Natural killer cells associate with epithelial cells in the pancreatic ductal adenocarcinoma

tumor microenvironment

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Abbreviations used in this paper

AdjNorm (adjacent-normal); cancer-associated fibroblast (CAF); CyTOF, cytometry by time-of-flight; ECM, extracellular matrix; FCSR, Flow Cytometry Shared Resourse, FFPE, formalin-fixed, paraffin-embedded; FN1, fibronectin; HTSR, Histopathology & Tissue Shared Resource; IC, immunocytochemistry; IF, immunofluorescence; IMC, imaging mass cytometry; LCCC, Lombardi Comprehensive Cancer Center; L-R, ligand-receptor; MMP, matrix-metalloproteinase; NK cell, natural killer; cell; PDAC, pancreatic ductal adenocarcinoma; PFA, paraformaldehyde; ROI, region-of-interest; TMA, tissue microarray; TME, tumor microenvironment.

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Disclosures

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Author contributions

Z.X.M. and L.M.W. conceived the idea, designed the study, obtained funding, and wrote the

manuscript. Z.X.M. conducted experiments and analyzed the data. Z.X.M., R.K.S., A.D., and

W.J.H. performed or assisted with computational analyses. Z.X.M. and R.K.S. wrote R scripts

and generated the computational figures. B.H. and A.D. assisted with data collection and tissue

pathology of human tissue samples. L.W. and M.C. assisted in performing 2D *in vitro* invasion

experiments. M.C. assisted with RT-qPCR, flow cytometry assays, and 3D *in vitro* invasion

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with experimental design.

Data transparency statement

Code used to perform IMC and scRNAseq analyses and generate the figures is available at

https://github.com/Weiner-Lab/NaturalKillerCells_PDAC. Raw .mcd files for all cores of the

pancreas tissue microarray imaged by IMC and IMC-derived datasets, including histoCAT-

derived single cell files, and Seurat, SingleCellExperiment, Cytomapper and distance data matrix

R objects, to reproduce figures are deposited at doi: 10.5281/zenodo.10582038. The scRNAseq

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supporting the findings of this study are available within the paper or its supplementary

information files. All other relevant data are available from the corresponding author upon

request.

Graphical Abstract

High CAF and Collagen Content
Block NK Cell Accumulation

Collagen Binds to NK Cell-
Associated CD44

Fibroblasts
Epithelial duct
NK cells
ECM
anti-CD44

Low CAF and Collagen Content
Permit NK Cell Accumulation

CD44 Neutralization
Promotes NK Cell Invasion

Abstract

Background

Pancreatic ductal adenocarcinoma (PDAC) is the most common form of pancreatic cancer.

PDAC's poor prognosis and resistance to immunotherapy are attributed in part to its dense,

fibrotic tumor microenvironment (TME), which is known to inhibit immune cell infiltration. We

recently demonstrated that PDAC patients with higher natural killer (NK) cell content and

activation have better survival rates. However, NK cell interactions in the PDAC TME have yet

to be deeply studied. We show here that NK cells are present and active in the human PDAC

TME.

Methods

We used imaging mass cytometry (IMC) to assess NK cell content, function, and spatial

localization in human PDAC samples. Then, we used CellChat, a tool to infer ligand-receptor

interactions, on a human PDAC scRNAseq dataset to further define NK cell interactions in

PDAC.

Results

Spatial analyses showed for the first time that active NK cells are present in the PDAC TME, and

both associate and interact with malignant epithelial cell ducts. We also found that fibroblast-

rich, desmoplastic regions limit NK cell infiltration in the PDAC TME. CellChat analysis

identified that the CD44 receptor on NK cells interacts with PDAC extracellular matrix (ECM)

components such as collagen, fibronectin and laminin expressed by fibroblasts and malignant

epithelial cells. This led us to hypothesize that these interactions play roles in regulating NK cell

motility in desmoplastic PDAC TMEs. Using 2D and 3D *in vitro* assays, we found that CD44

neutralization significantly increased NK cell invasion through matrix.

103 **Conclusions**

104 Targeting ECM-immune cell interactions may increase NK cell invasion into the PDAC TME.

105

106 **Keywords**

Introduction

Pancreatic ductal adenocarcinoma (PDAC) is the most common form of pancreatic cancer, with a 5-year survival rate of 12%.[1] PDAC is slated to become the most common contributor to cancer-related deaths in coming years, thus there is a need for the identification of novel therapeutic approaches.[2] PDAC is considered to be immunologically "cold" as its tumor microenvironment (TME), accounting for at least 50% of the tumor volume,[3] is primarily desmoplastic as a result of extracellular matrix (ECM) production by cancer-associated fibroblasts (CAFs), causing resistance to therapies, poor immunogenicity and immune cell infiltration.[4-7] Therefore, resolution of intratumoral cellular interactions within the PDAC TME is essential to identifying novel therapeutic approaches to treat this disease.

In recent years, immune-stromal cell interactions have been studied in a variety of diseases using emerging spatial technologies to further investigate cellular interactions that may have been missed through other conventional single-cell methodologies.[8-14] However, the roles and functions of natural killer (NK) cells in many solid tumors, including PDAC, remain to be elucidated. NK cells are cytotoxic effector cells of the innate immune system that are known to elicit anti-tumor effects.[15-18] We recently demonstrated that increased NK cell content was correlated with a statistically significant increase in overall patient survival, and that NK cells are necessary to elicit anti-tumor responses in a pre-clinical murine PDAC model.[15] However, NK cells remain understudied in this disease.

Here, we used multi-omics approaches to investigate the cellular relationships of NK cells within the human PDAC TME. First, we used imaging mass cytometry (IMC), a spatial proteomics platform that maintains tissue architecture while capturing single cell data,[19] and found that active NK cells co-localize, interact, and form a strong network with epithelial cells;

importantly, this co-localization was inversely related to fibroblast abundance and collagen-I

expression in the human PDAC TME. Secondly, we used a ligand-receptor network inference

tool, CellChat, to infer NK cell interactions in human PDAC scRNAseq samples and found that

the CD44 receptor on NK cells interacts with collagens, laminins, and fibronectin ligands on

malignant epithelial cells and fibroblasts; this has not been previously described. Since these

proteins are also present within the stroma of solid tumors, we hypothesized that neutralizing

CD44-mediated interactions with NK cells would increase NK cell invasion in the PDAC TME

and found that NK cell invasion through collagen-containing matrices significantly increased

upon CD44 neutralization. Hence, the human PDAC TME actively excludes invasion of NK

cells through the expression of ECM components, such as collagens. These results further

suggest a role for manipulating NK cell interactions to promote NK cell migration into the

PDAC TME and improve immunotherapy directed against this malignancy.

Methods

Tissue samples

The Lombardi Comprehensive Cancer Center (LCCC) Histopathology & Tissue Shared

Resource (HTSR) provided formalin-fixed, paraffin-embedded (FFPE) human PDAC and spleen

tissue samples. For IMC, we used a LCCC-curated FFPE human pancreas tissue microarray

(TMA) slide series containing 2 mm cores from normal pancreas, pancreatitis, pancreatic

neuroendocrine tumors, intraductal papillary mucinous neoplasm, pancreatic mucinous

adenocarcinoma, PDAC, colon adenocarcinoma, testicle, tonsil, and placenta samples, and

PDAC cell lines. Information for all TMA samples are available at doi:

10.5281/zenodo.10582038. This study was restricted to 44 cores from 21 previously untreated

PDAC patients who underwent Whipple resections or distal pancreatectomies (**Supplementary**

Table S2).

Antibody validation, metal-conjugation, and imaging mass cytometry

For IMC, we designed a metal-conjugated antibody panel. Carrier-free antibodies not

commercially metal-conjugated were validated by immunofluorescence (IF) in PDAC or spleen

tissue (**Supplementary Table S1**). Antibodies with expected expression patterns were metal-

conjugated using MaxPar X8 Multimetal Labeling Kits (Standard Bio Tools (SBI);

Supplementary Table S1). Metal-conjugation was validated by cytometry by time-of-flight

(CyTOF) (Hyperion Imaging System; SBI) at the LCCC Flow Cytometry Shared Resource

(FCSR). Metal-conjugated antibody dilutions were optimized in the pancreas TMA prior to final

IMC staining at the HTSR. Antigen retrieval and staining was performed (SBI) at the LCCC

HTSR, while image acquisition was performed at the LCCC Mass Spectrometry and Analytical

Pharmacology Shared Resource. A maximum of 2.25 mm^2 regions of interest (ROIs) on TMA

cores were selected, laser-ablated and analyzed by CyTOF to quantitate the metal-conjugated

antibodies per ROI, generating multiplex images.[20, 21] All data were collected using the Hyperion

Imaging System (SBI) and qualitatively validated in MCD Viewer (v1.0.560.6; SBI) and QuPath

softwares.

IMC image processing, data transformation, and single-cell clustering

Raw IMC data was processed following the widely used ImcSegmentationPipeline

(https://github.com/BodenmillerGroup/ImcSegmentationPipeline).[11, 22-24] In the Ilastik software,

DNA, E-cadherin, pan-cytokeratin, vimentin, and CD45RO markers were used to pixel-train and

generate cell segmentation probability maps for nuclear, cytoplasmic, cell membrane, and

background areas in all IMC images, which were imported into CellProfiler to generate cell

segmentation masks to then extract single cell data using histoCAT.[25, 26] 412,862 cells were

identified across 44 images from 21 PDAC patient samples. Extracted IMC-derived single cell

data were imported into R (v4.2.1) for downstream computational analyses. histoCAT-derived

single cell data files generated are available at doi: 10.5281/zenodo.10582038. All scripts

adapted from this pipeline for downstream analyses are available at https://github.com/Weiner-

Lab/NaturalKillerCells_PDAC. Single cell protein expression data was log-transformed, re-

integrated, and clustered using Seurat-based analysis.[27] Using a supervised clustering with

canonical cell markers (αSMA, CD3, CD4, CD8α, CD11b, CD16, CD20, CD45RO, CD56,

CD68, E-cadherin, FAP, FOXP3, NKG2D, NKp44, pan-cytokeratin, vimentin), we found that a

clustering resolution = 0.35 provided distinct immune, fibroblast, and epithelial cell populations.

Each cell population was subsetted and re-clustered to identify the functional state of subclusters

using the following markers: CD69, CD107α, cleaved-caspase 3, collagen-I, granzyme B, HLA-

A/B/C, HLA-A1, IFNγ, Ki67, MICA, PCNA, perforin, PD-1, PD-L1, and TGFβ. All subclusters

were reintegrated, annotated, and 29 unique cell populations were identified and validated

visually using the Cytomapper R package and MCD Viewer. Seurat objects containing all the

PDAC single cell metadata is available at doi: 10.5281/zenodo.10582038 and were converted to

SingleCellExperiment[28] objects for downstream spatial analyses.

IMC spatial analysis

We generated knn-based interaction graphs for the 15-nearest neighbors and used k-

means clustering to group cells into 8 distinct cellular neighborhoods using the

SpatialExperiment and imcRtools R packages.[24, 29-31] Using the imcRtools package, permutation

test-based cell-cell interaction analysis identified significant interactions or avoidances between

cell populations. Using FDR analysis, cell-cell interactions with $P < 0.01$ were considered

significant. Based on Euclidean distance metadata, distance and network analyses were

performed, as previously described.[9] Seurat's CellSelector function[27] was used to select and

quantify cells in epithelial-ductal ROIs of spatial images. From CellSelector, percentages of cell

populations in each epithelial-ductal ROI were quantified, and epithelial-ductal ROIs were

stratified in quartiles based on fibroblast abundance (Q1 = low fibroblast quartile, Q4 = high

fibroblast quartile). Mean total expression of all markers was quantified in representative

epithelial-ductal ROIs of pseudoimages using MCD Viewer. Cell-based expression in epithelial-

ductal ROIs was performed using Seurat.

Immunofluorescence

Human PDAC samples were used for multiplex IF to assess pan-cytokeratin, E-cadherin,

CD56, and NKG2D (**Supplementary Table S3**). Patient samples were from 4 males and 2

females with age ranges between 44-86, and had tumor diameters ranging from 3.7-18 cm.

Multiplex staining and imaging were performed as previously described,[32] except tissue images

were captured using Akoya Biosciences Inc.'s PhenoImager Fusion imaging platform at the

LCCC HTSR. Images were exported as *.qtiff* files and visualized using QuPath software.

Single-cell RNA-sequencing analysis

To infer ligand-receptor (L-R) interactions in PDAC, we utilized a previously published

human PDAC scRNAseq dataset[33] and subsetted NK cells, fibroblasts, and epithelial cells.

Malignant and normal epithelial cells were differentiated using CytoTRACE, a computational

framework that predicts cellular differentiation states by measuring the number of genes

expressed by each cell.[34] The CytoTRACE scores distribution was observed to be bi-modal and

using a mixed-model, an ideal cut-off value separating the two distributions was determined to

be 0.72 where scores greater than 0.72 indicated a malignant epithelial cells (**Supplementary**

Figure S7).[35] We then used CellChat, a manually curated protein database of approximately

2,000 L-R pairs[36] to infer potential L-R interactions between these cell populations. A wilcox test

with a Bonferroni correction from the FindMarkers Seurat function (v4.3) was used for

differential gene expression analysis of CellChat-identified L-R genes. Genes with an adjusted *P*

< 0.01 were considered significantly differentially expressed. R scripts for applied CytoTRACE

and CellChat analyses are available at https://github.com/Weiner-Lab/NaturalKillerCells_PDAC.

Cell culture

Human PANC-1 PDAC cells and donor NK cell lines were cultured, as previously

described,[37] except donor NK cells received 0.5% v/v of IL-2. Donor NK cells were stimulated

with the engineered K562 cell line, K562-mb21-41BBL (courtesy of Dr. Dean Lee at

Nationwide Children's).[38] K562-mb21-41BBL cells were cultured in supplemented RPMI (10%

FBS, 1% penicillin/streptomycin). For NK cell stimulation, K562-mb21-41BBL cells were

collected (5 minutes, 1,000 rpm, 4˚C), resuspended in supplemented RPMI with mitomycin C

(Sigma-Aldrich) ($C_f = 0.01$ mg/ml) and incubated for 4 hours (37˚C). Pre-treated K562-mb21-

41BBL cells were collected (5 minutes, 1,000 rpm, 4˚C), resuspended in NK cell medium, then

co-cultured with donor NK cells (E:T = 1:1); this process was repeated at least once per week.

Donor NK cells aged day 1-50 and stimulated 1-3 days prior to *in vitro* assays were used.

Flow cytometry

Cells were centrifuged (5 minutes, 1,000rpm, 4˚C) washed twice (1X PBS), then

resuspended in FACS staining buffer (1% BSA in 1X PBS). Human Fc block (BD Pharmigen,

CAT#: 564219) then α-CD44-BV605 (Biolegend, CAT#: 103047) antibodies were added per

manufacturer's recommendations (30 minutes, 4˚C). Cell pellets were washed twice (FACS

staining buffer), resuspended in fixative (1% PFA in 1X PBS), then processed by the LCCC

FCSR in a BD LSRFortessa Cell Analyzer (BD Biosciences). Analysis was performed using

FlowJo (v10.8.1).

NK cell 2D invasion assay

The bottom of 5 μm Transwells (Corning) were coated with Matrigel (Corning) diluted

1:3 in NK cell medium. CXCL9 ($C_f = 100$ ng/ml) (R&D Systems)-supplemented NK cell

medium was added to the bottom of each well. Donor NK cells were added to Transwells with or

without an α-CD44 neutralizing antibody (clone IM7; Bio X Cell; C_f = 10 µg/ml) and incubated

for 4 hours (37˚C). Transwells were removed, cells were stained with Trypan Blue Stain (Gibco)

and manually counted on a hemocytometer. Control cells were plated without Transwells to

count total cells to calculate percent invasion. Relative invasion is the percent of cells that

invaded through the transwell normalized to untreated NK cell conditions. A Wilcoxon matched-

pairs signed rank test was performed to determine statistical significance (GraphPad Prism v10).

NK cell 3D spheroid invasion assay

As previously described,[39, 40] PANC-1 cells were seeded in each well of a low-adhesion

U-bottom plate, spun (5 minutes, 1,000 rpm, 4˚C) and cultured overnight. Spheroids were

embedded with donor NK cells in an 80:20 Collagen-I (Invitrogen): Matrigel (Corning) mixture

in chamber wells (Lab-Tek). Embedded spheroids were treated with α-CD44 (clone IM7; Bio X

Cell; C_f = 10 µg/ml) for 24 hours (37˚C) prior to immunocytochemistry (IC). For IC, samples

were fixed with 4% paraformaldehyde (PFA; 10 minutes, 25˚C), washed for with 1X PBS (5

minutes), then permeabilized with 0.5% Triton-X100 (10 minutes). Cells were washed once,

blocked (1% BSA in 1X PBS, 30 minutes), then incubated with human Fc block (BD Pharmigen,

CAT#: 564219). Samples were incubated with α-pan-cytokeratin- eFluor™ 660 (Invitrogen,

CAT#: 50-9003-82) and α-CD56 (Invitrogen, CAT#: MA1-19129) antibodies overnight (25˚C).

An α-Mouse IgG2a-AF488 secondary antibody (Invitrogen, CAT#: A-21131; 1-4 hours, 25˚C),

cells were washed 3 times, incubated with DAPI (50 ng/ml; 10 minutes, 25˚C), then washed

twice. Coverslips were mounted with anti-fade mountant, then and dried. Z-stacks of spheroids

were imaged using a Leica SP8 AOBS microscope at the LCCC Microscopy and Imaging Shared

Resource. Z-stacks were $\leq$ 1 μm. Z-stack images were processed and using FIJI software

(v2.14.0) for manual NK cell quantitation into PANC-1 spheroids. Statistical significance was

determined using a Wilcoxon matched-pairs signed rank test (GraphPad Prism v10).

Effects of CD44 neutralization on MMP gene expression in human NK cells

Donor NK cell lines were incubated with or without α-CD44 (clone IM7; Bio X Cell; C_f

= 10 μg/ml) for 1 and 4 hours. Cells were collected (5 minutes, 1,000 rpm, 4˚C) and RNA was

isolated using the PureLink™ RNA Mini Kit (Ambion). RNA concentration was measured using

NanoDrop 8000 (ThermoFisher Scientific), then stored at -80˚C. Diluted RNA (20 ng/μl) was

treated with 10% v/v 10X DNase I Buffer and 10% v/v DNase I (Promega; 15 minutes, 25˚C).

10% v/v of RQ1 RNase/DNase Stop Solution (Promega) and 10% v/v Oligo(dT) nucleotides

(IDT) were added, then heat inactivated at 65˚C (10 minutes) then at 4˚C (5 minutes). cDNA was

synthesized with the GoScript™ Reverse Transcriptase Kit (Promega). qPCR was performed

using GoTaq qPCR Master Mix (Promega) with the StepOnePlus™ Real-Time PCR System

(ThermoFisher Scientific). Gene expression was quantified ($2^{-\Delta C_T}$; Ambion) using *HPRT*

(Forward 3'→5': CTTTCCTTGGTCAGGCAGTA, reverse 3'→5':

TGGCTTATATCCAACACTTCG) as an internal, endogenous control. Fold-change was

calculated using the $2^{-\Delta\Delta C_T}$ method and a One-Way ANOVA, Kruskal-Wallis test was performed

to determine statistical significance (GraphPad Prism v10).

Ethics statement

The human pancreas TMA used in this study was approved by the Georgetown University LCCC

Biospecimen Use Committee.

Results

Spatial proteomic analysis of the human PDAC TME resolves PDAC cell populations

To resolve the spatial landscape of the human PDAC TME, we performed IMC, a spatial

proteomics platform that maintains tissue architecture while capturing single cell data by using

metal-conjugated antibodies, eliminating autofluorescence from typical fluorescence-based

imaging, allowing for an increase in size of antibody panels to up to 40 markers. Using CyTOF

technology, tissue images are reconstructed with single cell resolution to enable higher order single

cell proteomic and spatial analyses.[19, 41, 42] For IMC, we designed a metal-conjugated antibody

panel containing epithelial cell, immune cell, and fibroblast markers (**Supplementary Table S1**)

and probed a human pancreas tissue microarray (TMA) curated at the Lombardi Comprehensive

Cancer Center (LCCC) Histopathology & Tissue Shared Resource (HTSR) containing primary

tumor samples from 21 untreated PDAC patients (**Supplementary Table S2**). Following a known

IMC cell segmentation pipeline[23-26] (**Figure 1A**), we identified 412,862 cells in 44 IMC

pseudoimages from these patients. Single-cell protein expression data were extracted using

histoCAT[26] for downstream single-cell proteomic and spatial analyses in R. Using Seurat-based

analysis, expression data was log-normalized and cell populations were identified using supervised

clustering approaches.[43] Canonical cell phenotype markers (CD11b, CD16, CD20, CD3,

CD45RO, CD4, CD56, CD68, CD8α, E-cadherin, FAP, FOXP3, NKG2D, NKp44, αSMA, pan-

cytokeratin, vimentin) were used to distinguish between immune cells, epithelial cells, and

fibroblasts during cell clustering, which identified 8 predominant cell types (**Figure 1B-C**):

αSMA[+] fibroblasts, B cells, CD4[+] T cells, CD8[+] T cells, epithelial cells, FAP[+] fibroblasts,

macrophages, and NK cells. These main cell types were then subclustered to identify the functional

state of these cell populations using the remaining markers in our IMC panel (**Supplementary**

Table S1), and we identified 29 distinct clusters to define active, proliferative, and apoptotic cell

states (**Supplementary Figure S1**). As expected in PDAC, the majority of cells were fibroblasts

and epithelial cells, and we were able to define distinct immune cell populations, including NK

cells (**Figure 1E-F**). We also observed that within our patient samples that there was a similar

proportion of NK cells to that of CD4$^+$ and CD8$^+$ T cell populations, suggesting the potential

relevance of NK cells in the human PDAC TME (**Figure 1D**).

Figure 1: Spatial proteomic analysis of the human PDAC TME resolves PDAC cell

populations. A. Schematic of IMC workflow. **B.** UMAP of IMC-defined cell populations from

21 untreated PDAC patient samples. **C.** Heatmap of averaged, log-normalized protein expression

of canonical markers used to phenotype human PDAC cell populations (legend in **B**). **D.** Bar plot

of cell percentages of cell populations per PDAC patient (legend in **B**). **E.** Representative IMC

pseudoimage of the human PDAC TME highlighting distinctions between epithelial cells (pan-

cytokeratin and E-cadherin; pink), fibroblasts (αSMA and FAP; blue), and immune cells

(CD45RO; yellow). **F.** Cytomapper image of **E** displaying all identified cell types from **B-D**,

colored according to the legend in **B**.

NK cells and epithelial cells co-localize and interact in the human PDAC TME

Qualitative evaluation of the IMC images suggested that NK cells co-localized with

epithelial cells in the human PDAC TME (**Figure 2A**). We validated NK cell-epithelial cell co-

localization in additional human PDAC tissue samples using multiplex immunofluorescence

(**Figure 2B**). To assess NK cells spatially in multicellular structures within the architecture of the

human PDAC TME, we performed a cellular neighborhood analysis (**Figure 2C**).[31] Briefly, this

neighborhood analysis aims to define characteristic groups of cellular co-localization from

spatial proteomics atlas datasets. Using this technique, we defined 8 distinct cellular

neighborhoods where cellular neighborhoods 1, 2, and 6 formed distinct structures representative

of epithelial-ductal regions, and both cellular neighborhoods 2 and 6 of epithelial-ductal regions

created a distinct tumor-stroma border (**Supplementary Figure S2**). Interestingly, we found that

cellular neighborhood 2 had a high composition of epithelial and NK cell populations (**Figure**

2C), and NK cells were more abundant than CD4$^+$ and CD8$^+$ T cells within the epithelial-ductal

cellular neighborhoods (**Supplementary Figure S3**). We also observed that while there was

minimal localization of cells from cellular neighborhood 6 at the tumor-stroma border, there

appeared to be a greater abundance of cells from cellular neighborhood 4, which was immune-

rich. Conversely, in epithelial-ductal regions encased with cells from cellular neighborhood 6,

primarily composed of proliferative epithelial cells and proliferative FAP$^+$ fibroblast populations,

there appeared to be more cells from cellular neighborhood 5, which was αSMA$^+$ fibroblast-rich

(**Supplementary Figures S2-S3**). These observations suggest that fibroblast-rich regions support

epithelial cell proliferation and prevent immune cell infiltration, supporting the concept that

fibroblasts act as immune decoys or deterrents in the PDAC TME.

While the majority of immune cells exist in cellular neighborhood 4, which also contains

the highest abundance of apoptotic epithelial cells, we observed that cellular neighborhood 8 had

the second highest abundance of apoptotic epithelial cells and active NK cells (**Figure 2C**),

suggesting that NK cells in these regions mediated anti-tumor immune responses. Of note, the

proportion of NK cells in cellular neighborhood 8 was larger than that of other immune cell

populations (**Supplementary Figures S3**). We also observed that cellular neighborhood 2

contained the highest abundance of IFNγ$^+$ epithelial cells; interestingly, NK cells comprised the

largest immune cell population in cellular neighborhood 2 (**Figure 2C**). These observations

support the hypothesis that NK cells are cytotoxic to malignant epithelial cells in human PDAC

and demonstrate that spatial analysis identifies NK cell-epithelial cell co-localization.

To further characterize significant cell-cell pairwise interactions, we performed a cellular

interaction analysis, a permutation test of these pairwise interactions,[26] to reveal cell populations

with significant interactions or avoidances. The cellular interaction analysis demonstrated that

NK cell populations interact with apoptotic epithelial cells more strongly than other active

immune cell subsets (**Figure 2D**), including active CD8$^+$ T cells. This phenomenon has not been

previously described and suggests that NK cells play an important role in anti-tumor immune

responses in the PDAC TME.

Next, we performed Euclidean distance-based analysis[9, 44] to quantitate NK cell

proximity to other cells in the PDAC TME, revealing that epithelial cells were in close proximity

to NK cells (**Figure 2E**). Interestingly, αSMA$^+$ fibroblasts were the closest fibroblast population

to NK cells, suggesting that NK cells that do not form strong interrelationships with epithelial

cells may be engaged and inhibited by stromal elements. To further contextualize the cellular

communication network in the PDAC TME, we performed a cellular network analysis, using

previously described methods,[9] where each node represents a distinct cell population (**Figure 2F**,

Supplementary Figure S1). In this network graph (**Figure 2F**), NK cell nodes were surrounded

by epithelial cell nodes and distant from CD4$^+$ and CD8$^+$ T cell nodes. Of note, the apoptotic

epithelial cell node was surrounded by NK cell and macrophage nodes and did not form strong

relationships with T cell nodes. These findings further demonstrate the relevance of innate

effectors cells in the human PDAC TME.

Figure 2: NK cells co-localize and interact with epithelial cells in the human PDAC TME.

A. Representative IMC pseudoimages displaying NK cell-epithelial cell co-localization (αSMA

= blue; E-cadherin, pan-cytokeratin = pink; NKG2D = yellow, scale bar = 100 μm). **B.**

Representative multiplex immunofluorescence image of human PDAC showing NK cell-epithelial cell co-localization (n = 6; pan-cytokeratin = pink, CD56 = yellow, NKG2D = cyan, scale bar = 50 μm). **C.** Cellular neighborhood analysis revealed 8 distinct cellular neighborhoods (red = high proportion of cells within cellular neighborhoods, blue = low proportion of cells within cellular neighborhoods). **D.** Cellular interaction analysis (blue = strong avoidance, red = strong interaction; FDR, $P < 0.01$) of IMC-defined cell subpopulations. **E.** Distance analysis per patient (n = 21) revealed that epithelial cells in PDAC are the closest to NK cells. Cell populations that were significantly distant from epithelial cells were calculated using 2-way ANOVA, Kruskal-Wallis test (*$P < 0.05$, ***$P < 0.001$, ****$P < 0.0001$;). **F.** Network graph of the top 75% of interactions between all IMC-defined cell populations in human PDAC showing epithelial cells and NK cells exist in similar networks.

NK cell abundance in human PDAC epithelial-ductal ROIs inversely relates to both fibroblast abundance and Collagen-I expression

While we observed significant NK cell-epithelial cell spatial relationships in the human PDAC TME, as demonstrated by cellular neighborhood, cellular interaction, distance, and network analyses (**Figure 2**), a hallmark phenotype of PDAC is the high abundance of CAFs that are known to cause immune suppression and decrease immune cell infiltration.[6] Therefore, we hypothesized that epithelial-ductal ROIs with high fibroblast abundance would have a decrease in immune cell infiltration. To test this hypothesis, we identified ROIs from epithelial-ductal structures previously defined by cellular neighborhood analysis (**Figure 2**, **Supplementary Figure S2**). We then used the CellSelector function from Seurat[27] to isolate these ROIs on IMC-derived single-cell spatial images for downstream analysis to quantify the abundance of each cell

population within these epithelial-ductal ROIs. The abundance of cell populations was quantified

as the percentage of the total cells within each epithelial-ductal ROI. After quantification,

epithelial-ductal ROIs were stratified into quartiles based on their percentage of fibroblast

abundance (**Figure 3**). We first confirmed statistically significant increases in fibroblast

abundance across the fibroblast abundance quartiles we defined (**Figure 3A**). We also found

statistically significant decreases in both NK cell and epithelial cell abundance across fibroblast

abundance quartiles (**Figure 3B-C**). Conversely, proliferative epithelial cells significantly

increased across fibroblast abundance quartiles (**Supplementary Figure S4E**), supporting

observations from cellular neighborhood analysis (**Figure 2C**, **Supplementary Figure S2**).

Interestingly, NKp44$^+$ and IFNγ^+ epithelial cell populations significantly decreased across

fibroblast abundance quartiles (**Supplementary Figure S4E**). As cellular neighborhood analysis

identified NK cells to be the most abundant cell population in cellular neighborhoods with

NKp44$^+$ and IFNγ^+ epithelial cell populations (**Figure 2C**, **Supplementary Figure S2-3**), this

suggests that NK cell functionality may be decreasing in epithelial-ductal ROIs with high

fibroblast abundance. Of note, there was no statistically significant difference in CD8$^+$ T cell

abundance across fibroblast abundance quartiles (**Supplementary Figure S6**), supporting

previous observations of T cell localization in desmoplastic regions in PDAC.[45]

To determine if decreased NK cell infiltration across fibroblast abundance quartiles

correlated with cell functionality, we quantified the total expression of functional markers

(CD69, CD107α, cleaved-caspase 3, collagen-I, granzyme B, HLA-A/B/C, HLA-A1, IFNγ,

Ki67, MICA, PCNA, perforin, PD-1, PD-L1, TGFβ), from the IMC antibody panel

(**Supplementary Table S1**), within these epithelial-ductal ROIs and observed no significant

difference in the total expression of the immune cell activation markers (CD69, CD107α,

granzyme B, perforin) within the PDAC TME (**Supplementary Figure S6**). We further

evaluated the cellular-based expression of these functional markers in NK cell populations within

these epithelial-ductal ROIs and observed that NK cells were more active in epithelial-ductal

ROIs with low fibroblast abundance as they exhibited higher expression of known immune cell

activation markers, including CD69, CD107α, granzyme B, and IFNγ (**Figure 3G-K**). While

there were no significant differences in the abundance of apoptotic epithelial cells across

fibroblast abundance quartiles of epithelial-ductal ROIs (**Supplementary Figure S4**), we did

observe that epithelial cells expressed more cleaved-caspase 3, an apoptosis marker, in epithelial-

ductal ROIs of lower fibroblast abundance (**Figure 3L**). These data demonstrate that NK cell

cytotoxic function is retained in epithelial-ductal ROIs with lower fibroblast abundance where

NK cells are more co-localized with epithelial cells. Since fibroblasts are known to deposit

collagen within the stroma, we measured the intensity of collagen-I expression within these

epithelial-ductal ROIs and found a statistically significant increase in total collagen-I expression

across fibroblast abundance quartiles (**Figure 3D**). These findings suggest that fibroblasts protect

and enhance the growth of malignant epithelial cells in the PDAC TME, in agreement with

known fibroblast biology, and also suggest that NK cell cytolytic function and infiltration into

malignant epithelial-ductal ROIs is inhibited by desmoplasia.

Figure 3: NK cell abundance in human PDAC epithelial-ductal ROIs inversely relates to

both fibroblast abundance and Collagen-I expression. Quantitation of **A.** total fibroblasts, **B.**

epithelial cells, and **C.** NK cells in epithelial-ductal ROIs ranked by fibroblast abundance

quartile (2-way ANOVA; ****$P < 0.0001$; n = 952, total epithelial-ductal ROIs). **B.** Quantitation

of total collagen-I expression in epithelial-ductal ROIs ranked by fibroblast abundance quartile

(2-way ANOVA; *$P < 0.05$, ***$P < 0.001$, ****$P < 0.0001$; n = 230, total epithelial ductal

ROIs). **E.** Representative IMC pseudoimages showing αSMA (left, light blue) or collagen-I

(right, dark blue) with pan-cytokeratin (panCK, pink), E-cadherin (Ecad, pink), and NKG2D

(yellow); scale bar = 100 μm with white boxes of each fibroblast abundance quartile. **F.** Insets of

representative epithelial-ductal ROIs from each fibroblast abundance quartile (Q1-Q4) shown in

the white insets in **E. G.** Heatmap of averaged, log-normalized protein expression of functional

markers in NK cells stratified by fibroblast abundance quartile (Q1-Q4) and stromal

compartments. Violin plots showing NK cell-based expression of **H.** CD69 **I.** CD107α **J.**

granzyme B, and **K.** IFNγ. **L.** Heatmap of averaged, log-normalized protein expression of

functional markers in epithelial cells stratified by fibroblast abundance quartile (Q1-Q4) and

stromal compartments.

CellChat identifies CD44 as a potential mediator of interactions between NK cells with

CAFs and malignant epithelial cells in human PDAC

Based on findings, from IMC analysis of the PDAC TME, that NK cells interact with

epithelial cells, and their infiltration is inhibited by fibroblasts, we next further elucidated their

potential molecular interactions using CellChat to infer ligand-receptor (L-R) interactions among

NK cells, fibroblasts, and epithelial cells. CellChat is a tool with a manually curated database to

infer L-R interactions from scRNAseq data.[36] We used this analysis pipeline against a recently

published human PDAC scRNAseq dataset containing adjacent-normal (AdjNorm) and PDAC

patient samples [33]. As malignant cells are more de-differentiated than normal, differentiated

cells,[46] and to infer if potential L-R pairs were from normal versus malignant epithelium, we first

distinguished between these two cell epithelial cell states using CytoTRACE (**Supplementary**

Figure S7), a computational framework that predicts cellular differentiation states from

scRNAseq data.[34]

Using CellChat, we assessed the interaction strength of NK cells, fibroblasts, and both

normal and malignant epithelial cells to determine which of these populations exhibited

significant changes in their outgoing or incoming signaling between AdjNorm and PDAC

disease states. CellChat revealed that fibroblasts demonstrate a substantial increase in outgoing

interaction strength in PDAC compared to fibroblasts in AdjNorm, while both NK cells and

malignant epithelial cells become strong receivers of cellular signals in PDAC (**Figure 4A**).

Normal epithelial cell signaling remains relatively unchanged between the two disease states

(**Figure 4A**). This suggests that fibroblasts orchestrate interactions amongst these three cell

populations in PDAC.

Accordingly, we identified the signaling pathways targeting NK cells with significant

changes in their communication probabilities, or activation. The collagen, fibronectin (FN1), and

laminin pathways became highly active, as they had the highest PDAC-enriched or PDAC-

specific communication probabilities based on their increased information flow (**Figure 4B**).

CellChat also identified ligands from these pathways to be the most highly enriched in PDAC

(**Supplementary Table S4**). We then investigated the L-R interactions from these pathways that

targeted NK cells. Using fibroblasts and epithelial cell populations as source cells and NK cells

as their targets, we determined that NK cells were primarily targeted by a variety of collagens,

laminins, and *FN1* through *CD44* on NK cells (**Figure 4C**). We next explored which of these L-

R pair genes were differentially expressed across disease states in these cell populations and

found that several genes in these L-R pairs were significantly increased in fibroblasts and

epithelial cell populations in PDAC samples (**Supplementary Figure S8**). Of note, while

malignant epithelial cells exhibited a significant increase in *CD44* gene expression, there was no

significant difference in normal epithelial cells nor fibroblasts (**Figure 4D-F**). Concurrently, the

only gene among the identified L-R pairs with a differential increase in NK cells in PDAC was

CD44 (**Figure 4G**). As fibroblasts and malignant epithelial cells highly expressed collagen,

laminin, and *FN1* genes, and their protein counterparts are typically highly expressed in the TME

of PDAC, it led us to hypothesize that NK cells get trapped in stromal-rich regions in the PDAC

TME and that CD44 may be targetable to enhance NK cell motility to target PDAC cells.

Figure 4: CellChat identifies CD44 as a potential mediator of interactions between NK cells

with CAFs and malignant epithelial cells in human PDAC. A. Incoming and outgoing

interaction strength for each cell population grouped by AdjNorm and PDAC disease states. **B.**

Communication probabilities of signaling pathways targeting NK cells between AdjNorm and

PDAC disease states as measured by information flow (pathway legend: pink = AdjNorm-

specific, teal = PDAC-specific, black = equally specific). **C.** Significant ligand-receptor pairs

from collagen, FN1, and laminin signaling pathways targeting NK cells upregulated in PDAC

compared to AdjNorm. Violin plots showing differential expression of *CD44* between PDAC

(teal) and AdjNorm (pink) disease states in **D.** normal epithelial cells, **E.** malignant epithelial

cells, **F.** fibroblasts, and **G.** NK cells (NS = not significant, **$P < 0.01$, ****$P < 0.0001$,

Bonferroni correction).

CD44 neutralization increases human donor NK cell invasion *in vitro*

The CD44 glycoprotein is highly expressed by a variety of cell types. While its main

ligand is hyaluronic acid (HA), which can be highly expressed by cancer and stromal cells,[47, 48]

CD44 is also known to bind to collagens, laminins, and FN1.[49] CD44 signaling is also known to

affect cellular proliferation, adhesion and migration.[48] Therefore, based on findings from

CellChat, we hypothesized that stromal elements in PDAC bind to CD44 on NK cells to prevent

NK cell invasion through the stroma to target PDAC epithelial cells. First, we validated CD44

expression of human donor NK cells by flow cytometry (**Supplementary Figure S9**). Since

collagens, laminins, and FN1 can also be found in the stroma, we assessed NK cell invasion

through basement-membrane and collagen-containing matrices *in vitro.* We performed a 2D

Boyden-Chamber Transwell assay with four human donor NK cells lines by coating the

Transwell membrane with Matrigel and incubating NK cells with or without the presence of a

CD44-neutralizing antibody (α-CD44) (**Figure 5A**). We found a statistically significant increase

in NK cell invasion in three of four human donor NK cell lines upon α-CD44 treatment (**Figure**

5B-E). To further build on these observations, we employed a 3D *in vitro* model using a tumor

spheroid assay (**Figure 5F**). We generated spheroids using the human PDAC PANC-1 cell line

and embedded them with human donor NK cells in a Collagen: Matrigel mixture with or without

α-CD44 for 24 hours. After incubation, spheroids were stained by immunocytochemistry and

imaged. To assess NK cell infiltration, we used pan-cytokeratin staining to outline the spheroids

and measured NK cell infiltration into PANC-1 spheroids. Again, under conditions of α-CD44

treatment, we observed a statistically significant increase of NK cell invasion using three human

donor NK cell lines (**Figure 5G-K**, **Supplementary Figure S10**).

To explore additional potential mechanisms of action for NK cell invasion, we

hypothesized that neutralizing CD44-mediated binding by NK cells would increase the

expression of matrix metalloproteinases (MMPs). MMPs are known to degrade ECM, including

collagen, can be regulated by CD44, and play a role in neutrophil, macrophage, and T cell

migration.[47, 50] Human donor NK cells were treated for 1 and 4 hours with or without α-CD44,

and these cells were assessed for expression of MMP genes (**Supplementary Table S5**). We

found no significant differences in MMP gene expression across both treatment conditions

(**Supplementary Figure S11**), suggesting that antibody-based CD44 neutralization mitigates NK

cell binding to ECM components to increase NK cell invasion through matrix-containing

environments.

Figure 5: CD44 neutralization increases human donor NK cell invasion *in vitro*. A.

Schematic for Transwell invasion assays. Average relative invasion ± SEM of **B.** Donor NK #1

(n = 9), **C.** Donor NK #2 (n = 12), **D.** Donor NK #3 (n = 6), and **E.** Donor NK #4 (n = 10) upon

CD44 neutralization. *P* < 0.05 as determined by Wilcoxon matched-pairs signed rank test. **F.**

Schematic of spheroid invasion assay. **G.** Representative 20X immunofluorescence images of

outlined (yellow) PANC-1 spheroids (pan-cytokeratin; red) embedded with NK cells (CD56;

green), pointed out with white arrows, treated with or without α-CD44. Scale bar = 250 μm. **H.**

Zoomed inset of NK cells in the α-CD44 treatment group in **G** (white box). Average number of

NK cells per PANC-1 spheroid ± SEM from **I.** Donor NK #1 (- α-CD44, n = 42; + α-CD44, n =

53), **J.** Donor NK #2 (- α-CD44, n = 43; + α-CD44, n = 29), and **K.** Donor NK #3 (- α-CD44, n =

47; + α-CD44, n = 27); n = # of spheroids analyzed; *P* < 0.05 as determined by Wilcoxon

matched-pairs signed rank test.

Discussion

While previous studies have used spatial approaches to examine the PDAC TME

landscape,[8, 45, 51] NK cells have not been studied extensively. Here, we utilized two single cell

methodologies to further characterize NK cells in PDAC. First, we used an IMC spatial

proteomics platform to define the spatial relationships of NK cells within the architecture of the

human PDAC TME and defined distinct epithelial, fibroblast, and immune cell populations,

including NK cells (**Figure 1**). We found for the first time, to our knowledge, that active NK

cells are abundant in the PDAC TME and form strong cellular relationships with PDAC

epithelial cells. Not only are NK cells relatively abundant and active, but they exist in similar

proportions to that of T cell populations across patient samples (**Figure 1-2**), suggesting their

potential relevance in PDAC. NK cells were also found within the same cellular neighborhoods

that comprise epithelial-ductal regions, and within cellular neighborhood 4, which was immune-

rich, thus demonstrating that NK cells localize near epithelial cells, although they are also

dispersed across the PDAC TME (**Figure 2C**, **Supplementary Figure S2**). Cellular interaction

analysis identified that apoptotic epithelial cells strongly interact with all identified NK cell

populations (**Figure 2D**). Distance and network analyses further showed that epithelial cell

populations are not only the closest to NK cells, but they also form a strong network with NK

cells, indicating they share more neighbors than with other immune cell populations (**Figure 2E-**

F). Lastly, spatial analyses showed that NK cell localization is inversely proportional to both

fibroblast abundance and collagen-I expression in the PDAC TME (**Figure 3**), suggesting that

desmoplasia affects NK cell infiltration in PDAC. Therefore, these findings provide novel

insights into the spatial relationships of NK cells in untreated human PDAC and highlight

potential mechanisms that may limit NK cell invasion in PDAC's malignant epithelial-ductal

ROIs.

The spatial proteomic analyses were performed in samples from surgically resected

primary tumors from previously untreated patients; hence the spatial and functional relationships

of NK cells from metastases or primary tumors in a therapeutic setting may differ and remain to

be examined. However, our findings provide a benchmark of NK cell function and localization in

an untreated setting in primary PDAC tumors. Previous work has primarily assessed or leveraged

T cells in monitoring patient prognosis or response to different chemotherapies and

immunotherapies.[52] Our findings support the future development of therapies to leverage the

biological properties of NK cells in PDAC.

Although spatial proteomic analyses provided powerful insights into the NK cellular

relationships within the PDAC TME, the IMC antibody panel size was focused to capture

representative cell populations across all tissue samples. Accordingly, the IMC panel did not

prospectively examine other potentially important proteins that might regulate cell-cell

communications. Therefore, to build upon our findings from IMC, we employed a single cell

analysis dataset,[33] utilizing CellChat as a secondary tool to further elucidate potential molecular

candidates for NK cell interactions in human PDAC. Using CellChat, we found that the *CD44*

receptor on NK cells potentially interacts with collagens, laminins, and *FN1* on fibroblasts and

malignant epithelial cells (**Figure 4**). As these ligands are known ECM components, and PDAC

has a dense, fibrotic stroma, we hypothesized that CD44 on NK cells binds to these molecules,

impairing NK cell infiltration towards malignant PDAC cells. Using 2D Transwell and 3D

spheroid *in vitro* assays, we made the novel observation that exposure to a CD44-neutralizing

antibody significantly increased NK cell invasion (**Figure 5**) through collagen-containing

matrices. While CellChat analysis does not provide insights into spatial interactions, as its input

requires scRNAseq data, this powerful tool uncovered potential molecular interactions that could

be validated *in vitro* and can be investigated further using other methodologies, such as spatial

transcriptomics to further uncover potential mechanisms in high versus low fibroblast abundance

quartiles in the human PDAC TME.

CD44 has been studied in cancer, and its expression is known to be associated with worse

prognosis and an increase in metastatic potential in several solid tumors.[47] A recent study

showed that liver cancer epithelial cells form cell-in-cell structures of NKp46[+] NK cells, which

has been described to be mediated by loss of CD44 in liver cancer cells.[53] The current IMC

dataset identified a NKp44[+] epithelial cell population. Further studies are needed to determine if

these cells contain similar structures to address this phenomenon. CD44 expression in cancers

has also been associated with macrophage infiltration and polarization in preclinical models.[54-56]

However, there have been limited studies of CD44 in NK cells. CD44 was previously found to

be constitutively expressed on IL-2 and IL-15 activated donor NK cells[57, 58] and increased NK

cell cytotoxic function.[59] Another study demonstrated that NK cells can elicit redirected lysis

through CD44 and CD69 in IL-2 activated NK cells.[57] These studies focused on the role of CD44

in NK cell activation, but its role in NK motility has not previously been reported. Interestingly,

a study examining the effects of catecholamines in exercise found that NK cells decrease their

expression of CD44 and are increased in circulating NK cells in PBMCs, suggesting that CD44

plays a role in NK cell adhesion to endothelium and that a decrease in CD44 expression allows

for an increase in NK cell extravasation.[60] Therefore, neutralizing NK cell-based CD44 may

increase their extravasation, but this has yet to be explored.

Here we showed that neutralizing CD44 engagement with ECM components increases

NK cell invasion *in vitro*. This is significant because the NK cell-ECM interactome previously

has been minimally investigated, even though immune cells are known to express ECM receptors

that may affect their motility and immune responses, with implications in solid tumors and

fibrotic diseases. One example is LAIR-1, an inhibitory receptor expressed by leukocytes

containing collagen-binding domains.[61-63] Another recent study found that fibronectin

localization in the center of spheroids composed of small cell renal cell carcinoma cells regulated

NK cell infiltration, further supporting a role for ECM components in NK cell migration.[64] These

findings, along with data presented here, warrant further investigation, particularly in solid

tumors such as PDAC. Hence, targeting selected ECM-NK cell interactions may increase NK

cell motility and cytotoxic function for therapeutic benefit. Future studies can determine if CD44

plays a role in promoting NK cell-mediated anti-tumor immune responses.

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874