



(A-E) Box plots show the value of (A) ARI, (B) NMI, (C) ASW_celltype, (D) ASW_batch_Donor and (E) ASW_batch_Study for seven different methods in 41 tumor types. **(F)** Scatter plots show the value of BatchKL_Study (X-axis) and iLISI_Study (Y-axis) across 17 distinct tumor types incorporating data from different studies. Points situated closer to the upper right of the plot correspond to superior performance. The error bands depicted in the plots signifies the 95% confidence interval surrounding the smoothed curve, which was achieved through B-spline smoothing with a degree of 3.





(A-D) Box plots show the value of (A) ARI, (B) NMI, (C) ASW_celltype and (D) ASW_batch_Cancer for seven different methods in the pan-tumor TIME integration.

(E) Scatter plots show the value of BatchKL_Cancer (X-axis) and iLISI_Cancer (Y-axis) across

four different tumor infiltrating immune cells in pan-tumor TIME integration. Points situated closer to the upper right of the plot correspond to superior performance. The error bands depicted in the plots signifies the 95% confidence interval surrounding the smoothed curve, which was achieved through B-spline smoothing with a degree of 3.



Figure S3. Summary of the single-cell atlas across 44 tumor types.

(A) Summary of the single-cell atlas across 36 solid tumor types. The upper panel depicts number of cells identified for each tumor type. The lower panel depicts the number of patients collected for each tumor type.

(B) Summary of the single-cell atlas across 8 hematological malignancies. The upper panel depicts number of cells identified for each tumor type. The lower panel depicts the number of patients collected for each tumor type.



Figure S4. Cell types annotated in the single-cell atlas.

The heatmaps show the cell type annotated in all tumor types, including (A) solid tumors and

(B) hematological malignancies.



Figure S5. The expression levels of marker genes in different immune cell subsets. The dot-plot heatmaps depict the expression levels of marker genes in different immune cell subsets identified from B cells (A), *CD4*⁺ T cells (B), *CD8*⁺ T cells (C), and myeloid cells (D). The color intensity represents the average gene expression level, and the size of dot

represents the percentage of cell within each immune cell subsets expressing the marker gene.



Figure S6. Statistics of cell-type-specific interactome networks guided by four different reference networks.

(A) The bar plot depicts the number of nodes in four different reference networks, including

STRING, ConsensusPathDB, Reactome, and HumanNet.

(B) The bar plot depicts the number of edges in each reference network.

(C-D) Density plots show the number of nodes (C) and number of edges (D) in all cell-type-

specific interactome networks inferred using four different reference networks.



Figure S7. Network performance of recovering DisGeNET disease gene sets.

(A-B) The network performance score (A) and network performance gain (B) were evaluated on DisGeNET disease genes associated with specific tumor types in malignant networks. This analysis is conducted across 16 solid tumor types, where there is an overlap of more than 20 genes between the malignant network nodes and the disease genes of particular tumor type.
(C) The network performance gain was correlated with network performance score of malignant networks generated by four reference networks across 16 solid tumor types.

(D) The average ranked performance of malignant networks generated by each reference networks on the recovery of the DisGeNET disease genes compared with the number of interactions of reference networks. Error bars are one standard deviation of the average ranked network performances across each collection of recovery tasks.



Figure S8. Comparison of topological specificity and transcriptional specificity scores in myeloid cells of pan-tumor TIMEs.

Scatter plots show corresponding topological and transcriptional specificity scores across genes of each myeloid subset-specific networks. Blue line represents the best linear regression fit.



Figure S9. Connectivity of cytotoxic gene sets within *CD8*⁺ T cell-specific networks across different tumor types.

The Scatter plot illustrates correlation between the fraction of *CD8*⁺ T cells and the scaled weighted connectivity of cytotoxic genes in 33 solid tumor types. Blue line represents the best linear regression fit.



Figure S10. Network similarity across 17 solid tumor types.

The heatmap depicts the comparison of interactome networks specific to 8 cell types identified from 17 solid tumor types. The topology similarity and shared-edge similarity are calculated.





(A-B) Upset plots show node (A) and edge (B) overlap of *CD8*⁺ T cell-specific networks among 17 solid tumor types.



Figure S12. Network similarity across five hematologic malignancies.

The heatmap depicts the comparison of interactome networks specific to six cell types identified from five hematologic malignancies. The topology similarity and shared-edge similarity are calculated.



Glycolysis / Gluconeogenesis 0.0 2.5 5.0 7.5 -log₁₀(P-value)

2 4 6 -log₁₀(P-value)

Response to heat

Metabolic path ways

Glucose catabolic process Response to endoplasmic reticulum stress

Protein processing in endoplasmic reticulum

Figure S13. Comparative analysis of interactome networks specific to CD8⁺ T cells.

(A) The heatmap depicts the comparison of interactome networks specific to *CD8*⁺ T cells identified from different tumor types. The red gradient panel represents the topology similarity estimated from shared nodes' topological specificity. The green gradient panel represents the edge similarity estimated from shared edges' interaction strengths. Network sizes are shown by number of nodes (red bars) and number of edges (blue bars).

(B-E) The graph plots depict four representative core subnetworks identified from the shared network of ER positive breast cancer and HER2 positive breast cancer. The centrality of each gene implicated in the subnetwork is labeled in color. The bar plots under each graph plot shows the GO (yellow bars) and KEGG (blue bars) pathway enriched for each core subnetwork.

Figure S14. Comparative analysis of interactome networks specific to CD4⁺ T cells.

(A) The heatmap depicts the comparison of interactome networks specific to $CD4^+$ T cells identified from different tumor types. The red gradient panel represents the topology similarity estimated from shared nodes' topological specificity. The green gradient panel represents the edge similarity estimated from shared edges' interaction strengths. Network sizes are shown by number of nodes (red bars) and number of edges (blue bars).

(B-E) The graph plots depict four representative core subnetworks identified from the shared network of bladder urothelial carcinoma and prostate adenocarcinoma. The centrality of each gene implicated in the subnetwork is labeled in color. The bar plots under each graph plot shows the GO (yellow bars) and KEGG (blue bars) pathway enriched for each core subnetwork.

Figure S15. Comparing four network-based gene prioritization methods.

(A-F) Histograms show the distribution of overlap genes between top-ranked 200 genes and NCG genes used four gene prioritization methods in various malignant networks for acute myeloid leukemia (A), B cell acute lymphoblastic leukemia (B), chronic lymphocytic leukemia (C), ER positive breast cancer (D), papillary thyroid carcinoma (E) and uveal melanoma (F). The line charts show the overlap genes size of top-ranked 300 genes (x-axis) and NCG genes (y-axis).

In supplement to **Figure 6A**, this figure shows results of risk gene prioritization using the malignant melanocytes-specific interactome networks inferred from ConsensusPathDB **(A)**, HumanNet **(B)**, and Reactome **(C)**. The bar plots depict the stationary probability for each top-ranked gene from random walk with restart. The reported cancer driver genes in the NCG 6.0 database are labeled in red.

In supplement to **Figure 6B**, this figure shows results of risk gene prioritization using the malignant myeloid cell-specific interactome networks inferred from ConsensusPathDB **(A)**, HumanNet **(B)**, and Reactome **(C)**. The bar plots depict the stationary probability for each top-ranked gene from random walk with restart. The reported cancer driver genes in the NCG 6.0 database are labeled in red.

Figure S18. Prioritize risk genes for T cell exhaustion.

In supplement to **Figure 6C**, this figure shows the results of risk gene prioritization using the interactome networks specific to exhausted T cells in the pan-tumor TIMEs inferred from ConsensusPathDB (A), HumanNet (B), and Reactome (C). The bar plots depict the stationary probability for each top-ranked gene from random walk with restart.

Figure S19. The expression levels of risk genes prioritized for T cell exhaustion in ICB cohorts.

The expression levels of *PTPN6* (A), *CD80* (B), *CD8A* (C), *PRDM1* (D), *CD96* (E), and *CSK* (F) in six ICB therapy cohorts. The boxplots show the difference of their expression levels between ICB therapy response and non-response groups. The asterisks represent the degree of significance calculated using Limma (* *P*-value < 0.05, ** *P*-value < 0.01, *** *P*-value < 0.001).