber at all five time points (linear mixed model).

(G) Stacked column charts showing the percentage of each complex lipid in cluster 2 and cluster 3.

(H) Chemical classification enrichment analysis of complex lipids. The pathway direction is the

change in significant molecules in each classification relative to D1 (blue, downregulated; red,

upregulated). The size of the dot represents the significance of the pathway.

1105

SUPPLEMENTAL INFORMATION

Supplementary Figure 1. Effects of high altitude on physiological parameters during

mountaineering.

(A) Box plots showing the dynamic changes in SpO$_2$ and heart ratHR with increasing altitude;

sample points from the same mountain climber are connected with the same color (n = 11). The

two-sided p values from the paired Wilcoxon rank-sum test are shown, $^*p < 0.05$, $^{**}p < 0.01$, $^{***}p <$

0.001.

(B) Box plots showing the changes in SpO_2 and HR when re-exposed to the same altitude (4,400

m and 5,500 m); sample points from the same mountain climber are connected with the same

color (n = 11). The two-sided p values from the paired Wilcoxon rank-sum test are shown, $^*p <$

0.05, $^{**}p < 0.01$, $^{***}p < 0.001$.

(C) Box plots showing the changes in body composition during mountaineering; sample points

from the same mountain climber are connected with the same color. The two-sided p values from

the paired Wilcoxon rank-sum test are shown, but no significant differences were detected. Body

mass index (BMI), body fat percentage (BFP%), muscle mass (MM, kg) and fat mass (FM, kg)

were measured.

1122

Supplementary Figure 2. Effects of high altitude on routine blood parameters during

mountaineering.

Violin plots showing the changes in routine blood parameters before (D1) and after (D16)

mountaineering, divided into three groups: red blood cell-related parameters, platelet-related

parameters and white blood cell-related parameters. The complete names of these parameters are

displayed in Table S1. The two-sided p values from the paired Wilcoxon rank-sum test are shown,

$^*p < 0.05$, $^{**}p < 0.01$, $^{***}p < 0.001$.

1130

Supplementary Figure 3. Quality control of the scRNA-seq data.

(A) Violin plots showing the distributions of gene counts per cell, unique molecular identifier

(UMI) per cell, and percentage of mitochondrial transcripts per cell across five time points from

eleven mountain climbers.

(B) Bar plots showing the number of cells at each time point and the number of cells from each

volunteer. D1 (n = 69,847 cells), D4 (n = 100,271 cells), D9 (n = 48,686 cells), D11 (n = 97,447

cells), and D16 (n = 5,9471 cells).

1138

Supplementary Figure 4. Single-cell analysis of circulating immune cells in mountain

climbers.

(A) Violin plots depicting the normalized expression levels of canonical markers associated with

each main immune cell subgroup.

(B) Stacked column charts showing the proportions of each cell type from each volunteer and

different sampling time points.

(C) Boxplots showing the relative proportions of immune cell subsets during mountaineering (day

1, day 4, day 7, day 11 and day 16, n = 11); sample points from the same mountain climber are

connected with the same color. The two-sided p values from the paired Wilcoxon rank-sum test

are shown, $^*p < 0.05$, $^{**}p < 0.01$, $^{***}p < 0.001$.

(D) UMAP plot of all immune cell subtypes identified from single-cell samples from climbers at

different time points, colored according to their respective subgroup.

1151

Supplementary Figure 5. Transcriptional changes in monocyte subsets during

mountaineering.

(A) Stacked column charts showing the proportions of myeloid cell subsets from each volunteer

and different sampling time points.

(B) Boxplots showing the relative proportions of myeloid cell subsets during mountaineering (day

1, day 4, day 7, day 11 and day 16, n = 11); sample points from the same mountain climber are

connected with the same color. The two-sided p values from the paired Wilcoxon rank-sum test

are shown, $^*p < 0.05$, $^{**}p < 0.01$, $^{***}p < 0.001$.

(C) Dot plots showing the enriched biological processes by GO analysis of upregulated and

downregulated DEGs on day 4, day 7, day 11 and day 16 compared to day 1. Dot color indicates

the statistical significance of the enrichment, and dot size represents the gene ratio annotated to

each term.

(D) Violin plots showing dynamic changes in the expression of selected DEGs in FCN1$^+$ CD14$^+$

Monos ($|\log_2 FC| \geqslant 0.7$, adjusted $p < 0.05$). $^*p < 0.05$, $^{**}p < 0.01$, $^{***}p < 0.001$.

1166

Supplementary Figure 6. Transcriptional changes in pDCs during mountaineering.

(A) The twenty enriched biological processes identified by GO analysis of downregulated DEGs

in pDCs. The dot color indicates the statistical significance of the enrichment, and the dot size

represents the ratio of genes annotated to each term.

(B) Heatmap illustrating scaled expression values of selected DEGs at various time points in pDCs.

The two-sided p values from the Wilcoxon rank-sum test are shown, $^*p < 0.05$, $^{**}p < 0.01$, $^{***}p <$

0.001.

(C) Heatmap showing the regulon scenic scores for pDCs across different time points, calculated

using the SCENIC algorithm.

1176

Supplementary Figure 7. Changes in transcription in CD4$^+$ T, CD8$^+$ T and NK cell subsets

during mountaineering.

(A) UMAP plot showing six subsets of CD4$^+$ T cells.

(B) Dot plot depicting the percentages and average expression levels of canonical genes in six

subsets of CD4$^+$ T cells.

(C) UMAP plot showing five NK cell subsets.

(D) Dot plot depicting the percentages and average expression levels of canonical genes in five

NK cell subsets.

(E) Box plots showing the changes in the alpha/beta T cell activation pathway over time in naive

CD4$^+$ T and Th2 cells; sample points from the same mountain climber are connected with the

same color. The two-sided p values from the paired Wilcoxon rank-sum test are shown, $^*p < 0.05$,

$^{**}p < 0.01$, $^{***}p < 0.001$.

(F) The regulatory networks of *TBX21* and *EOMES* and their target genes in CD8$^+$ T cells.

1190

Supplementary Figure 8. Dynamic changes in the proportions of CD4$^+$ T, CD8+ T and NK

cell subsets in mountain climbers.

(A) Stacked column charts showing the proportions of CD4$^+$ T cell subsets from each volunteer

and different sampling time points.

(B) Stacked column charts showing the proportions of CD8$^+$ T cell subsets from each volunteer

and at different sampling time points.

(C) Stacked column charts showing the proportions of NK cell subsets from each volunteer and

different sampling time points.

(D) Boxplots illustrating the relative proportions of identified subsets of CD4$^+$ T, CD8$^+$ T and NK

cells during mountaineering (day 1, day 4, day 7, day 11 and day 16, n = 11); sample points from

the same mountain climber are connected in the same color. The two-sided p values from the

paired Wilcoxon rank-sum test are shown, $^*p < 0.05$, $^{**}p < 0.01$, $^{***}p < 0.001$.

1203

Supplementary Figure 9. Dynamic changes in the compositions of B cell subsets in mountain

climbers.

(A) Stacked column charts showing the proportions of B cell subsets from each volunteer and

different sampling time points.

(B) Boxplots showing the relative proportions of B cell subsets during mountaineering (day 1, day

4, day 7, day 11 and day 16, n = 11); sample points from the same mountain climber are

connected with the same color. The two-sided p values from the paired Wilcoxon rank-sum test

are shown, $^*p < 0.05$, $^{**}p < 0.01$, $^{***}p < 0.001$.

(C) Regulatory networks of *XBP1* and its target genes in plasma B cells.

1213

Supplementary Figure 10. Metabolic pathway analysis of circulating immune cells in

mountain climbers.

(A) Heatmap showing the scaled expression of genes in the hypoxia pathway and dot plots

illustrating the scaled expression and percentages of *HIF1A* in the T, NK and B cell subgroups

across different time points. The two-sided p values from the Wilcoxon rank-sum test are shown,

$^*p < 0.05$, $^{**}p < 0.01$, $^{***}p < 0.001$.

(B) Heatmap showing the scaled expression of genes in AMPK-related pathways ('CAMKK

AMPK Signaling Cascade') across different time points. The two-sided p values from the

Wilcoxon rank-sum test are shown, $^*p < 0.05$, $^{**}p < 0.01$, $^{***}p < 0.001$.

(C) Heatmap showing the expression levels of AMPK-related genes in immune cell subgroups

across different time points. The two-sided p values from the Wilcoxon rank-sum test are shown,

$^*p < 0.05$, $^{**}p < 0.01$, $^{***}p < 0.001$.

1226

1227 **Supplementary Figure 11. Hypoxia-induced glycolysis pathway during mountaineering.**

1228 Correlation analysis between hypoxia scores and glycolysis scores in immune cells (A) and each

1229 immune subgroup (B) (linear mixed model).

1230

Supplementary Figure 12. Alterations in plasma metabolites during mountaineering.

(A) Sankey diagram illustrating the metabolites contained in metabolic pathways that were

enriched in cluster 1 and cluster 4.

(B) Pathway enrichment analysis of metabolites from cluster 2 and cluster 3. The red horizontal

dashed line indicates the threshold of statistical significance for the y-axis calculated by the

hypergeometric test ($p < 0.05$). The red vertical dashed lines indicate pathway impact values $\geqslant$

0.1.

(C) Dynamic changes in key metabolites in the citrate cycle (TCA cycle). Dots represent the mean

$\log_2$-fold change relative to D1, and horizontal bars represent the standard error of the mean

(SEM).

(D) Heatmaps representing changes in the levels of carnitines or acylcarnitines and fatty acids.

Clusters are labeled on the left side of the heatmap. Fatty acids with different chain lengths are

indicated by different colors.

(E) Box plots representing the 3-hydroxybutyric acid levels at different time points; the horizontal

line represents the median value. The p values from the two-sided Wilcoxon rank-sum test are

shown, [*]$p < 0.05$, [**]$p < 0.01$, [***]$p < 0.001$.

1247

1248

1249

1250

1251

1252

1253

1254

1255

1256

1257

1258

1259

REFERENCES

1. Apollo, M., *The true accessibility of mountaineering: The case of the High Himalaya.* Journal of Outdoor Recreation and Tourism, 2017. **17**: p. 29-43.

2. Luks, A.M. and P.H. Hackett, *Medical Conditions and High-Altitude Travel Reply.* New England Journal of Medicine, 2022. **386**(19): p. 1866-1867.

3. Palmer, B.F., *Physiology and Pathophysiology With Ascent to Altitude.* American Journal of the Medical Sciences, 2010. **340**(1): p. 69-77.

4. Burtscher, J., et al., *Immune consequences of exercise in hypoxia: A narrative review.* J Sport Health Sci, 2023.

5. Bosco, G., et al., *Body Composition and Endocrine Adaptations to High-Altitude Trekking in the Himalayas.* Advancements and Innovations in Health Sciences, 2019. **1211**: p. 61-68.

6. Basnyat, B. and J.M. Starling, *Infectious Diseases at High Altitude.* Microbiol Spectr, 2015. **3**(4).

7. Simpson, R.J., et al., *Can exercise affect immune function to increase susceptibility to infection?* Exercise Immunology Review, 2020. **26**: p. 8-22.

8. Nieman, D.C. and L.M. Wentz, *The compelling link between physical activity and the body's defense system.* Journal of Sport and Health Science, 2019. **8**(3): p. 201-217.

9. Manella, G., et al., *The human blood transcriptome exhibits time-of-day-dependent response to hypoxia: Lessons from the highest city in the world.* Cell Reports, 2022. **40**(7).

10. Rohm, I., et al., *Hypobaric hypoxia in 3000 m altitude leads to a significant decrease in circulating plasmacytoid dendritic cells in humans.* Clin Hemorheol Microcirc, 2016. **63**(3): p. 257-65.

11. Facco, M., et al., *Modulation of immune response by the acute and chronic exposure to high altitude.* Medicine and Science in Sports and Exercise, 2005. **37**(5): p. 768-774.

12. Chen, F., et al., *Transcriptome and Network Changes in Climbers at Extreme Altitudes.* Plos One, 2012. **7**(2).

13. Miller, L.E., et al., *Blood Oxidative-Stress Markers During a High-Altitude Trek.* International Journal of Sport Nutrition and Exercise Metabolism, 2013. **23**(1): p. 65-72.

14. Mrakic-Sposta, S., et al., *OxInflammation at High Altitudes: A Proof of Concept from the Himalayas.* Antioxidants, 2022. **11**(2).

15. Nieman, D.C. and B.D. Pence, *Exercise immunology: Future directions.* Journal of Sport and

Health Science, 2020. **9**(5): p. 432-445.

16. Mariggiò, M.A., et al., *Peripheral Blood Lymphocytes: A Model for Monitoring*

Physiological Adaptation to High Altitude. High Altitude Medicine & Biology, 2010. **11**(4): p.

333-342.

17. Morabito, C., et al., *Responses of peripheral blood mononuclear cells to moderate exercise*

and hypoxia. Scandinavian Journal of Medicine & Science in Sports, 2016. **26**(10): p. 1188-

1199.

18. Chi, H.B., *Immunometabolism at the intersection of metabolic signaling, cell fate, and*

systems immunology. Cellular & Molecular Immunology, 2022. **19**(3): p. 299-302.

19. O'Brien, K.A., et al., *Metabolomic and lipidomic plasma profile changes in human*

participants ascending to Everest Base Camp. Scientific Reports, 2019. **9**.

20. Yu, Y.L., et al., *Single-cell sequencing of immune cells after marathon and symptom-limited*

cardiopulmonary exercise. Iscience, 2023. **26**(4).

21. Ehrchen, J.M., et al., *The endogenous Toll-like receptor 4 agonist S100A8/S100A9*

(calprotectin) as innate amplifier of infection, autoimmunity, and cancer. Journal of

Leukocyte Biology, 2009. **86**(3): p. 557-566.

22. Swanson, K.V., M. Deng, and J.P.Y. Ting, *The NLRP3 inflammasome: molecular activation*

and regulation to therapeutics. Nature Reviews Immunology, 2019. **19**(8): p. 477-489.

23. van de Sande, B., et al., *A scalable SCENIC workflow for single-cell gene regulatory network*

analysis. Nature Protocols, 2020. **15**(7): p. 2247-2276.

24. Pham, K., K. Parikh, and E.C. Heinrich, *Hypoxia and Inflammation: Insights From High-*

Altitude Physiology. Frontiers in Physiology, 2021. **12**.

25. Lin, N. and M.C. Simon, *Hypoxia-inducible factors: key regulators of myeloid cells during*

inflammation. Journal of Clinical Investigation, 2016. **126**(10): p. 3661-3671.

26. Swiecki, M. and M. Colonna, *The multifaceted biology of plasmacytoid dendritic cells.*

Nature Reviews Immunology, 2015. **15**(8): p. 471-485.

27. Iwakoshi, N.N., M. Pypaert, and L.H. Glimcher, *The transcription factor XBP-1 is essential*

for the development and survival of dendritic cells. Journal of Experimental Medicine, 2007.

204(10): p. 2267-2275.

28. Yilmaz, A., et al., *Decrease in circulating plasmacytoid dendritic cells during short-term*
systemic normobaric hypoxia. European Journal of Clinical Investigation, 2016. **46**(2): p.
115-122.

29. Wobben, R., et al., *Role of hypoxia inducible factor-1α for interferon synthesis in mouse*
dendritic cells. Biological Chemistry, 2013. **394**(4): p. 495-505.

30. Vignali, D.A.A., L.W. Collison, and C.J. Workman, *How regulatory T cells work.* Nature
Reviews Immunology, 2008. **8**(7): p. 523-532.

31. Fang, M., et al., *CD94 Is Essential for NK Cell-Mediated Resistance to a Lethal Viral*
Disease. Immunity, 2011. **34**(4): p. 579-589.

32. Li, Q., et al., *Upregulation of CX3CR1 expression in circulating T cells of systemic lupus*
erythematosus patients as a reflection of autoimmune status through characterization of
cytotoxic capacity. International Immunopharmacology, 2024. **126**.

33. Le Bouteiller, P., et al., *CD160: A unique activating NK cell receptor.* Immunology Letters,
2011. **138**(2): p. 93-96.

34. Tu, T.C., et al., *CD160 is essential for NK-mediated IFN-γ production.* Journal of
Experimental Medicine, 2015. **212**(3): p. 415-429.

35. Li, M.O. and R.A. Flavell, *TGF-β:: A master of all T cell trades.* Cell, 2008. **134**(3): p. 392-
404.

36. Knox, J.J., et al., *Characterization of T-bet and eomes in Peripheral Human immune Cells*
(vol 5, 217, 2014). Frontiers in Immunology, 2016. **7**.

37. Krzyzak, L., et al., *CD83 Modulates B Cell Activation and Germinal Center Responses.*
Journal of Immunology, 2016. **196**(9): p. 3581-3594.

38. Ricci, D., T. Gidalevitz, and Y. Argon, *The special unfolded protein response in plasma*
cells*. Immunological Reviews, 2021. **303**(1): p. 35-51.

39. Chohan, I.S., et al., *Immune response in human subjects at high altitude.* Int J Biometeorol,
1975. **19**(3): p. 137-43.

40. Reimold, A.M., et al., *Plasma cell differentiation requires the transcription factor XBP-1.*
Nature, 2001. **412**(6844): p. 300-307.

41. Romero-Ramirez, L., et al., *XBP1 is essential for survival under hypoxic conditions and is*
required for tumor growth. Cancer Research, 2004. **64**(17): p. 5943-5947.

42. Lee, P., N.S. Chandel, and M.C. Simon, *Cellular adaptation to hypoxia through hypoxia*
inducible factors and beyond. Nature Reviews Molecular Cell Biology, 2020. **21**(5): p. 268-
283.

43. Tanner, L.B., et al., *Four Key Steps Control Glycolytic Flux in Mammalian Cells.* Cell
Systems, 2018. **7**(1): p. 49-+.

44. Krzeslak, A., et al., *Expression of GLUT1 and GLUT3 Glucose Transporters in Endometrial*
and Breast Cancers. Pathology & Oncology Research, 2012. **18**(3): p. 721-728.

45. Herzig, S. and R.J. Shaw, *AMPK: guardian of metabolism and mitochondrial homeostasis.*
Nature Reviews Molecular Cell Biology, 2018. **19**(2): p. 121-135.

46. Rolf, J., et al., *AMPKα1: A glucose sensor that controls CD8 T-cell memory.* European
Journal of Immunology, 2013. **43**(4): p. 889-896.

47. Wang, J., et al., *The regulation effect of AMPK in immune related diseases.* Science China-
Life Sciences, 2018. **61**(5): p. 523-533.

48. Cui, Y.X., et al., *The role of AMPK in macrophage metabolism, function and polarisation.*
Journal of Translational Medicine, 2023. **21**(1).

49. Blagih, J., et al., *The Energy Sensor AMPK Regulates T Cell Metabolic Adaptation and*
Effector Responses In Vivo. Immunity, 2015. **42**(1): p. 41-54.

50. Halliwell, B., *Understanding mechanisms of antioxidant action in health and disease.* Nature
Reviews Molecular Cell Biology, 2024. **25**(1): p. 13-33.

51. Flynn, J.M. and S. Melov, *SOD2 in mitochondrial dysfunction and neurodegeneration.* Free
Radical Biology and Medicine, 2013. **62**: p. 4-12.

52. Kaspar, J.W., S.K. Niture, and A.K. Jaiswal, *Nrf2:INrf2 (Keap1) signaling in oxidative stress.*
Free Radical Biology and Medicine, 2009. **47**(9): p. 1304-1309.

53. Lee, S., S.M. Kim, and R.T. Lee, *Thioredoxin and Thioredoxin Target Proteins: From*
Molecular Mechanisms to Functional Significance. Antioxidants & Redox Signaling, 2013.
18(10): p. 1165-1207.

54. Zito, E., *PRDX4, an Endoplasmic Reticulum-Localized Peroxiredoxin at the Crossroads*
Between Enzymatic Oxidative Protein Folding and Nonenzymatic Protein Oxidation.
Antioxidants & Redox Signaling, 2013. **18**(13): p. 1666-1674.

55. Adeva-Andany, M.M., et al., *Metabolic effects of glucagon in humans.* J Clin Transl

Endocrinol, 2019. **15**: p. 45-53.

56.   Tipton, K.D., D.L. Hamilton, and I.J. Gallagher, *Assessing the Role of Muscle Protein Breakdown in Response to Nutrition and Exercise in Humans.* Sports Medicine, 2018. **48**: p. S53-S64.

57.   Lushchak, V.I., *Glutathione homeostasis and functions: potential targets for medical interventions.* J Amino Acids, 2012. **2012**: p. 736837.

58.   Yang, L., S. Venneti, and D. Nagrath, *Glutaminolysis: A Hallmark of Cancer Metabolism.* Annu Rev Biomed Eng, 2017. **19**: p. 163-194.

59.   Liu, D., et al., *Moderate altitude exposure impacts host fasting blood glucose and serum metabolome by regulation of the intestinal flora.* Science of the Total Environment, 2023. **905**.

60.   Cruzat, V., et al., *Glutamine: Metabolism and Immune Function, Supplementation and Clinical Translation.* Nutrients, 2018. **10**(11).

61.   Jin, Z., S.K. Mendu, and B. Birnir, *GABA is an effective immunomodulatory molecule.* Amino Acids, 2013. **45**(1): p. 87-94.

62.   Schrauzer, G.N., *The nutritional significance, metabolism and toxicology of selenomethionine.* Adv Food Nutr Res, 2003. **47**: p. 73-112.

63.   Ayala, A., M.F. Munoz, and S. Arguelles, *Lipid peroxidation: production, metabolism, and signaling mechanisms of malondialdehyde and 4-hydroxy-2-nonenal.* Oxid Med Cell Longev, 2014. **2014**: p. 360438.

64.   Makrecka-Kuka, M., et al., *Plasma acylcarnitine concentrations reflect the acylcarnitine profile in cardiac tissues.* Sci Rep, 2017. **7**(1): p. 17528.

65.   Nelson, A.B., et al., *Metabolic Messengers: ketone bodies.* Nat Metab, 2023. **5**(12): p. 2062-2074.

66.   Tsekouras, Y.E., et al., *A single bout of whole-body resistance exercise augments basal VLDL-triacylglycerol removal from plasma in healthy untrained men.* Clin Sci (Lond), 2009. **116**(2): p. 147-56.

67.   Liu, P., et al., *The mechanisms of lysophosphatidylcholine in the development of diseases.* Life Sci, 2020. **247**: p. 117443.

68.   van der Veen, J.N., et al., *The critical role of phosphatidylcholine and*

phosphatidylethanolamine metabolism in health and disease. Biochimica Et Biophysica

Acta-Biomembranes, 2017. **1859**(9): p. 1558-1572.

69.   Nieman, D.C., et al., *Serum Metabolic Signatures Induced By a Three-Day Intensified*

Exercise Period Persist After 14 h of Recovery in Runners. Journal of Proteome Research,

2013. **12**(10): p. 4577-4584.

70.   Iqbal, J., et al., *Sphingolipids and Lipoproteins in Health and Metabolic Disorders.* Trends in

Endocrinology and Metabolism, 2017. **28**(7): p. 506-518.

71.   Da Rosa, P.C., et al., *The physical exercise-induced oxidative*

inflammatory response in peripheral blood mononuclear cells: Signaling cellular energetic stress

situations. Life Sciences, 2023. **321**.

72.   Laddu, R., et al., *Physical activity for immunity protection: Inoculating populations with*

healthy living medicine in preparation for the next pandemic. Progress in Cardiovascular

Diseases, 2021. **64**: p. 102-104.

73.   Pham, K., et al., *Inflammatory gene expression during acute high-altitude exposure.* Journal

of Physiology-London, 2022. **600**(18): p. 4169-4186.

74.   Spaulding, H.R. and Z. Yan, *AMPK and the Adaptation to Exercise.* Annual Review of

Physiology, 2022. **84**: p. 209-227.

75.   Kammerer, T., et al., *Hypoxic-Inflammatory Responses under Acute Hypoxia: In Vitro*

Experiments and Prospective Observational Expedition Trial. International Journal of

Molecular Sciences, 2020. **21**(3).

76.   McNicholas, W.T., *Chronic Obstructive Pulmonary Disease and Obstructive Sleep Apnea*

Overlaps in Pathophysiology, Systemic Inflammation, and Cardiovascular Disease.

American Journal of Respiratory and Critical Care Medicine, 2009. **180**(8): p. 692-700.

77.   Rius, J., et al., *NF-κB links innate immunity to the hypoxic response through transcriptional*

regulation of HIF-1α. Nature, 2008. **453**(7196): p. 807-U9.

78.   Mingyuan, X., et al., *Hypoxia-inducible factor-1alpha activates transforming growth factor-*

beta1/Smad signaling and increases collagen deposition in dermal fibroblasts. Oncotarget,

2018. **9**(3): p. 3188-3197.

79.   Regis, S., et al., *NK Cell Function Regulation by TGF-β-Induced Epigenetic Mechanisms.*

Frontiers in Immunology, 2020. **11**.

80. Murray, A.J. and J.A. Horscroft, *Mitochondrial function at extreme high altitude.* Journal of

1441   Physiology-London, 2016. **594**(5): p. 1137-1149.

1442   81. Sinha, S., et al., *Different adaptation patterns of antioxidant system in natives and sojourners*

1443   *at high altitude.* Respiratory Physiology & Neurobiology, 2009. **167**(3): p. 255-260.

1444   82. Dobin, A., et al., *STAR: ultrafast universal RNA-seq aligner.* Bioinformatics, 2013. **29**(1): p.

1445   15-21.

1446   83. Butler, A., et al., *Integrating single-cell transcriptomic data across different conditions,*

1447   *technologies, and species.* Nature Biotechnology, 2018. **36**(5): p. 411-+.

1448   84. McGinnis, C.S., L.M. Murrow, and Z.J. Gartner, *DoubletFinder: Doublet Detection in*

1449   *Single-Cell RNA Sequencing Data Using Artificial Nearest Neighbors.* Cell Systems, 2019.

1450   **8**(4): p. 329-+.

1451   85. Yu, G.C., et al., *clusterProfiler: an R Package for Comparing Biological Themes Among*

1452   *Gene Clusters.* Omics-a Journal of Integrative Biology, 2012. **16**(5): p. 284-287.

1453   86. Liberzon, A., *The Molecular Signatures Database (MSigDB) hallmark gene set collection.* .

1454   Cell systems, 2015.

1455   87. Tyanova, S., et al., *The Perseus computational platform for comprehensive analysis of*

1456   *(prote)omics data.* Nature Methods, 2016. **13**(9): p. 731-740.

1457   88. Pang, Z.Q., et al., *Using MetaboAnalyst 5.0 for LC-HRMS spectra processing, multi-omics*

1458   *integration and covariate adjustment of global metabolomics data.* Nature Protocols, 2022.

1459   **17**(8): p. 1735-1761.

1460   89. *Mfuzz: a software package for soft clustering of microarray data.* 2007.

1461   90. Lee, J.W., et al., *Integrated analysis of plasma and single immune cells uncovers metabolic*

1462   *changes in individuals with COVID-19.* Nature Biotechnology, 2022. **40**(1): p. 110-+.

1463   91. Bolker, B.M., et al., *Generalized linear mixed models: a practical guide for ecology and*

1464   *evolution.* Trends in Ecology & Evolution, 2009. **24**(3): p. 127-135.

1465

Figure 1

Figure 2

Figure 3

A CD8+ T & other T cells
n = 135,616

MAIT, Proliferating T, CD8+ Tem, γδT, CD8+ Tcm, NK-like T, Naive CD8+ T, TE-like CD8+ T, Cytotoxic CD8+ T

B

C Treg, Th2, Cytotoxic CD8+ T, γδT, CD16+ NK, CD8+ Tem

Volunteer — V1 — V2 — V3 — V4 — V5 — V6 — V7 — V8 — V9 — V10 — V11

D Cytotoxic CD8+ T, γδT, CD16+ NK, CD8+ Tem

Cytotoxic score
T cell activation
Immune effector process
NK cell mediated immunity
NK cell activation involved in immune reponse
T cell activation involved in immune reponse
T cell receptor signaling pathway

Scaled score

E Cytotoxic CD8+ T, γδT, CD16+ NK, CD8+ Tem

GZMA, GZMB, GZMK, GZMH, GNLY, NKG7, PRF1, IFNG

Scaled expression

F Cytotoxic CD8+ T, γδT, CD16+ NK, CD8+ Tem

KLRD1, CX3CR1, TGFB1, CD160, CD69, HLA-DRB5, REL

G SCENIC Regulon AUCell Scores in CD8+ T cells

H EOMES(+), TBX21(+)

Figure 4

Figure 5

Figure 6

Figure 7

Supplemental Figure 1

Supplemental Figure 2

Red Blood Cell Related Parameters

Platelet Related Parameters

White Blood Cell Related Parameters

Supplemental Figure 3

A

Number of Genes

Number of UMIs

Percentage of Mitrochondrial Genes

B

Sampling Time Points

Volunteer

Supplemental Figure 4

Supplemental Figure 5

Supplemental Figure 6

A

GO analysis of downregulated DEGs in pDCs

B

Gene Expression in pDCs

C

SCENIC Regulon AUCell Scores in pDCs

Supplemental Figure 7

Supplemental Figure 8

Supplemental Figure 9

A

C SCENIC Regulon Target Genes

B

Supplemental Figure 10

Supplemental Figure 11

A

B

Supplemental Figure 12