Nuclear FAK aggravates CD8[+] T cell exhaustion via the SP1-IL-6 axis in colorectal cancer

Hao Kong[1, %], Xiangji Wu[1, %], Qingxin Yang[1, %], Chunwei Wu[1, %], Xin Yu[1], Jie Yang[1], Dai Xie[1], Yu Dai[1], Lang Chen[4], Panpan Ma[4], Siqi Dai[1], Libin Huang[5], Chong Chen[1], Peng Mi[1], Yong Peng[1,8], Hubing Shi[7], Dunfang Zhang[1], Nengwen Ke[2], Zongguang Zhou[5], Dan Cao[6], Bing Hu[9], Ping Wang[1, *], Lu Chen[3*], Yun-Hua Liu[4*], Hong Jiang[1, 2, *, #]

[1]Department of Biotherapy, State Key Laboratory of Biotherapy and Cancer Center, West China Hospital, Sichuan University, Chengdu 610041, China.

[2]Department of Pancreatic Surgery, West China Hospital, Sichuan University, Chengdu 610041, China.

[3]Key Laboratory of Birth Defects and Related Diseases of Women and Children of MOE, Department of Laboratory Medicine, State Key Laboratory of Biotherapy, West China Second University Hospital, Sichuan University, Chengdu 610041, China.

[4] Department of Surgical Oncology of the Second Affiliated Hospital, and Department of Pathology & Pathophysiology, Zhejiang University School of Medicine, Hangzhou 310058, China.

[5]Laboratory of Digestive Surgery, State Key Laboratory of Biotherapy and Cancer Center, Sichuan University, Chengdu 610041, China.

[6]Abdominal Oncology Ward, Division of Medical Oncology, Cancer Center, State Key Laboratory of Biotherapy, West China Hospital, Sichuan University, Chengdu 610041, China

[7]Institute for Breast Health Medicine, State Key Laboratory of Biotherapy, West China Hospital, Sichuan University and Collaborative Innovation Center, Chengdu 610041, China, 610041

[8]Frontiers Medical Center, Tianfu Jincheng Laboratory, Chengdu 610212, China

[9]Department of Gastroenterology and Hepatology, Digestive Endoscopy Medical Engineering Research Laboratory, West China Hospital, Sichuan University, Chengdu 610064, China

Lead contact

% These authors contributed equally.

*Corresponding authors: Hong Jiang, hjiang@scu.edu.cn; Yun-Hua Liu, yunhualiu@zju.edu.cn; Lu Chen, luchen@scu.edu.cn; and Ping Wang, pingw1202@gmail.com

SUMMARY

Although immune checkpoint blockade (ICB) therapy has shown promise in colorectal cancer
patients with high microsatellite instability (MSI-H), response rates remain low for the majority
of patients. Key challenges include the exhaustion of CD8$^+$ T cells and the presence of
immunosuppressive cells within the tumor microenvironment. By integrating digital spatial
profiling and scRNA sequencing, we found that the tumor-intrinsic activation of focal adhesion
kinase (FAK) was strongly correlated with the heterogeneity and exhaustion of CD8$^+$ T cells
within the spatial context of the tumor microenvironment and correlated with patient survival.
Pharmacological inhibition or genetic loss of FAK enhanced antitumor immune responses and
synergistically potentiated αPD-1 and αTIM-3 immunotherapy by augmenting CD8$^+$ T cell
cytotoxicity and restoring exhaustion in preclinical models of colorectal cancer. Mechanistically,
nuclear FAK was found to regulate SP1/IL-6-mediated T cell exhaustion and the transcription of
proinflammatory cytokines/chemokines. These findings underscore FAK's pivotal role in CD8$^+$
T cell exhaustion within the immunosuppressive tumor microenvironment, suggesting that FAK
is a promising target for advancing cancer immunotherapy.

INTRODUCTION

The treatment of colorectal cancer remains challenging despite advances in multimodal therapy,
such as radiation, chemotherapy, and surgery.[1–3] While these approaches improve local disease
control, the high distant recurrence rate of nearly 30% and substantial side effects underscore the
need for novel therapeutic strategies.[4,5] Immunotherapy has revolutionized cancer treatment for
several malignancies, such as melanoma, but has shown limited benefit in colorectal cancer,
particularly in microsatellite stable (MSS) tumors.[6,7] Only a small portion of patients with high
microsatellite instability (MSI-H) in colorectal cancer, estimated to be approximately 15%, are
eligible for immunotherapy targeting PD-1, PD-L1, or CTLA-4.[8–10] Most colorectal cancers are
microsatellite stable (MSS) and are not responsive to immunotherapies.[11,12] This disparity
highlights the urgent need for innovative immunotherapeutic approaches tailored to colorectal
cancers.

Studies have shown that a unique tumor microenvironment characterized by fibrotic stroma, exhaustion of CD8[+] tumor-infiltrating lymphocytes (TILs), and extensive infiltration by immunosuppressive cell populations contributes to the failure of therapies.[13–17] However, the heterogeneity and exhaustion of CD8[+] T cells within the spatial context of the tumor microenvironment and their correlation with treatment response and patient survival are still largely unknown.[18] Moreover, the mediators driving CD8[+] T cell exhaustion and limiting the response to immunotherapy in colorectal cancer are still elusive,[19] representing significant challenges in cancer immunotherapy.[20] A better understanding of these mediators is needed to develop more effective immunotherapies for colorectal cancer and improve patient outcomes.

To address these challenges, we performed digital spatial profiling (DSP) analysis[21] integrating single-cell RNA sequencing datasets of 64 human CRC tissues and 36 normal tissues[22] to elucidate the spatial heterogeneity and functional characteristics of CD8[+] TILs. Our findings revealed that the activation of focal adhesion kinase (FAK) correlates with TIL heterogeneity and exhaustion within the tumor microenvironment. Using MC38 and CT26 mouse models of colorectal cancer, we demonstrated that pharmacological inhibition or genetic loss of FAK enhances antitumor immune responses by suppressing SP1/IL-6-mediated T cell exhaustion. Importantly, targeting FAK with an inhibitor enhances the efficacy of αPD-1 and αTIM-3 immunotherapy by boosting the cytotoxicity of tumor-resident CD8[+] T cells and reversing exhaustion states in preclinical models. These results suggest that FAK inhibition represents a promising strategy for improving immunotherapy outcomes in human colorectal cancer patients.

RESULTS

Characterizing the immune microenvironment in human colorectal cancer through single-cell transcriptional and spatial proteomic profiling

To evaluate the tumor immune microenvironment (TIME) in human colorectal cancer (CRC), we reanalyzed published single-cell RNA sequencing (scRNA-seq) data from 62 individuals (34 MMRd and 28 MMRp) with primary untreated tumors and adjacent normal colon tissue from 36 individuals,[22] aiming to identify transcriptomic signatures (**Fig. 1a**). By scrutinizing 35 key

TIME-related genes (immune cell markers, immune checkpoints, tumor cell markers and
fibroblast markers) (**Supplementary Table 1**), we established an immuno-oncology profile
across different colorectal tumor subtypes (**Fig. 1b**). Overall, colorectal cancer tissues exhibited
a more complex immune composition than adjacent normal tissues, reflecting immune
infiltration heterogeneity. Specifically, while MMRd tumors had greater TIL infiltration than
MMRp tumors, as reported previously,[11,23] both tumor subtypes presented signs of TIL
exhaustion within the TIME, irrespective of TIL infiltration levels or MMR deficiency status.

Next, we conducted in-depth spatial proteomics on tumor tissues from 9 selected CRC patients
(1 MMRd and 8 MMRp) along with adjacent normal colon tissue from 1 patient, aiming to
thoroughly explore the spatial TIME of human CRC. The 116 circular regions of interest (ROIs)
were categorized into three spatial types (intratumoral, proximal and distal) based on their spatial
features (**Extended Data Fig. 1a, b**). Supported by the clustering of T cell markers, these 9
tumors were assigned to 3 TIME subtypes (inflamed, excluded and desert) (**Fig. 1c upper panel**
and Extended Data Fig. 1c). Consistent with the scRNA-seq results, inflamed tumors exhibited
increased infiltration of immune cells, including CD8$^+$ T cells, particularly in the intratumoral
region (**Fig. 1c, lower panel**). More importantly, we observed high expression of immune
checkpoints (ARG-1, IDO-1, TIM-3, PD-1, LAG-3 and CTLA-4) in regions enriched with CD8$^+$
T cells across all three TIME subtypes, indicating a tendency toward exhaustion among CD8$^+$
TILs (**Fig. 1c**).

To identify the predominant factor that determines the functional and spatial heterogeneity of
TILs among those 9 tumors, we compared proteins that were differentially expressed between
every two TIME subtypes of the same histological region. Compared with those in adjacent
normal tissues, significantly elevated levels of exhaustion markers, notably TIM-3 and PD-1,
were detected in the intratumoral region (**Extended Data Fig. 1d, e, f**). Subsequently, we
established an exhaustion scoring system using a set of classic checkpoint genes (*PDCD1,*
HAVCR2, TOX, LAG3, TIGIT, EOMES and *ENTPD1*) (**Fig. 1d**) to quantify T cell exhaustion
and found a significantly greater T cell exhaustion score in tumors (**Fig. 1e**). When applied to
bulk RNA-seq data from external colorectal cancer patient cohorts, the exhaustion scoring
system demonstrated remarkable clinical value, as patients with higher exhaustion scores in these

datasets experienced poorer survival outcomes than those with lower scores (**Fig. 1f**). Together,

these findings suggest that intratumoral T cells in colorectal cancers often exhibit signs of

exhaustion compared to those in adjacent normal tissues, irrespective of MMR deficiency status

or TIME subtype.

Spatial TIL exhaustion is associated with tumor-intrinsic FAK activation

To explore potential drivers of T cell exhaustion, we integrated single-cell RNA sequencing

(scRNA-seq) data to compare gene expression profiles between tumor and normal tissues (**Fig.**

2a). Differential expression analysis highlighted significant changes in several signaling

pathways, including negative regulation of immune processes, cytokine production, and notably,

the progression of focal adhesion, prominently represented by *PTK2* (encoding **f**ocal **a**dhesion

kinase, FAK). Retrospective analysis of the DEGs also revealed differential expression of *PTK2*

along with a series of other oncogenes and exhaustion-related genes (**Fig. 2b, c**). Consistent with

our findings, CIBERSORT analysis revealed an association between immune cell infiltration

levels and *PTK2* expression across many tumor types.[24] In particular, in colorectal

adenocarcinoma (COAD), we observed a negative correlation between *PTK2* expression and

CD8[+] T cell infiltration (**Extended Data Fig. 2a**). Additionally, correlation analysis between

PTK2 expression and exhaustion score revealed a clear positive correlation with CD8[+] T-cell

exhaustion (**Extended Data Fig. 2b**).[25,26]

PTK2, a ubiquitously expressed nonreceptor tyrosine kinase, has been reported to be expressed

in tumor cells, pericytes and fibroblasts.[27] However, in COAD, scRNA-seq analysis indicated

that PTK2 was predominantly expressed in epithelial cells, particularly in stem-like epithelial

cells (**Fig. 2d-g**). Moreover, *PTK2* was overexpressed in tumors, especially in the MMRp

subtype (**Fig. 2h**). Immunohistochemistry (IHC) further confirmed hyperactivation of FAK

signaling at the protein level in CRC tumors compared to adjacent normal tissue (**Fig. 2i**).

Consistent with these findings, both the mRNA and protein levels of FAK were upregulated in

tumors compared to normal tissues across multiple cancers, as evidenced by TIMER2 and the

Human Protein Atlas database (**Extended Data Fig. 2c-g**).

To assess whether FAK activation was associated with T-cell exhaustion, we examined pFAK

expression levels using DSP data and found a positive correlation between pFAK expression and

immune checkpoint proteins (PD-1, TIM-3, and LAG-3) in the intratumoral region (**Fig. 2j**).

This positive correlation was further validated using multiplex immunofluorescence (mIHC)

staining. Cell classification and spatial distribution analysis of 45 regions of interest (ROIs) from

the high and low pFAK expression groups in two sets of formalin-fixed paraffin-embedded

(FFPE) sections revealed consistent findings (**Fig. 2k-l, Extended Data Fig. 3a-f**). Tumors with

high pFAK expression exhibited a greater proportion of TIM-3$^+$ TILs than did those with low

pFAK expression (**Fig. 2m, n**). Spatial analysis within 100 μm of CK19$^+$pFAK$^+$ tumor cells

further supported these findings, revealing a greater proportion of TIM-3$^+$ TILs in tumors with

high pFAK expression **(Fig. 2o, p).** Collectively, these data suggest that tumor-intrinsic FAK

activation may play a critical role in driving T cell exhaustion.

Pharmacological inhibition of FAK leads to stable disease progression by reprogramming

the TIME.

To investigate the impact of FAK inhibition on tumor progression and alterations in the TIME,

we assessed the effects of the clinically available FAK inhibitor VS-4718 in murine colorectal

tumor models, including MC38 (microsatellite instability, MSI) and CT26 (microsatellite stable,

MSS) models. Compared with control mice, MC38 tumor-bearing mice treated with 50 mg/kg

FAK inhibitor (FAKi) exhibited significantly reduced tumor growth and stable disease (**Fig. 3a**).

This tumor-suppressive effect was consistently observed in the CT26 subcutaneous tumor model

(**Fig. 3b**).

Subsequent scRNA-seq analysis of CT26 tumors allowed us to map the transcriptional landscape

of the TIME. After quality control, we obtained transcriptomes from 47,442 cells and identified

13 main cell types, including various T/NK cell subsets, B cells, myeloid cells, endothelial cells,

fibroblasts, and tumor cells, using the uniform manifold approximation and projection (UMAP)

algorithm (**Fig. 3c, Extended Data Fig. 4a-i**). Notably, treatment with FAKi led to significant

changes in T/NK cell clusters compared to those in controls (**Fig. 3d**). Differentially expressed

gene analysis revealed that compared with control tumors, FAKi-treated tumors exhibited

upregulated expression of cytotoxicity-associated genes (*Gzma, Ifngr1, Cxcl10*) and

downregulated expression of exhaustion-related genes (*Pdcd1, Lag3, Tox*) in CD8[+] T cells (**Fig.**

3e, f). Gene set enrichment analysis (GSEA) further indicated that FAKi treatment was

associated with enhanced T cell differentiation and activation pathways (**Fig. 3g, h**). Given the

reduction in CD8[+] T cells after FAKi treatment, we noticed that this reduction stemmed from the

presence of a *Pdcd-1^high* CD8[+] T cell population (**Fig. 3i**). Notably, analysis of CD8[+] T cell

differentiation trajectories using Monocle 2 revealed distinct branches representing stem-like

CD8[+] T cells (*Slamf6* and *Tcf7*), exhausted CD8[+] T cells (*Pdcd1 and Tox*), and proliferating

CD8[+] T cells (*Birc5 and Top2a*) (**Fig. 3j, k**). FAKi treatment notably suppressed the exhaustion

of stem-like CD8[+] T cells, maintaining them in a less differentiated state (**Fig. 3j-l**).

To explore changes in intercellular communication involving CD8[+] T cells, we analyzed the

network of pathways associated with exhaustion (PD-L1 signaling) and cytotoxicity (TNF

signaling). FAKi treatment was associated with reduced exhaustion pathway activity and

enhanced cytotoxicity among CD8[+] T cells and other cell types (**Fig. 3m, n**). Validation through

mIHC and flow cytometric analysis confirmed that FAKi treatment significantly reduced the

proportion of terminally exhausted TIM-3[+]PD-1[+]TOX[+]CD8[+] T cells (Tex cells) while increasing

the percentage of stem-like CD8[+] T cells expressing TCF-1 in CT26 tumors (**Fig. 3o-r**).

Furthermore, FAKi treatment increased the proportions of GZMB[+]CD8[+] T cells (effector CTLs)

and IFNγ[+]CD8[+] T cells in both CT26 and MC38 tumors (**Fig. 3 s, Extended Data Fig. 5a-c**).

Analysis of myeloid subsets also indicated a reduction in TIM-3[+] dendritic cells in FAKi-treated

tumors, suggesting improved antigen-presenting cell (APC)-T cell interactions (**Extended Data**

Fig. 6a, b). Together, these findings suggest that FAK inhibition suppresses tumor progression

by preventing T cell exhaustion, maintaining a stem-like state, and enhancing T cell effector

functions, thereby reshaping the tumor immune microenvironment toward an antitumor response.

Tumor-intrinsic FAK regulates TIL exhaustion in colorectal tumors

To investigate the role of tumor-intrinsic FAK in regulating the antitumor immune response, we

utilized CRISPR-Cas9 gene editing to knock down *Ptk2* (encoding FAK) expression in CT26

tumor cells. Two single guide RNA sequences targeting *Ptk2* (sgPtk2) effectively reduced FAK

protein expression without significantly impacting cell proliferation (**Fig. 4a, b**). Subsequently,

we evaluated the impact of FAK knockdown on tumor growth in immunocompetent BALB/c

mice and immunodeficient BALB/c-nude mice. Strikingly, depletion of FAK resulted in a

significant delay in tumor progression, especially in immunocompetent mice (**Fig. 4c, d**),

suggesting an enhanced antitumor immune response upon FAK inhibition.

To dissect the cellular and molecular mechanisms underlying the regulation of the antitumor

immune response by tumor-intrinsic FAK, we performed single-cell transcriptome analysis of

sgPtk2 and control (Cas9) tumors. After stringent quality control, transcriptomes from 87,383

cells revealed 13 main cell types, with notable changes observed in T cell clusters in sgPtk2

tumors (**Fig. 4e-g, Extended Data Fig. 7a-h**). Differential expression analysis highlighted

significant gene changes in $CD8^+$ T cells, macrophages, and monocytes within sgPtk2 tumors

(**Extended Data Fig. 8a**). GSEA demonstrated enrichment of pathways related to lymphocyte

differentiation and immune regulation in $CD8^+$ T cells from sgPtk2 tumors (**Extended Data Fig.**

8b, c). $CD8^+$ T cells from sgPtk2 tumors were enriched in genes related to T cell activation,

lymphocyte proliferation and cytokine□cytokine receptor interactions (**Extended Data Fig. 8d**).

Trajectory analysis revealed that FAK knockdown in tumor cells promoted the differentiation of

$CD8^+$ T cells toward a proliferative state rather than an exhausted state (**Fig. 4h, Extended Data**

Fig. 8e, f). Consistent with these findings, analysis of intercellular communication pathways

revealed a reduction in the exhaustion pathway network (PD-L1 signaling) among $CD8^+$ T cells

and other cells in sgPtk2 tumors compared to that in Cas9 tumors, suggesting a rescue from

$CD8^+$ T cell exhaustion upon loss of tumor-intrinsic FAK (**Fig. 4i**). The reduction in $CD8^+$ T cell

exhaustion in sgPtk2 tumors was further validated through mIHC analysis, revealing decreased

$PD-1^+TIM-3^+TOX^+CD8^+$ T cells (exhausted T cells) and increased $TCF-1^+CD8^+$ T cells (stem-

like T cells) compared to those in control tumors (**Extended Data Fig. 8g-i**). Spatial analysis of

$CD8^+$ T cell exhaustion confirmed these findings, showing a significant decrease in exhausted T

cells and an increase in functional $CD8^+$ T cells in the intratumoral area in sgPtk2 tumors (**Fig. 4j,**

k). Furthermore, *in vitro* coculture experiments demonstrated that sorted $CD8^+$ T cells cocultured

with sgPtk2 tumor cells exhibited reduced proportions of $PD-1^+TIM-3^+TOX^+CD8^+$ exhausted T

cells and increased proportions of $Ki67^+CD8^+$ T cells, along with an expansion of $TCF-1^+$ stem-

like T cells (**Fig. 4l-p**). In summary, these findings illustrate that tumor-intrinsic FAK plays a

crucial role in regulating $CD8^+$ T cell exhaustion, highlighting its potential as a therapeutic target

to enhance antitumor immunity in colorectal cancer.

Nuclear FAK promotes CD8[+] T-cell exhaustion by transcriptionally regulating the SP1-IL-
6 axis

To investigate how tumor-intrinsic FAK regulates T cell exhaustion, we first examined whether
FAK translocates to the nucleus and functions as a transcription factor (TF). mIHC and
immunofluorescence staining revealed the nuclear localization of FAK protein in human CRC
tumor cells and CT26 cells, which was confirmed by colocalization studies and western blot
analysis (**Fig. 5a-d**). To uncover the potential mechanism of nuclear FAK-targeted genes, we
performed cleavage under targets and tagmentation (CUT&Tag) in CT26 cells (**Fig. 5e**).
Strikingly, approximately 54.71% of the total FAK binding peaks were located within ±1 kb of
the TSSs of a total of 3,823 identified peaks (**Fig. 5f**). Pathway enrichment analysis revealed that
FAK-binding genes were enriched in the cell cycle, cytokine, TGF-beta and interleukin-6 (IL-6)
signaling pathways (**Extended Data Fig. 9a**). Further analysis revealed FAK-targeted
transcription factors, including SP1 (specificity protein 1) (**Fig. 5g**). Specifically, increased
binding was observed at the SP1 promoter region, as predicted by computational models (**Fig. 5h,**
i and **Extended Data Fig. 9b**). Validation through CUT&Tag-qPCR confirmed reduced FAK
enrichment at the SP1 promoter and decreased SP1 mRNA expression in FAK-knockdown
(sgPtk2) cells compared to controls (**Fig. 5j, k**). Immunofluorescence staining confirmed
decreased SP1 protein levels in sgPtk2 cells (**Fig. 5l**). Based on the findings that FAK-regulated
transcription factors might be involved in inflammatory cytokine signaling pathways, we further
validated cytokine/chemokine gene expression differences between cas9 and sgPtk2 cells. The
results showed that the expression of *Il6*, *Csf1* and *Csf2* was significantly reduced and that the
expression of *Cxcl10* was significantly increased in sgPtk2 cells. Strikingly, there was an
approximately 10-fold decrease in the mRNA expression of the SP-1 target *Il6* in sgPtk2 cells
compared to that in control cells (**Fig. 5m**).[28] All these data indicated that FAK could induce IL-
6 production through SP1 transcriptional regulation.

To investigate the downstream effects of IL-6 on T cell exhaustion, splenic CD8[+] T cells were
isolated and then exposed to IL-6 *in vitro*. The results showed that IL-6 significantly promoted
the expression of the exhaustion genes *Pdcd1* and *Havcr2* in T cells, while the expression of the
effector gene *Ifng* was suppressed by IL-6 (**Extended Data Fig. 10a, b**). We further confirmed
that IL-6 promoted the expression of exhaustion markers, such as PD-1, TIM-3 and TOX, in

CD8$^+$ T cells and increased the proportion of exhausted CD8$^+$ T cells (PD-1$^+$TOX$^+$CD8$^+$ T cells,

TIM-3$^+$TOX$^+$CD8$^+$ T cells and PD-1$^+$TIM-3$^+$TOX$^+$CD8$^+$ T cells) in a time-dependent manner

(**Fig. 5n, o**). To verify the downstream mediators of IL-6-driven T cell exhaustion, we

investigated the status of its downstream target, STAT3.[29] As expected, IL-6 promoted both the

mRNA and protein expression of STAT3 in a time-dependent manner (**Extended Data Fig. 10c,**

d).

To validate these results *in vivo*, we examined IL-6 mRNA expression in scRNA-seq data from

both sgPtk2 tumors and cas9 tumors. As expected, there was a lower expression level of IL-6

mRNA in sgPtk2 tumors than in Cas9 tumors, and these results were confirmed by ELISA

(**Extended Data Fig. 10e, f**). Next, we performed mIHC analysis of Cas9, pFAK, IL-6, CD8 and

p-STAT3 in Cas9 and sgPtk2 tumors and found a significant reduction in the IL-6 protein in

FAK-deficient tumors (**Fig. 5p-r**). More importantly, we observed a dramatic increase in the IL-

6 protein in pFAK$^+$ tumor cells, suggesting that IL-6 is mainly secreted by FAK-activated tumor

cells (**Fig. 5 s**). In addition, consistent with the *in vitro* results, p-STAT3 expression and the

proportion of p-STAT3$^+$CD8$^+$ T cells were also significantly lower in sgPtk2-treated tumors than

in control tumors (**Extended Data Fig. 10g-j**).

To further understand the mechanism by which FAK inhibition influences the TME, we

performed GSEA. The GSEA results revealed that the DEGs associated with CD8$^+$ T cells were

correlated with cytokines. Analysis of cell☐cell communication revealed that the CXCL

signaling pathway network was increased in CD8$^+$ T cells in tumors from FAKi-treated mice. In

contrast, the CSF signaling pathway network was decreased in FAKi-treated tumors compared to

control tumors (**Extended Data Fig. 11a-c**). Therefore, we further validated changes in cytokine

secretion between FAKi-treated and control CT26 cells and found that FAKi significantly

reduced the secretion of cytokines, including IL-6, involved in T cell recruitment and activation

(**Extended Data Fig. 11d-f**). In conclusion, these results elucidate a mechanism by which

nuclear FAK enhances T cell exhaustion through transcriptional regulation of the SP1-IL-6 axis

in tumor cells, highlighting FAK as a potential therapeutic target for modulating immune

responses in the tumor microenvironment.

FAK inhibitors potentiate immune checkpoint blockade (ICB) therapy *in vivo*.

Given that FAK inhibition suppresses tumor growth by reprogramming the tumor microenvironment, we aimed to further investigate its potential to improve immunotherapy efficacy. We found that FAKi synergized strikingly with immunotherapies when combined with low-dose 5-fluorouracil (20 mg/kg, i.p., '5-Fu[20]') in both CT26 (MSS) and MC38 (MSI) tumor models of human CRC, resulting in notable suppression of tumor growth compared with those treated with a FAK inhibitor or immunotherapy alone (**Fig. 6a, b**).

To decipher the underlying cellular and molecular mechanisms, we conducted scRNA-seq on tumor-infiltrating CD45[+] immune cells (**Fig. 6c**). After quality control, T-distributed stochastic neighbor embedding (t-SNE) analysis identified a total of 11 main cell types based on known expression markers (**Fig. 6d-e, Extended Data Fig. 12a-d**). Recluster analysis of CD8[+] T cells from four identified subsets revealed the following: precursor effector/memory CD8[+] T cells (Tpem) expressing stem-like markers (*Tcf7*, *Cd69* and *Mki67*) and effector/memory markers (*Ifngr1* and *Ccr2*); proliferating CD8[+] T cells (Tprolif) expressing proliferation markers (*Mki67*, *Bicr5* and *Top2a*); effector/memory CD8[+] T cells (Tem) expressing effector/memory markers (*Tnf*, *Ifngr1* and *Cd200*); and exhausted CD8[+] T cells (Tex) expressing exhaustion markers (*Tox*, *Havcr2* and *Pdcd1*) (**Fig. 6f, Extended Data Fig. 13a**). Notably, we observed significant expansion of Tpem clusters and Tem cell clusters in combination-treated tumors, whereas the proportions of Tex cells were dramatically lower in combination-treated tumors than in the other three groups (**Fig. 6g**). Furthermore, compared with those in the other three groups, CD8[+] T cells from combination-treated tumors exhibited reduced expression levels of exhaustion-related genes (*Havcr2*, *Pdcd1* and *Tox*) and increased expression levels of cytotoxicity-related genes (*Cd69*, *Ifngr1* and *Tnf*) (**Fig. 6h**).

Next, we computationally imputed pseudotime trajectories by utilizing Tpem cells as the root population, and Tpem cells differentiated toward two different trajectories (the Tem cell branch and Tex cell branch) through Tprolif cells, consequently forming a cytotoxic CD8[+] T lineage and an exhausted CD8[+] T lineage (**Fig. 6i**). We observed that there were significantly lower levels of exhaustion marker genes in the cytotoxic CD8[+] T lineage from the combination-treated tumors than in the other three groups. In contrast, the expression of cytotoxic marker genes was

significantly greater in CD8$^+$ T cells from the combination-treated group than in those from the

other three groups (**Fig. 6j** and **Extended Data Fig. 13b**). We used GSEA to determine the

pathways involved in CD8$^+$ T cells among the combination group and three other groups. As

expected, CD8$^+$ T cells from combination-treated tumors were enriched in various pathways

related to T-cell activities, including lymphocyte migration, proliferation, activation and

interferon-beta production (**Fig. 6k**). The results of intercellular communication among CD8$^+$ T

cells and other immune subsets revealed that combination treatment led to the loss of PD-L2

signaling, coupled with an increase in TNF signaling in CD8$^+$ T cells (**Extended Data Fig. 13c,**

d).

To validate the findings from the scRNA-seq data, we carried out mIHC and flow cytometry to

profile the CD8$^+$ T cell status in both CT26 and MC38 tumors. We confirmed that there was a

significant decrease in IL-6 protein expression in the combination-treated group as well as in the

FAKi alone group (**Extended Data Fig. 13e, f**). We also detected a significant reduction in

pSTAT3$^+$CD8$^+$ T cells and TOX$^+$TIM-3$^+$CD8$^+$ T cells in the combination and FAKi groups (**Fig.**

6l-n). We further confirmed that there was a significant increase in the proportion of CD8$^+$ T

cells exhibiting an effector phenotype (CD44$^+$ CD62L$^-$) in tumors from combination-treated

mice compared with those from the other three groups (**Extended Data Fig. 13g**). More

importantly, combination treatment also augmented the production of cytolytic granules

(GZMBs) and cytokines (IFNγ) in tumor-infiltrating CD8$^+$ T cells (**Extended Data Fig. 13h**).

Taken together, these findings demonstrate that inhibition of FAK enhances checkpoint therapy

across CRC models by potentiating tumor-resident CD8$^+$ T cell functionality and cytotoxicity

and reinvigorating exhausted states through suppression of the SP1-IL-6 proinflammatory axis

(**Fig. 6o**).

DISCUSSION

This work demonstrated that the dysregulation of FAK signaling was associated with the

heterogeneity and exhaustion of CD8$^+$ T cells within the spatial context of the tumor

microenvironment and strongly correlated with patient survival in CRC patients. Importantly,

our findings provide proof of concept that targeting FAK using small molecule inhibitors

enhances the efficacy of αPD-1 and αTIM-3 immunotherapies by bolstering cytotoxicity among

tumor-resident $CD8^+$ T cells and reversing exhausted states in mouse models of CRC.

Mechanistically, we elucidated that nuclear FAK orchestrates SP1/IL-6-mediated T cell

exhaustion and governs the transcriptional regulation of proinflammatory cytokines and

chemokines.

In solid tumors such as CRC, the infiltration of T cells into tumor beds has long been associated

with favorable outcomes.[30,31] However, little is known about how the spatial immune

microenvironment impacts cancer and whether it plays a role in regulating the TIL exhaustion

status and the efficacy of immunotherapies in the tumor suppressive microenvironment.[32]

Moreover, the mediators contributing to immune suppression and the limited response to

immunotherapy in patients with colorectal cancer remain unexplored. Our previous work and

others have shown that targeting FAK in pancreatic cancer cells reduces the number of tumor-

promoting macrophages and MDSCs and improves the response to anti-PD1/CTLA4 checkpoint

therapy.[33,34] In this work, we demonstrate that FAK contributes to spatial immune suppression

and T cell exhaustion in human colorectal cancers by integrating digital spatial analysis and

scRNA-seq datasets. FAK inhibition could reprogram the immune microenvironment and

reinvigorate the exhausted state, and FAK inhibitor treatment reduced the number of terminally

exhausted $PD1^+TIM-3^+CD8^+$ T cells, resulting in slowed tumor progression in mouse models of

human CRC.

The exhausted state of T cells is characterized by an overactive immune checkpoint response,

which is regulated by the expression of inhibitory receptors such as PD-1, LAG-3, TIM-3,

CTLA-4, and PD-1; in particular, this response has received much attention in the field of

immuno-oncology due to its central role in regulating T cell function and its correlation with

disease progression and treatment responses in various cancers.[14,16,35,36] Targeting PD-1 with

checkpoint inhibitors, such as nivolumab and pembrolizumab, has been shown to be effective in

reversing T cell exhaustion and restoring antitumor responses, leading to clinical benefits in

some cancer patients.[37,38] However, while targeting PD-1 has shown promising results in some

cancers, a significant proportion of patients still do not respond to this treatment,[39,40] highlighting

the need for additional therapeutic targets and a better understanding of the complex mechanisms

underlying T-cell exhaustion in cancer. T-cell immunoglobulin and mucin-domain-containing

protein 3 (TIM-3) is considered an immune checkpoint molecule similar to PD-1 and CTLA-

4.[41,42] Studies have highlighted the role of TIM-3 expression on CD8[+] T cells in relation to

disease stage in human colorectal cancer (CRC), as well as the potential benefits of TIM-3

blockade in enhancing antitumor responses.[43,44] Despite the promising preclinical data, most

clinical trials targeting TIM-3 with monoclonal antibodies in cancer have not met their primary

endpoints or shown significant clinical benefits.[45,46] These outcomes highlight the complexity of

cancer immunotherapy and the need for multifaceted treatment approaches. Studies have shown

that long-term persistence of TCF1[+] stem-like T cells is important for achieving durable

responses to immunotherapies, such as checkpoint inhibitors.[47–49] In this work, we demonstrated

that hyperactivation of FAK in tumor cells is a key contributor to CD8[+] T cell exhaustion and

immune suppression within the tumor microenvironment. More importantly, pharmacological

targeting or genetic loss of FAK dramatically reduces TIM-3 expression on CD8[+] T cells,

pushing T cells toward a cytotoxic state with proliferative and functional capacities.

FAK is well known as a nonreceptor protein tyrosine kinase that clusters at focal adhesion

structures and plays a role in regulating cell adhesion, migration and survival. David Schlaepfer

reported that FAK translocated to the nucleus and defined a scaffolding role for nuclear FAK in

facilitating cell survival.[50] Recently, Margaret Frame demonstrated that nuclear FAK is

associated with chromatin and interacts with TFs to control evasion of antitumor immunity.[51]

Consistent with these reports, we also observed that FAK is located in the cell nucleus in the

context of colorectal cancer. We speculate that FAK might function directly as a core

transcriptional machinery. Strikingly, CUT&Tag analysis revealed that approximately 54.71% of

the total FAK binding peaks were located within ±1 kb of the TSSs of a total of 3,823 identified

peaks, confirming that FAK functions as a transcription factor (TF). More importantly,

consistent with the binding sites predicted for FAK by AlphaFold3,[52] we identified SP1 as a

direct target of nuclear FAK. We propose a model in which nuclear FAK binds to the promoter

of SP1, which induces SP1 transcription and thereby leads to an increase in the production of IL-

6, a direct target of SP1.[28] Indeed, we demonstrated that IL-6 was a key contributor to T cell

exhaustion through the activation of STAT3 both *in vitro* and *in vivo*. We also observed that

there was a significant increase in the number of NK cells upon inhibition of FAK, suggesting

that loss of FAK might enhance the tumor-killing ability of NK cells. The detailed underlying

mechanisms warrant further exploration.

Combining FAK inhibitors with ICB therapy represents a strategy for anticancer therapy.[53,54]

Our previous work demonstrated that a combination of FAK inhibitors and anti-PD-1/CTA4

antibodies reduced the number of immunosuppressive cells and improved overall survival in

mouse models of human pancreatic cancer.[33] Consistent with previous reports,[51] here, we found

that targeted inhibition of FAK dramatically improved the efficacy of anti-PD1/TIM-3

checkpoint therapy in both MSS and MSI mouse models of human CRC as a result of

reinvigorating exhausted states of tumor-infiltrating lymphocytes and potentiating effector T cell

cytotoxicity. Taken together, the results of these studies provide promising evidence that

targeting the FAK pathway may represent a promising strategy for cancer immunotherapy.

In summary, our data demonstrate the importance of the spatial status of infiltrating immune

cells in human colorectal cancer patients, with an emphasis on spatial profiling of $CD8^+$ TILs in

the tumor microenvironment. These results highlight the importance of considering the spatial

distribution of immune cells and the underlying mechanisms of immune exhaustion in the design

of cancer immunotherapies. We found that nuclear FAK functions as a core transcriptional

machinery to aggravate $CD8^+$ T cell exhaustion by regulating the SP1-IL-6 axis in CRC. These

insights provide a compelling rationale for targeting FAK to enhance the effectiveness of

immunotherapy in CRC and advocate for future investigations into spatially nuanced

immunotherapeutic strategies.

METHODS

Human tumor specimen collection

Human colorectal cancer specimens were collected from patients with histologically confirmed

colorectal cancer who underwent curatively surgical resection at the Department of

Gastrointestinal Surgery, West China Hospital, Sichuan University, China. This project was

approved by the West China Hospital Medical Committee approval (2020-374). The clinical and

pathological parameters of the included patients were obtained from the patient's electronic

medical records (**Supplemental Table 6**).

Digital spatial profiling (DSP)

NanoString's GeoMx digital spatial profiling (DSP) was used for multiplexed and spatially

resolved profiling analysis of pretreated tumor samples. The FFPE tissue slides were stained with

a Texas red-labeled CD45 antibody (NanoString Technologies, US), Alexa Fluor 532-labeled

PanCK, and SYTO13 to facilitate the identification of tissue morphology, and the regions of

interest (ROIs) were defined according to these morphological marker antibodies. Then, the

FFPE tissue slides were incubated with unique oligonucleotide-labeled antibodies, including the

immune cell profiling core panel and the IO drug target module panel, which are described in

detail in **Supplemental Table 1**. The stained slides were loaded onto a GeoMx instrument and

scanned. The information contained in the collected ROI was analyzed by an nCounter Analyzer

(NanoString Technologies, US) and then returned to the DSP system for data analysis and

visualization.

Digital spatial profiling (DSP) was performed on the 10 tissue samples, applying 2 panels

(immune cell panel and IO drug target panel, **Supplemental Table 2**), to demonstrate the

proteomic characteristics of colorectal cancer. The DSP workflow is shown in **Extended Data**

Fig. 1a. Then, 116 circular regions of interest (ROIs) were selected from 10 tissue slices and

divided into intratumoral (%PanCK$^+$ area>95%), proximal (5%<%PanCK$^+$ area <95%) and

distal (%PanCK$^+$ area <5%) regions based on their histological features (**Extended Data Fig.**

1b).

Immunohistochemical staining

All involved tissue samples were processed into paraffin. Paraffin-embedded tissues were cut at

5 μm and stained for immunohistochemistry. Slides were immersed in antigen retrieval buffer

(Gene Tech, China) at a 1:500 dilution in distilled water. Antigen retrieval was then performed in

a microwave oven for ∼20 min. Then, 2% BSA (BioFroxx, Germany) was used for blocking for

10 min, and the primary antibody (details of the antibodies are described in **Supplemental Table**

3) was diluted in PBS containing 1% BSA and applied overnight. A secondary antibody (Thermo

Fisher Scientific, US) was added after washing the slides for 30 min. After washing, DAB

solution (Gene Tech, China) was added for coloring.

Immunofluorescence staining

FAK and SP1 expression and location were analyzed in CT26 cells. A total of 5×10^4 cells were

seeded in confocal dishes in DMEM supplemented with 10% FBS. After cell adherence, the

medium was replaced with DMEM supplemented with 1% FBS, and the cells were starved for

12 h. Immunofluorescence staining was performed according to standard procedures. Rabbit

anti-FAK antibody and rabbit anti-SP1 antibody were used as the primary antibodies (details of

the antibodies are described in **Supplemental Table 3**), and the secondary antibody was an

AF555-labeled goat anti-rabbit IgG (H + L) antibody (Invitrogen, US). The fluorescence was

imaged using a laser confocal microscope (Leica-STELLARIS, Germany) and quantified using

ImageJ.

Multiplex immunohistochemistry (IHC)

Multiplex IHC staining was performed using an Opal 7-color kit (Akoya Bioscience, US).

Briefly, the sections were dewaxed with xylene for 20 minutes. Then, ethanol was used for

rehydration. Microwave treatment was performed for antigen retrieval with antigen retrieval

buffer. Next, all sections were cooled at room temperature for 30 minutes. Endogenous

peroxidase activity was blocked using Antibody Diluent/Block (Akoya Bioscience, US) for 10

minutes at room temperature. The slides were then incubated for 1 hour at room temperature

with the primary antibody (details of the antibodies are described in **Supplemental Table 3**), for

20 minutes at 37°C with the secondary reagents, and for 10 minutes at room temperature with

Opal working buffer. The above procedures were repeated for other antibodies, and the

antibodies were removed by microwave treatment before another round of staining was

performed. Nuclear staining was performed using DAPI (Akoya Bioscience, US) for 5 minutes

at room temperature. Slides were scanned at 20× magnification using the Vectra Polaris system

(Akoya Biosciences, US). Whole-tissue scans were analyzed with Qupath software

(https://qupath.github.io) using area quantification and a cytonuclear module.[55]

Image analysis

The slides were visualized using the Vectra Polaris system (Akoya Biosciences, US), and a

multispectral image of the whole slide was scanned using a 20× objective lens. Multispectral

image unmixing was performed using QuPath software (version 3.0).[55] Briefly, the DAPI-

positive cells were identified by the "cell detection" command, and each single channel intensity

threshold was selected using "Object classification." We determined the number of positive cells

with the "Load classifier" and counted the areal proportions by dividing the channel-positive cell

counts by all the cells detected as DAPI positive. Then, all detected cells were divided into

different subgroups for further analysis, and defective TMA cores or areas with ruptured or

folded tissue were reanalyzed or excluded. Spatial distance is calculated by "distance to centroid

distances 2D". All other multispectral image unmixing methods were performed using HALO

software. Image analysis algorithms were built using the Indica Labs High-Plex FL v2.0 module

to perform DAPI-based nuclear segmentation and detect fluorescence-positive cells by setting a

dye cytoplasm positive threshold. The spatial analysis module was used for proximity analysis,

infiltration analysis and density analysis.

Cell proliferation

For CT26_cas9 and CT26_sgPtk2 cells, 2000 cells per well were seeded into 96-well plates in

DMEM supplemented with 10% FBS. After 3 days and 6 days, CCK-8 solution (Life-ilab, China)

was added to each well, and the plates were then incubated at 37°C. After 2 h, the absorbance at

450 nm was measured using a microplate reader (Thermo Fisher Scientific, US).

Western blot

Cells were lysed in RIPA lysis and extraction buffer (Thermo Fisher Scientific, USA). The

protein concentration was assessed using the BCA Protein Assay Kit (Life-ilab, China). Proteins

were loaded into each lane of a polyacrylamide gel. After electrophoretic separation, the proteins

were transferred to a PVDF membrane (Sigma□Aldrich, Germany). The membranes were

blocked for 1 h in Tris-buffered saline containing 0.05% Tween 20 (TBS) and 5% nonfat dry

milk. Then, the cells were incubated with a primary antibody (the details of the antibodies used

are described in **Supplemental Table 3**) at 4°C overnight. The membranes were washed 3 times

with TBS for 5 minutes each and then incubated with a secondary antibody (Thermo Fisher

Scientific, US). An enhanced chemiluminescence (ECL) detection system (Tanon 5500, China)

was used to image specific blots.

Generation of stable cell lines

Crispr-Cas9 genome editing technology was used to knock down Ptk2 gene expression in CT26

cells. The sequences for sgPtk2_1 and sgPtk2_2 were as follows: sgPtk2_1 F:

CACCGGTGCACCTCCTCCGATCGC; sgPtk2_1 R: AAACGCGATCGGAGGAGGTGCACC;

sgPtk2_2 F: CACCGTCGAGTACTAAGACTCACC; and sgPtk2_2 R:

AAACGGTGAGTCTTAGTACTCGAC.

The annealed sgPtk2_1 and sgPtk2_2 were cloned and inserted into the BsmBI restriction sites of

the V2TC plasmid to construct the transfer plasmids used for lentiviral packaging. Then, the

293T cells were transfected with the packaging plasmids pMD2. G, psPAX2, and the transfer

plasmid using the calcium phosphate transfection method. The quantities of packaging plasmids

used for the 6-well plates were pMD2. G, 1 µg; psPAX2, 2 µg; and shuttle plasmid, 4 µg. At 36

and 48 hours posttransfection, the culture supernatants were collected and filtered through a 0.45

µm filter to harvest the lentiviral particles.

CT26 cells were infected with Lenti-V2T to generate a Cas9-expressing CT26 cell line. The cells

were selected using DMEM containing 10% FBS, 1% penicillin☐streptomycin, and 8 µg/µL

puromycin for one week. The resulting cell line stably expressing the Cas9 protein was termed

CT26-Cas9. To obtain the FAK-knockdown CT26 cell line, CT26-Cas9 cells were infected with

Lenti-V2TC-Ptk2-gRNA, which expresses both sgPtk2 and mCherry, and then cells positive for

mCherry expression were sorted. The knockdown efficiency of FAK in the CT26 cell line was

validated using a T7 endonuclease assay and Western blot analysis.

Isolation and activation of CD8$^+$ T cells

The spleens of C57BL/6 mice were dissected and grinded with a syringe plunger, followed by

filtration with a 40 µm cell filter and treatment with 1x RBC lysis buffer (Invitrogen, USA). The

cells were collected by centrifugation at 1500 rpm for 5 min, and the naïve T cells were

harvested using a MojoSort™ mouse CD8$^+$ T cell isolation kit (#480008, Biolegend, US)

following the manufacturer's instructions. For CD8$^+$ T cell activation, 24-well flat-bottom plates

were coated with 1.5 µg/mL of anti-CD3 (#BE0001, BioXcell, US) and anti-CD28 (#BE0015,

BioXcell, US) antibodies and incubated at 4°C overnight. The wells were subsequently washed

with PBS, after which 5×10^5 T cells were seeded and cultured at 37°C with 5% CO_2 in RPMI-

1640 medium (HyClone, US) supplemented with 10% heat-inactivated fetal calf serum (ZETA

LIFE, US), 1% penicillin and streptomycin (Gibco, US), 1% nonessential amino acids (Gibco,

US), 1% sodium pyruvate (Gibco, US), 2% HEPES (Gibco, US), and 10 ng/mL IL-2 (#AF-212-

12, PeproTech, US) for 24 h.

In an IL-6-induced Stat3 phosphorylation T cell assay, T cells were activated in the presence or

absence of recombinant mouse IL-6 (5, 10, 50, 100 ng/mL, #AF-216-16, PeproTech, US) for 0, 5,

10, 30, or 60 min, and p-Stat3 expression was assessed by western blot analysis.

In the IL-6-induced exhaustion of T cells assay, T cells were activated in the presence or absence

of recombinant mouse IL-6 (10 ng/mL) for 3 days or 6 days, whereas exhaustion markers were

assessed by qPCR and flow cytometric analysis.

Tumor-CD8$^+$ T cell coculture system

Unless otherwise stated, CT26_cas9 and CT26_sgPtk2 cells were seeded at a 1:5 ratio (tumor

cell:CD8$^+$ T cell) into a 24-well plate. Activated T cells (5×10^5 cells/well) were added to plates

containing tumor cells. After approximately 6 days, all cells were collected and analyzed by flow

cytometry.

Enzyme-linked immunosorbent assay (ELISA)

ELISA was carried out using a mouse IL-6 ELISA kit (#VAL604G, Novusbio, US) according to

the manufacturer's instructions. Tissues were disrupted using a Bullet Blender Tissue

Homogenizer (Next Advance, US) and lysed in RIPA lysis and extraction buffer (Thermo Fisher

Scientific, US). The protein concentration was assessed using the BCA Protein Assay Kit (Life-

ilab, China) to normalize the ELISA results.

Animal models

The CT26 cells and MC38 cells were maintained at 37°C with 5% CO_2 in RPMI-1640 medium

(HyClone, US) supplemented with 10% heat-inactivated fetal calf serum (ZETA LIFE, US),

penicillin (Gibco, US), and streptomycin (Gibco, US). In all animal experiments, the
mycoplasma detection results for all cell lines were negative. Six- to eight-week-old female
C57BL/6, BALB/C and BALB/C nude mice were used for the subcutaneous tumor mouse
models. Briefly, 2.5×10^5 CT26 cells and 5×10^5 MCA205 cells in 50 μL of Matrigel (Corning,
US) were injected subcutaneously into each mouse's right back. Tumor volume (length $\times$
(width^2)/2) was assessed by caliper measurements every other day, and cohorts of mice were
randomized into different treatment groups according to tumor volume. All animal studies were
approved by the West China Hospital Animal Ethics Committee (2020361A)

Inhibitors and neutralizing antibodies
FAKi was purchased from Selleck, Inc. (#S7685, US). VS-4718 was dissolved in DMSO for *in*
vitro study. For animal experiments, 50 mg/kg of VS-4718 was dissolved in vehicle (0.5%
carboxymethyl cellulose (Sigma Aldrich, Germany) and 0.1% Tween-80 (Sigma Aldrich,
Germany) in sterile water) and administered orally by gavage every 12 hours. 5-Fu (#HY90006,
MCE, USA) was dissolved in PBS and administered by intraperitoneal (i.p.) injection every 2
days at 20 mg/kg. Monoclonal anti-TIM-3 antibodies (#BE0115, BioXCell, US) and anti-PD-1
antibodies (#BE0146, BioXCell, US) were given by intraperitoneal (i.p.) injection every 4 days
at 10 mg/kg. Isotype controls (#BE0089, BioXCell, US) were used at the same concentration in
control mice.

CUT&Tag
The CUT&Tag assay was conducted following the manufacturer's protocol (#HD101, Vazyme,
China). Briefly, Concanavalin A-coated magnetic beads were incubated with CT26_cas9 or
CT26_cas9_sgPtk2 cells at room temperature for 10 min, and anti-FAK antibody (1:50, #3285s,
CST, US) was added and rotated at 4°C for 12 h. The samples were washed 3 times and then
incubated with a secondary antibody (goat anti-rabbit IgG H&L, #AB206-01-AA, Vazyme,
China) at 37°C for 30 min. After washing, the samples were incubated with Hyperactive pA/G-
Transposon Pro and fragmented with MgCl$_2$. The fragmented DNA was extracted from the
samples and amplified by PCR. Libraries were constructed using the TruePrep Index Kit V2 for
Illumina (#TD202, Vazyme, China) and sequenced on an Illumina NovaSeq platform, and 150-
bp paired-end reads were generated.

For CUT&Tag-qPCR, DNA samples were obtained according to the Hyperactive Universal

CUT&Tag Assay Kit (#TD904, Vazyme, China), in which the target DNA fragments with DNA

spike-in as a standard reference fragmented by pA/G-Tn5 were specifically recovered for qPCR

to quantify the abundance of the target gene.

Flow cytometry

Single−cell suspensions of the tumors were obtained by incubating minced tissues with 3 mg/mL

collagenase A (Roche, Germany) and 1 mg/mL DNase I (Roche, Germany) in RPMI 1640

medium at 37°C for 30 min. The resulting cell suspensions were passed through a 40 μM cell

filter and treated with 1× RBC lysis buffer (Invitrogen, USA). Finally, the suspension was

washed with PBS, and the cells were counted for flow cytometric analyses. First, the cells were

incubated with Fixable Viability Stain 700 to gate viable cells. Then, the cells were washed with

flow cytometry staining buffer (PBS containing 2% BSA), and the Fc receptor (FcR) was

blocked with TruStain FcX™ (anti-mouse CD16/32) antibody (BioLegend, US). The cells were

incubated with cell surface antibodies for 30 min at 4°C. The cells were then washed twice with

flow cytometry staining buffer. For intracellular staining, the cells were cultured in fixation

buffer at 4°C for 45 min (eBioscience, USA). The cells were then washed twice with

permeabilization buffer (eBioscience, US). The cells were incubated with the appropriate

intracellular antibodies for an additional 30 min at 4°C. The details of the antibodies used are

described in **Supplemental Table 4**. The cells were then washed twice with permeabilization

buffer and resuspended in flow cytometry staining buffer.

RT□qPCR

RNA was prepared according to the TRIzol reagent (Invitrogen, US) protocol. After the

generation of complementary DNA, qPCR with reverse transcription was performed as described

previously, and all expression levels were normalized to those of an internal housekeeping gene

(*Gapdh*). The primers used are listed in **Supplemental Table 5**.

Protein arrays

CT26 cells were stimulated overnight with FAKi (1 μM) or DMSO (Sigma Aldrich, Germany).

The cell supernatants were then collected after centrifugation. Cytokines in the cell supernatants

were then analyzed with the Proteome Profiler Mouse Cytokine Array Kit A (#ARY006, R&D

Systems, US). The blots were visualized with chemiluminescence using a detection system

(Tanon 5500, China) and quantified using ImageJ.

Isolation of CD45$^+$ cells for scRNA-seq

Single−cell suspensions of the tumors were obtained by incubating minced tissues with 3 mg/mL

collagenase A (Roche, Germany) and 1 mg/mL DNase I (Roche, Germany) in RPMI 1640

medium at 37°C for 30 min. The resulting cell suspensions were passed through a 40 μM cell

filter and treated with 1× RBC lysis buffer (Invitrogen, USA). Finally, the suspension was

washed with PBS and counted for isolation. Then, the Fc receptor (FcR) in the cells was blocked

with a TruStain FcX™ (anti-mouse CD16/32) antibody (#101319, BioLegend, US). After

blockade, the cells were incubated with a PE-conjugated anti-mouse CD45 antibody (#103106,

BioLegend, US) for 20 min at 4°C. After washing, anti-PE MicroBeads (#130-048-801, Miltenyi,

Germany) were added, and the mixture was mixed well and refrigerated for 15 minutes. After

washing, the cell suspension was applied to the column, and labeled CD45$^+$ cells were collected

for analysis.

Associations between *PTK2* expression and immune status

CIBERSORT (https://cibersort.stanford.edu/) was used to calculate the proportions of 20 types

of immune cells via a cancer relative score, which allows for the prediction of the immune cell

phenotype.

Analysis of *PTK2* expression

PTK2 expression was assessed in both tumor and normal tissues utilizing TIMER2, which can be

accessed at http://timer.cistrome.org/.[26]

Differences in PTK2 protein expression were also investigated using the HPA database. We

acquired and examined immunohistochemical (IHC) images of PTK2 protein expression in 4

tumor types. The HPA database is accessible through the website https://www.proteinatlas.org/.

Bioinformatics

Cut&Tag data preprocessing.

CUT&Tag data processing and analysis were performed following a standard protocol

(https://yezhengstat.github.io/CUTTag_tutorial/index.html). The raw Cut-Tag reads were

trimmed and filtered for quality using Trimmomatic (v. 0.39).[56] Paired-end reads were aligned

[57]against mm10 genomes and spike-in sequences from *E. coli* genomes using Bowtie2 (v.2.5.1)

with the parameters --local --very-sensitive-local --no-mixed --no-discordant --phred33 -I 10 -X

700 -p 15. Aligned reads were sorted, and nonuniquely mapped reads were marked using Picard

(v.3.0.0) (http://broadinstitute.github.io/picard/). PCR duplicates and reads of low mapping

quality (MAPQ < 10) were filtered using SAMtools (v.1.18).[58] We then identified peaks using

MACS2 (v.2.2.7.1), [59] employing parameters with preprocessed bamfiles as follows: -t pathway

of the two FAK antibody group bamfiles -c pathway of the two control group bamfiles -f

BAMPE -g mm -B -p 0.01. Peaks were annotated using the R package ChIPseeker (v1.24.0).[60]

The enrichment of gene ontology terms in sets of peaks was calculated using ClusterProfiler

(v4.9.0.002).[61]

Peak heatmaps and genome coverage plots

To visualize CUT&Tag data coverage across the genome within protein-coding genes, read

counts were normalized to the corresponding total reads aligned to the spike-in genome (*E. coli*).

Normalized bigwigs were generated with the bamCoverage function from deepTools (v3.5.4).[62]

The heatmaps were generated with the indicated regions (TSSs $\pm$ 3000 bp) with the

computeMatrix function followed by the plotHeatmap functions of deepTools. Candidate gene

coverage plots were generated using pyGenomeTracks (v3.8).[63]

Single-cell transcriptomic analysis

Library preparation and sequencing

The scRNA-seq libraries described in this study were generated utilizing the DNBelab C4

system. Initially, a suspension of single cells was processed through several stages, including

droplet encapsulation, emulsification, and fragmentation. This was followed by the collection of

mRNA capture beads, reverse transcription, cDNA amplification, and subsequent purification.

According to the manufacturer's protocol, an indexed sequencing library was then assembled.

The concentration of the sequencing library was determined using the Qubit ssDNA Assay Kit

(Thermo Fisher, US). Sequencing was performed on the DIPSEQ T1 platform at the National

Gene Bank (CNGB, BGI-SHENZHEN, China). For data processing, the raw FASTQ files were

analyzed using DNBelab_C4scRNA (v1.0.1) software (available at https://github.com/MGI-tech-

bioinformatics/DNBelab_C_Series_scRNA-analysissoftware) and converted into a format

compatible with Cell Ranger.[64]

Alignment and quantification

The sequencing data were processed using STAR software (v2.5.3) [57] with default parameters

and mapped to the mm10 reference genome. The aligned reads were subsequently screened to

identify valid cell barcodes and unique molecular identifiers (UMIs), which facilitated the

creation of a gene-cell matrix for further analysis.

Quantity of scRNA-seq data

The gene-cell matrix was loaded by the Read10X function of the R package Seurat (v4.1.1).[65]

Genes expressed in fewer than 3 cells were identified. Additionally, cells were filtered based on

four standards: UMIs, the number of genes, the percentage of mitochondrial (Mt) genes, and the

percentage of ribosomal protein large/small (Rpl/s) genes. The percentage of Mt/Rpl/s genes was

calculated by the PercentageFeatureSet function. These filtering standards vary across different

datasets and depend on the data characteristics. In the FAK inhibitor and FAK KO experiments,

cells were removed if they had UMIs less than 1100 or greater than 60000, number of genes less

than 700 or greater than 7500, Mt gene percentage greater than 15%, or Rpl/s gene percentage

greater than 30% (Fig S4, S7). Similarly, in the therapeutic experiments, cells were excluded if

they had UMIs less than 1000 or greater than 17000, number of genes less than 900 or greater

than 4700, Mt gene percentage greater than 10%, or Rpl/s percentage greater than 30%

(**Extended Data Fig. 12**). Additionally, only CD45$^+$ cells were retained in the therapeutic group

samples. Following quality control, the analysis included 47,442 single cells from FAKi

experiments, 87,383 from FAK KO experiments, and 75,631 from therapeutic experiments for

downstream analysis.

Dimensionality reduction and cell type classification

After quality control of the cells and genes, dimensionality reduction and unsupervised clustering
were performed by the R package Seurat (v4.1.1).[65] To address batch effects, each sample was
individually processed using the NormalizeData and FindVariableGenes functions. Subsequently,
batch integration was achieved through the FindIntegrationAnchors and IntegrateData functions,
setting the dims parameter to 50. This integrated dataset was then scaled for principal component
analysis, utilizing the first 20 principal components to construct a shared nearest neighbor (SNN)
network. The Louvain algorithm was employed to identify cell clusters, with resolution settings
adjusted according to the specific characteristics of each dataset. Visualization of these clusters
in two-dimensional space was accomplished using either UMAP or t-SNE, implemented via the
RunUMAP or RunTSNE functions, respectively. Markers for each cluster were detected using
the FindAllMarkers function in Seurat with the following parameters: min.pct = 0.1,
logfc.threshold = 0.25, pseudocount.use = 0.1, only.pos = T. To annotate each cluster as a
specific cell type, we selected some classic markers of immune cells, epithelial cells and
fibroblasts. The cell types were annotated using a violin or dot diagram.

Single-cell level differentially expressed gene (DEG) analysis
Differential gene expression analysis was conducted using the FindMarkers function from the
Seurat R package. For this analysis, the cell populations of interest were specified as ident.1 and
ident.2. We calculated the fold changes in the mean gene expression levels between these
populations. Only genes that exhibited a Bonferroni-adjusted P value of less than 0.05 and an
absolute log2-fold change greater than 0.25 were selected for subsequent analysis.

Discriminate between malignant and nonmalignant cells
Single-CEll Variational ANeuploidy Analysis (SCEVAN) is a rapid variational algorithm
designed for deconvoluting the clonal substructure of tumors using single-cell RNA-seq data[66]
that can automatically and accurately discriminate between malignant and nonmalignant cells.
The R package SCEVAN is user-friendly, and the pipelineCNA function can perform almost all
analyses when provided with a raw gene-cell matrix.

Monocle2 pseudotime trajectory inference

We constructed the single-cell trajectory of CD8$^+$ T cells by using a reversed graph embedding
method implemented by the R package Monocle2 (v. 2.16.0)[65] in the FAK inhibitor and FAK
KO experiments. The raw gene-cell matrix of CD8$^+$ T cells was extracted by the GetAssayData
function of Seurat. Then, we integrated the expression matrix of CD8 T cells from each sample
using the newCellDataSet function of Monocle2. After this, the expression matrix was
normalized by the estimateSizeFactors and estimateDispersions functions of Monocle2. The top
900 highly expressed genes identified by the FindVariableFeatures function of Seurat were used
to order cells in Monocle to construct a CD8+ T-cell DDRtree trajectory plot using the
setOrderingFilter and reduceDimension functions of Monocle2. The signature of each state was
calculated based on genes that were differentially expressed among the other states. States were
annotated as stem-like CD8 T cells (*Slam6f*, *Tcf7*), proliferating CD8 T cells (*Birc5*, *Top2a*), or
exhausted CD8 T cells (*Pdcd1*, *Tox*).

Slingshot pseudotime trajectory inference

We used Slingshot (v1.6.0)[67] to construct cell trajectories to discover cell-state transitions in
CD8+ T cells in therapeutic experiments. CD8 T cells were annotated as CD8_Tpem (*Tcf7*, *Cd69*,
Mki67, *Ifngr1*, *Ccr2*), CD8_Tprolif (*Mki67*, *Bicr5*, *Top2a*), CD8_Tem (*Tnf*, *Ifngr1*, *Ccr7*, *Cd200*,
Tnfrsf4, *Tnfrsf18*), and CD8_Tex (*Tox*, *Havcr2*, *Pdcd1*, *Tigit*, *Entpd1*) (**Fig. 6f, Fig. S13a**). We
selected CD8_Tem cells as the root state when calculating the trajectories and pseudotime using
the slingshot function of the R package Slingshot (v1.6.0).[67] CD8$^+$ T cells were split into two
lineages: cytotoxic and exhausted trajectories. The results were visualized using the R package
ggplot2 (v3.4.4) (https://github.com/tidyverse/ggplot2/).

Construction of the cell☐cell communication network

Intercellular communication networks were constructed and visualized using the CellChat R
package (version 2.1.2)[68] (https://github.com/jinworks/CellChat?tab=readme-ov-file). The
CellChat database for mice, which encompasses 2,377 cell☐cell communication interactions
across three categories—Secreted Signaling, ECM-Receptor, and Cell☐Cell Contact—was used.
The downstream analysis included inferring the cell☐cell communication probability using the
computeCommunProb and filterCommunication functions. The communication probabilities at
both the signaling pathway and gene levels were calculated by the computeCommunProb and

computeCommunProbPathway functions. All the results were integrated by the aggregateNet

function. Significant signaling pathways were visualized as circle plots using the

netVisual_individual function.

Public Bulk RNA-seq and ScRNA-seq data analysis

Pseudobulk expression matrix. To investigate the differences between colorectal cancer

(including mismatch repair-deficient (MMRd) and mismatch repair-proficient (MMRd) tumors)

and adjacent normal tissues, we conducted an integrated single-cell pseudobulk analysis of 100

previously published scRNA-seq datasets (GEO: GSE178341). The pseudobulk expression

matrix was constructed by merging the single-cell gene read counts from each sample via the

average expression function of Seurat. Then, the DEGs from the tumor groups compared to those

from the adjacent normal groups were identified using DESeq2 (v1.26.0),[69] and the genes with

an absolute log2-fold change > 0.25 and Bonferroni-adjusted P values < 0.05 were subjected to

downstream analysis. The immune cell markers, immune checkpoints, tumor markers and

fibroblast markers in tumors and adjacent normal tissues were visualized by ComplexHeatmap

(v2.0.0).[70]

Exhaustion signature score calculation

The exhausted signature was composed of eight typical genes that have been reported: *PDCD1*,

HAVCR2, *TOX*, *LAG3*, *CTLA4*, *TIGIT*, *EOMES*, and *ENTPD1*. We calculated the Spearman's

correlation between every two exhaustion characteristics in T cells, including $CD8^+$ T cells and

$CD4^+$ T cells, from all samples, and the results were visualized by corrplot (v0.90)

(https://github.com/taiyun/corrplot).

For the scRNA-seq data, we calculated module scores for the exhaustion signature with the

Seurat function AddModuleScore per cell and compared the differences between the tumor and

adjacent groups. For the bulk RNA-seq data, module scores for the exhaustion signature were

computed using the gsva function from GSVA (v1.36.3),[71] employing the ssgsea method.

Survival analysis

To explore the relationship between the exhaustion signature and patient prognosis, we

downloaded data on colorectal cancer patients from the TCGA[72] database in UCSC Xena[73]

(https://xenabrowser.net/datapages/?cohort=TCGA%20Colon%20and%20Rectal%20Cancer%20

(COADREAD)&addHub=https%253A%252F%252Fgdc.xenahubs.net&removeHub=https%3A

%2F%2Fxena.treehouse.gi.ucsc.edu%3A443). Patients were divided into high- and low-risk

groups based on the 80th percentile risk score. K☐M curves were used to compare the prognostic

differences between the two groups through the survfit function of the R package survival (v3.2-

13) (https://cran.r-project.org/web/packages/survival/index.html).

GO enrichment

870 The enrichGO and enrichKEGG of the R package ClusterProfiler (v4.9.0.002) were used to

871 perform Gene Ontology (GO) and Kyoto Encyclopedia of Genes and Genomes (KEGG) analyses

872 via the org.Mm.eg.db (v3.18.0) package. The results were visualized using the dotplot function

873 of the R package enrichplot (v1.20.0) (https://github.com/YuLab-SMU/enrichplot).

Gene Set Enrichment Analysis

876 Gene Set Enrichment Analysis (GSEA) was performed using the ClusterProfiler (v4.9.0.002)

877 package. Genes were initially sorted based on their log2-fold change. The enrichment was then

878 performed using the gseGO function with the org.Mm.eg.db (v3.18.0) package. Visualization

879 was achieved with the GseaVis (v0.0.5, github.com/junjunlab/GseaVis) package.

Statistics and reproducibility

All the statistical analyses were performed using Prism 10 (GraphPad). The data are presented as

the mean ± SEM, and two-tailed Student's t test, one-way ANOVA, or two-way ANOVA was

used as indicated in the figure legends. The exact value of n (number of biological or

experimental replicates) can be found in the figure legends, and the exact P values are indicated

in the graphed data. A P value < 0.05 was considered to indicate statistical significance. Most

experiments were carried out at least two or three times, and the findings of all key experiments

were reliably reproduced.

Data and Code Availability

All the raw mouse sequencing data have been deposited in the CNCB (https://ngdc.cncb.ac.cn/)

BIG subproject under accession number PRJCA027119. All sequencing data are publicly

available as of the date of publication.

The software and R package used in this paper are public or previously reported tools. The

methods refer to the official suggestions of the tools, and the pipeline running the tools was

described in the methods section of the manuscript, which did not involve the newly developed

codes or tools. The codes supporting the current study are available from the corresponding

authors upon request.

Conflicts of interest

The authors declare no potential conflicts of interest.

Authors' Contributions

HJ, YHL and PW designed the research; HK, PW and HJ wrote the paper; ZGZ, DC and BH

supervised the clinical research design; Lu C and HBS supervised the scRNA-seq data analysis;

NWK, LBH and HK collected the clinical samples; HK, JY, QXY and Lang C analyzed the

clinical sample data; QXY, HK and PPM scRNA-seq data; XJW, SQD and CC performed the

CRISPR knockdown of FAK; XJW, CWW, DX and HK generated the *in vivo* mouse models;

PM and YP supervised the *in vivo* studies; HK, XY and YD performed the mIHC and analyzed

the data; and DFZ and Lu C proofread the paper.

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Figure legends

Fig. 1 Characterization of the tumor immune microenvironment through scRNA
sequencing and spatial proteomic profiling.

a, t-SNEs (t-distributed stochastic neighbor embedding) by major cell partitions of all samples
(left). MMRp tumors (n = 35), MMRd tumors (n = 29), and MMRp and MMRd normal (n=36)
from 62 individuals (34 MMRd and 28 MMRp). **b,** Heatmap of immune cell marker, immune
checkpoint, tumor marker and fibroblast marker expression in tumor cells and adjacent normal
cells from MMRp and MMRd CRC patients. **c,** Unsupervised hierarchically clustered heatmap of
protein expression in regions of interest in tumor or adjacent normal tissues from CRC patients
(n=9) based on DSP data. **d,** Correlations between two checkpoints. **e,** Exhaustion score

comparison between normal and tumor tissues. The data are presented as the means ± s.e.m.ss

(normal, n =36; tumor, n = 64), as determined by two-tailed unpaired t tests. **f,** OS in patients

with high and low exhaustion scores according to Kaplan□Meier analysis of TCGA CRC

datasets.

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Fig. 2 Spatial TIL exhaustion is associated with hyperactivation of FAK signaling.

a, Principal component analysis (PCA) plot of single-cell RNA-seq data for MMRp tumors,

MMRd tumors, MMRp normal tissues and MMRd normal tissues. **b,** Volcano plot of

differentially expressed genes (DEGs) between normal and tumor tissues, log2 (fold change) ≥

0.1. **c,** Enrichment analysis of DEGs between normal and tumor tissues using KEGG/GO

pathways. **d,** t-SNE plot of all cells shown in **Fig. 1a,** with *PTK2*-expressing cells colored

according to cell density. **e,** t-SNE plot of tumor cells in scRNA-seq data clustered into 11

subtypes. **f,** t-SNE plot of tumor cells shown in **Fig. 2e**, with *PTK2*-expressing cells colored

according to cell density. **g,** *PTK2* expression in 11 subtypes of tumor cells. **h,** *PTK2* expression

in the MMRp, MMRd, MMRP and MMRd normal groups. **i,** Representative

immunohistochemistry images and analysis of total and phosphorylated FAK (p-FAK, Tyr397)

in human adjacent normal colon and CRC tumor tissues. The data are presented as the means ±

s.e.m.ss (n = 5), as determined by two-tailed unpaired t tests. **j,** Simple linear regression

correlation plot of PD-1/TIM-3/LAG-3 expression per unit CD45 expression from the DSP data

with the percentage of pFAK area. The data are presented as the means ± 95% confidence

intervals (95% CIs). **k,** Representative merged images of multiplexed staining for DAPI (blue),

CK19 (green), pFAK (red), CD3 (cyan) and TIM-3 (yellow). **l,** Representative composite images

of rectal carcinoma tissue from the pFAK high or low groups with multiplexed staining and

imaging of five individual markers (DAPI, blue; CK19, green; pFAK, red; CD3, cyan; TIM-3,

yellow) (left) and a representative proximity distance map showing TIM-3[+] TILs within or

outside a radius of 100 μm from the nuclear center of tumor cells (pFAK[+]CK19[+] cells) (right). **m,**

Comparisons of the percentage of pFAK[+] cells among all cells between the pFAK high group

(ROIs, n=28) and the pFAK lwo group (ROIs, n=17). The data are presented as the means ±

s.e.m.s, as determined by two-tailed unpaired t tests. **n,** Comparisons of the percentages of TIM-

3[+] TILs among all cells between the pFAK high group (ROIs, n=28) and the pFAK lwo group

(ROIs, n=17). The data are presented as the means ± s.e.m.s, as determined by two-tailed

unpaired t tests. **o,** Comparisons of the percentage of TIM-3$^+$ TILs within 100 μm from

pFAK$^+$CK19$^+$ cells between the pFAK high group (ROIs, n=28) and pFAK low group (ROIs,

n=17). The data are presented as the means ± s.e.m.s, as determined by two-tailed unpaired t

tests. **p,** Schematic depicting the spatial distribution of TIM-3$^+$ cells in CRC patients with high or

low pFAK expression.

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Fig. 3 FAK inhibition leads to stable disease progression by reshaping the TIME.

a, Growth rate of MC38 subcutaneous tumors treated with a FAK inhibitor (FAKi, VS-4718, 50

mg/kg) or vehicle. Vehicle or FAKi was administered intragastrically twice per day. The data are

presented as the mean ± s.e.m. (vehicle, n = 5; FAKi, n = 6), as determined by one-way ANOVA.

b, Growth rate of subcutaneous CT26 tumors treated with a FAK inhibitor (FAKi, VS-4718, 50

mg/kg) or vehicle. Vehicle or FAKi was administered intragastrically twice per day. The data are

presented as the means ± s.e.m.s (n = 6 mice per group), as determined by one-way ANOVA. **c,**

UMAP plot of 47,442 cells from vehicle (n = 2)- or FAKi (n = 3)-treated tumor tissues, colored

according to annotated cell type. **d,** Relative fraction of each cluster in **Fig. 3c of** vehicle- or

FAKi-treated tumors**. e,** Numbers of differentially expressed genes (up- or downregulated) in

each cluster. **f,** Differentially expressed genes in CD8$^+$ T cells from the FAKi group versus those

from the vehicle group. **g-h,** Gene set enrichment analysis (GSEA) of the scRNA-seq data of all

cells revealed enrichment of genes related to the positive regulation of T-cell differentiation and

activation. **i,** Percentages of *Pdcd-1^{high}* and *Pdcd-1^{low}* CD8$^+$ T cells among CD8$^+$ T cells from

vehicle- or FAKi-treated tumors. **j,** Trajectory analysis of CD8$^+$ T cells in vehicle- or FAKi-

treated tumors. Three branches of stem-like CD8$^+$ T cells, proliferating CD8$^+$ T cells and

exhausted CD8$^+$ T cells were clustered. **k,** Expression of *Slamf6*, *Tcf7*, *Birc5*, *Top2a*, *Pdcd1* and

Tox in stem-like CD8$^+$ T cells, proliferating CD8$^+$ T cells and exhausted CD8$^+$ T cells. **l,**

Percentages of stem-like CD8$^+$ T cells, proliferating CD8$^+$ T cells and exhausted CD8$^+$ T cells

among CD8$^+$ T cells in vehicle- or FAKi-treated tumors. **m-n,** Inferred PD-L1 and TNF

signaling networks in FAKi- or vehicle-treated tumors. **o,** Representative mIHC images of DAPI

(blue), CD8 (pink), TIM-3 (yellow), TOX (red), PD-1 (cyan), and TCF-1 (green) in tumors from

vehicle- or FAKi-treated mice. **p,** Representative image and percentage of PD-1$^+$TIM-3$^+$TOX$^+$

CD8$^+$ T cells among CD8$^+$ T cells in CT26 tumors from vehicle (n=4)- or FAKi (n=5)-treated

mice. The data are presented as the means ± s.e.m.s, as determined by two-tailed unpaired t tests.

q, Representative image and percentage of TCF-1$^+$CD8$^+$ cells among CD8$^+$ cells in CT26 tumors

from vehicle-treated mice (n=4) or FAKi-treated mice (n=5). The data are presented as the

means ± s.e.m.s, as determined by two-tailed unpaired t tests. **r,** Percentages of exhausted (TIM-

3$^+$PD-1$^+$) CD8$^+$ T cells among CD8$^+$ T cells determined by flow cytometry in CT26 tumors from

vehicle-treated mice (n=5) and FAKi-treated mice (n=4). The data are presented as the means ±

s.e.m.s, as determined by two-tailed unpaired t tests. **s,** Percentages of cytotoxic (GZMB$^+$) CD8$^+$

T cells among CD8$^+$ T cells in MC38 tumors from vehicle-treated mice (n=6) and FAKi-treated

mice (n=6) determined by flow cytometry. The data are presented as the means ± s.e.m.s, as

determined by two-tailed unpaired t tests.

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Fig. 4 Knockdown of tumor-intrinsic FAK reversed CD8$^+$ T-cell exhaustion in colorectal

tumors.

a, Western blot of total FAK expression in Cas9 or sgPtk2 CT26 cell lysates. **b,** Cell viability

measurements of Cas9 or sgPtk2 CT26 cells on day 3 and day 5. **c,** Tumor growth curves of

Cas9- and FAK-knockdown CT26 tumors in BALB/c-nude mice. The data are presented as the

means ± s.e.m.ss (n = 5 mice per group), as determined by one-way ANOVA. **d,** Growth curves

of Cas9- and FAK-knockdown CT26 tumors in BALB/c mice. The data are presented as the

means ± s.e.m.s (n = 7 mice per group), as determined by one-way ANOVA. **e,** UMAP plot of

87,383 cells from CT26 Cas9 (n = 2), sgPtk2_1 (n = 3) and sgPtk2_2 (n = 3) tumor tissues,

colored by annotated cell type. **f,** Violin map showing the expression levels of specific markers

in each cell type. **g,** Relative fraction of each cluster in **Fig. 4e** in CT26 Cas9, sgPtk2_1 and

sgPtk2_2 tumors. **h,** Trajectory analysis of CD8$^+$ T cells in CT26 Cas9, sgPtk2_1 and sgPtk2_2

tumors. Three branches of stem-like CD8$^+$ T cells, proliferating CD8$^+$ T cells and exhausted

CD8$^+$ T cells were clustered. **i,** Inferred PD-L1 signaling networks in CT26 Cas9, sgPtk2_1 and

sgPtk2_2 tumors. **j,** Representative mIHC images of Cas9, sgPtk2_1 and sgPtk2_2 tumors

showing DAPI (blue), tumor cell (green), CD8 (pink), PD-1 (cyan) and TOX (red) staining. **k,**

Comparisons of the percentages of exhausted T cells (PD-1$^+$TIM-3$^+$), terminally exhausted T

cells (PD-1$^+$TIM-3$^+$TOX$^+$) and stem-like T cells (TCF-1$^+$) among CD8$^+$ T cells within

intratumoral regions from Cas9 tumors, sgPtk2_1 tumors and sgPtk2_2 tumors. The data are

presented as the means ± s.e.m.s (n = 6 ROIs per group), as determined by one-way ANOVA. **l,**

Schematic depicting the *in vitro* coculture system of CD8$^+$ T cells and CT26 Cas9 or sgPtk2

tumor cells. **m,** Percentage of TIM-3$^+$TOX$^+$CD8$^+$ T cells among CD8$^+$ T cells determined by

flow cytometry from a coculture system of CD8$^+$ T cells and CT26 Cas9 or sgPtk2 tumor cells.

The data are presented as the means ± s.e.m.s (n = 3 per group), as determined by two-tailed

unpaired t tests. **n,** Percentages of PD-1$^+$TIM-3$^+$TOX$^+$CD8$^+$ T cells among CD8$^+$ T cells

determined by flow cytometry in a coculture system of CD8$^+$ T cells and CT26 Cas9 or sgPtk2

tumor cells. The data are presented as the means ± s.e.m.s (n = 3 per group), as determined by

two-tailed unpaired t tests. **o,** Percentages of TCF-1$^+$CD8$^+$ T cells among CD8$^+$ T cells

determined by flow cytometry in a coculture system of CD8$^+$ T cells and CT26 Cas9 or sgPtk2

tumor cells. The data are presented as the means ± s.e.m.ss (n = 3 per group), as determined by

two-tailed unpaired t tests. **p,** Percentage of Ki67$^+$CD8$^+$ T cells among CD8$^+$ T cells determined

by flow cytometry from a coculture system of CD8$^+$ T cells and CT26 Cas9 or sgPtk2 tumor

cells. The data are presented as the means ± s.e.m.s (n = 3 per group), as determined by two-

tailed unpaired t tests.

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Fig. 5 Nuclear FAK promotes CD8$^+$ T cell exhaustion by transcriptionally regulating the

SP1/IL-6 axis.

a, Representative mIHC images of human CRC tissue stained with DAPI (blue), PanCK (green)

and FAK (red). **b,** Representative immunofluorescence staining of FAK in CT26 cells. **c,**

Fluorescence colocalization analysis of FAK and DAPI in CT26 cells. **d,** Western blot showing

FAK expression in the cytoplasm and nucleus of CT26 cells. **e,** CUT&Tag sequencing analysis

of FAK in CT26 cells with or without FAK antibody. **f,** Distribution of peaks identified from

CUT&Tag sequencing across gene regions using MACS2. **g,** Ranking of the top genes by

CUT&Tag-seq using MACS2. The top transcription factors among all genes are highlighted. **h,**

Representative illustration of FAK binding patterns analyzed by CUT&Tag-seq at the genomic

loci of *Sp1*. The promoter regions of the three genes are highlighted in pink. **i,** Structural

prediction of FAK-*Sp1* promoter binding by AlphaFold3. **j,** Real-time quantitative PCR

(RT□qPCR) of the FAK binding promotor of *Sp1* in the CUT&Tag library constructed from

Cas9 and sgPtk2 CT26 cells. The data are presented as the mean ± s.e.m. (n = 2 per group), as

determined by one-way ANOVA. **k,** Real-time quantitative PCR (RT−qPCR) of *Sp1* transcript

levels in CT26 Cas9, sgPtk2_1 and shPtk2_2 cells. The data are presented as the mean ± s.e.m.

(n = 3 per group), as determined by one-way ANOVA. **l,** Representative immunofluorescence

staining of SP1 in CT26 Cas9, sgPtk2_1, and sgPtk2_2 cells. The mean fluorescence intensity

was calculated and is presented as the mean ± s.e.m. (Cas9, n = 134; sgPtk2_1, n = 129;

sgPtk2_2, n = 112), as determined by one-way ANOVA. **m,** Real-time quantitative PCR (RT–

qPCR) of cytokine transcript levels in CT26 Cas9, sgPtk2_1, and sgPtk2_2 cells. The data are

presented as the mean ± s.e.m. (n = 3 per group), as determined by two-tailed one-way ANOVA.

n, Representative flow cytometry gating of PD-1$^+$, TIM-3$^+$ or TOX$^+$ CD8$^+$ T cells among CD8$^+$

T cells treated with or without IL-6 for 3 days or 6 days. **o,** Percentages of PD-1$^+$TOX$^+$, TIM-

3$^+$TOX$^+$ and PD-1$^+$TIM-3$^+$TOX$^+$ CD8$^+$ T cells among CD8$^+$ T cells treated with or without IL-6

for 3 days or 6 days, as determined by flow cytometry. The data are presented as the means ±

s.e.m.s (n = 3 per group), as determined by two-tailed unpaired t tests. **p,** Representative mIHC

images of CT26 Cas9 tumors, sgPtk2_1 tumors and sgPtk2_2 tumors stained with DAPI (blue),

tumor cells (green), pFAK (cyan) and IL-6 (red). **q,** Percentage of IL-6$^+$ cells among all cells

from CT26 Cas9 tumors, sgPtk2_1 tumors and sgPtk2_2 tumors. The data are presented as the

means ± s.e.m.s (n = 4 per group), as determined by one-way ANOVA. **r,** Percentage of pFAK$^+$

cells among all cells from CT26 Cas9 tumors, sgPtk2_1 tumors and sgPtk2_2 tumors. The data

are presented as the means ± s.e.m.s (n = 4 per group), as determined by one-way ANOVA. **s,**

Percentage of pFAK$^+$ tumor cells among IL-6$^+$ cells from CT26 Cas9 tumors, sgPtk2_1 tumors

and sgPtk2_2 tumors. The data are presented as the means ± s.e.m.s (n = 4 per group), as

determined by one-way ANOVA.

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Fig. 6 Inhibition of FAK improves the efficacy of immune checkpoint blockade (ICB)

therapy *in vivo*.

a, Growth curves of subcutaneous MC38 tumors treated with combination therapies. In the

Immuno group, 5-Fu (20 mg/kg) combined with anti-TIM-3 (10 mg/kg) and anti-PD-1 (10

mg/kg) was used. Vehicle or FAKi was administered intragastrically twice per day. 5-Fu or

vehicle was intraperitoneally administered once every two days. Isotype or anti-TIM-3 combined

with anti-PD-1 was intraperitoneally administered once every 4 days. The data are presented as

the means ± s.e.m.ss (n = 6 mice per group), as determined by two-way ANOVA. **b,** Growth

curves of subcutaneous CT26 tumors treated with combination therapies. In the Immuno group,

5-Fu (20 mg/kg) combined with anti-TIM-3 (10 mg/kg) and anti-PD-1 (10 mg/kg) was used.

Vehicle or FAKi was administered intragastrically twice per day. 5-Fu or vehicle was

intraperitoneally administered once every two days. Isotype or anti-TIM-3 combined with anti-
PD-1 was intraperitoneally administered once every 4 days. The data are presented as the means
± s.e.m.s (n = 5 mice per group), as determined by two-way ANOVA. **c,** Schematics depicting
the $CD45^+$ cell sorting strategy for subsequent scRNA-seq. **d,** t-SNE plot of 75,631 cells from
vehicle-, immuno-, FAKi- or combination-treated tumor tissues (n = 2 per group), colored
according to the annotated cell type. **e,** Relative fraction of each cluster in **Fig. 6d** in the vehicle-,
immuno-, FAKi- or combination-treated groups. **f,** UMAP plot of $CD8^+$ T cells from all cells
collected from the scRNA-seq data. $CD8^+$ T cells were clustered into Tprolif, Tpem, Tem and
Tex subsets. Key markers of the clustering process are highlighted in the map. **g,** Relative
fraction of each cluster in **Fig. 6f** in the vehicle-, immune-, FAKi- or combination-treated groups.
h, Violin map of the expression of exhaustion markers (*Havcr2*, *Pdcd1*, and *Tox*) and cytotoxic
markers (*Cd69*, *Ifngr1* and *Tnf*) in the vehicle, immuno-, FAKi- or combination-treated groups. **i,**
Two trajectories (cytotoxic trajectory and exhausted trajectory) of $CD8^+$ T cells based on
Slingshot and the $CD8^+$ T-cell phenotype (left) and pseudotime (right) are displayed. **j,** Plot of
exhaustion and cytotoxicity markers along the cytotoxic $CD8^+$ T-cell lineage based on
pseudotime. **k,** Gene set enrichment analysis of DEGs in $CD8^+$ T cells. **l,** Representative mIHC
images of DAPI (blue), CD8 (pink), pSTAT3 (green), TOX (red) and TIM-3 (yellow) in tumors
from vehicle-treated mice, immune-treated mice, FAKi-treated mice and combination-treated
mice. **m,** Percentage of $pSTAT3^+CD8^+$ T cells among $CD8^+$ T cells in CT26 tumors from vehicle-
treated mice (n = 5), immuno-treated mice (n = 5), FAKi-treated mice (n = 4) and combination-
treated mice (n = 5) determined by mIHC. The data are presented as the means ± s.e.m.s, as
determined by one-way ANOVA. **n,** Percentage of $TOX^+TIM-3^+CD8^+$ T cells among $CD8^+$ T
cells in CT26 tumors from vehicle-treated mice (n = 5), immuno-treated mice (n = 5), FAKi-
treated mice (n = 4) and combination-treated mice (n = 5) determined by mIHC. The data are
presented as the means ± s.e.m.s, as determined by one-way ANOVA. **q,** Schematic of how
combination therapy influences the microenvironment and the differences between high pFAK
CRC and low pFAK CRC patients.
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Figure1

Figure 2

Figure 3

Figure 4

Figure 5

a *Human CRC*

Merge / DAPI / PanCK / FAK — 20 µm

b *CT26*

DAPI / FAK / Merge — 10 µm / 2.5 µm

c

FAK (green), DAPI (blue). Intensity vs Distance (µm)

d *CT26*

Cytoplasm / Nucleus
FAK ¹¹⁹ kDa
LaminB ⁶⁶ kDa
GAPDH ³⁷ kDa

e CUT&Tag — Ctrl (rep1, rep2) / FAK (rep1, rep2), genes, Gene distance (bp), TSS

f Pie chart:
- Promoter (<=1kb) (54.71%)
- Promoter (1–2kb) (8.03%)
- Promoter (2–3kb) (5.14%)
- 5' UTR (0.04%)
- 3' UTR (1.36%)
- 1st Exon (0.1%)
- Other Exon (2.19%)
- 1st Intron (5.54%)
- Other Intron (8.04%)
- Downstream (<=300) (0.13%)
- Distal Intergenic (14.73%)

g Gene Rank vs -log10(p.adjust): Sp1, Klf16, Mafa, Atf5, Atf4, Tfb1m, Bclaf1, Mypop, Klf13, F4f1

h 102,405–102,435 Kb, Sp1

i Structure prediction of FAK-Sp1 promoter binding by AlphaFold3

j *CUT&Tag Sp1 validation*
Relative Sp1 promoter expression; Cas9, sgPtk2_1, sgPtk2_2; P = 0.0010, P = 0.0058

k *Sp1 mRNA expression*
Relative mRNA expression; Cas9, sgPtk2_1, sgPtk2_2; P = 0.0025, P = 0.0008

l Cas9 / sgPtk2_1 / sgPtk2_2; Merge, DAPI, SP1 — 10 µm
Mean Fluorescence Intensity of SP1; P < 0.0001, P < 0.0001

m Relative mRNA expression: Ccl5, Cxcl10, Il6, Tgfb1, Csf1, Csf2
Cas9, sgPtk2_1, sgPtk2_2
Ccl5: P = 0.982, P = 0.5146; Cxcl10: P < 0.0001, P = 0.0482; Il6: P = 0.0002, P < 0.0001; Tgfb1: P = 0.6516, P = 0.7031; Csf1: P = 0.6536, P = 0.0505; Csf2: P = 0.0138, P = 0.0002

n Day 3 / Day 6; Control / IL-6
CD8_FITC vs PD-1_BV786: 47.1, 48.33, 47.43, 52.97
CD8_FITC vs TIM-3_BUV395: 14.83, 27, 11.49, 60.53
Histogram vs TOX_PE: 57.33, 61.27, 59.27, 84.8

o Control / IL-6
% PD-1+TOX+ in CD8+ cells; Time (day) 3, 6; P = 0.0044, P = 0.077
% TIM-3+TOX+ in CD8+ cells; P < 0.0001, P = 0.0104
% PD-1+TIM-3+TOX+ in CD8+ cells; P = 0.0019, P = 0.0237

p Cas9 / sgPtk2_1 / sgPtk2_2 — 20 µm / 100 µm
DAPI / Tumor cell / pFAK / IL-6

q % IL-6+ in All cells; Cas9, sgPtk2_1, sgPtk2_2; P < 0.0001, P < 0.0001

r % pFAK+ in All cells; P = 0.0001, P = 0.0004

s % pFAK+Tumor cell in IL-6+ cells; P = 0.0021, P = 0.0182

Figure 6