

1 **Integrated analysis of single-cell and bulk transcriptomics develops a robust**
2 **neuroendocrine cell-intrinsic signature to predict prostate cancer progression**

3 Tingting Zhang^{1,2#}, Faming Zhao^{1,2#*}, Yahang Lin³, Mingsheng Liu⁴, Hongqing
4 Zhou⁴, Fengzhen Cui^{1,2}, Yang Jin⁵, Liang Chen⁶, Xia Sheng^{1,2*}

5 ¹Key Laboratory of Environmental Health, Ministry of Education & Ministry of
6 Environmental Protection, School of Public Health, Tongji Medical College, Huazhong
7 University of Science and Technology, Wuhan, China.

8 ²School of Life and Health Sciences, Hainan University, Haikou, China.

9 ³Department of Neurology, Wuhan Fourth Hospital/Pu'ai Hospital, Wuhan, China.

10 ⁴The Second Ward of Urology, Qujing Affiliated Hospital of Kunming Medical
11 University, Qujing, China.

12 ⁵Institute for Cancer Genetics and Informatics, Oslo University Hospital, Oslo, Norway.

13 ⁶Department of Urology, Tongji Hospital, Tongji Medical College, Huazhong
14 University of Science and Technology, Wuhan, China.

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16 #These authors contributed equally to this work.

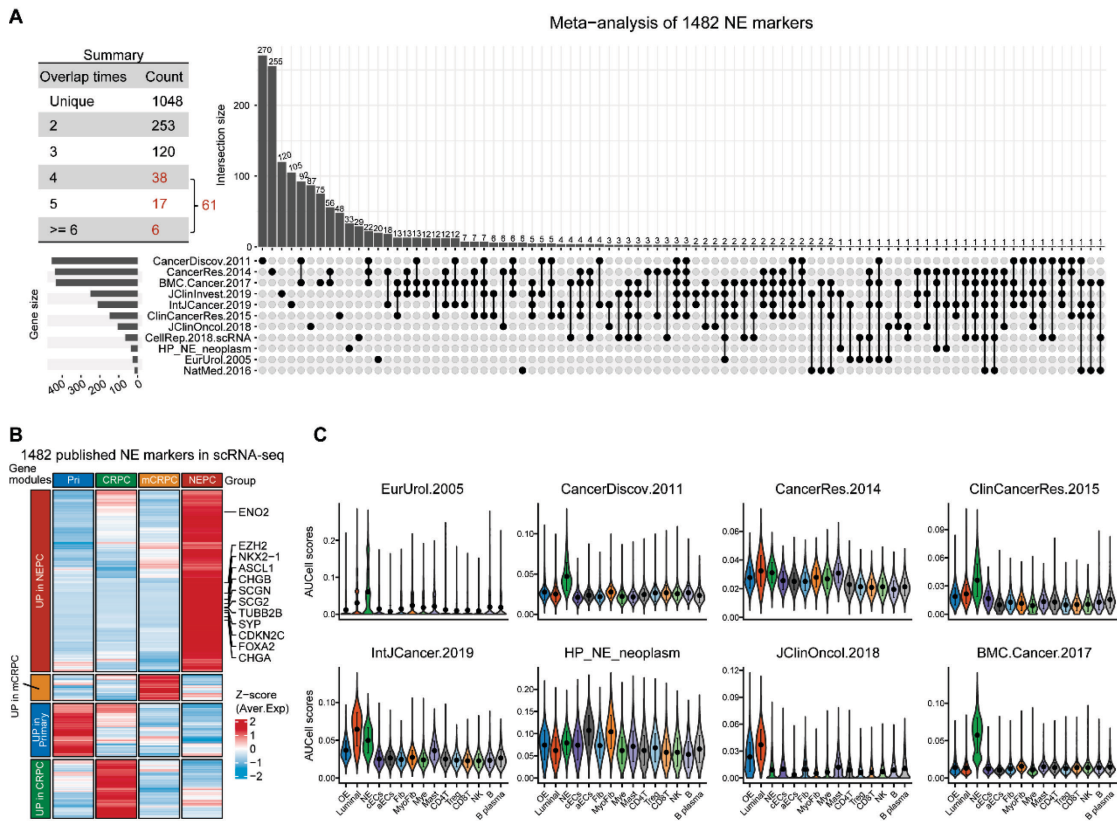
17 *Corresponding authors: Faming Zhao (famingzhao@hust.edu.cn) and Xia Sheng
18 (xiasheng@hust.edu.cn).

19 **Keywords:** neuroendocrine prostate cancer, single-cell, biomarker, computational
20 biology and bioinformatics, machine learning

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22 Supplemental Figures

23 Figure S1



24
25 **Figure S1. NE meta-gene sets comprise a total of 1482 genes with low overlap rate.**

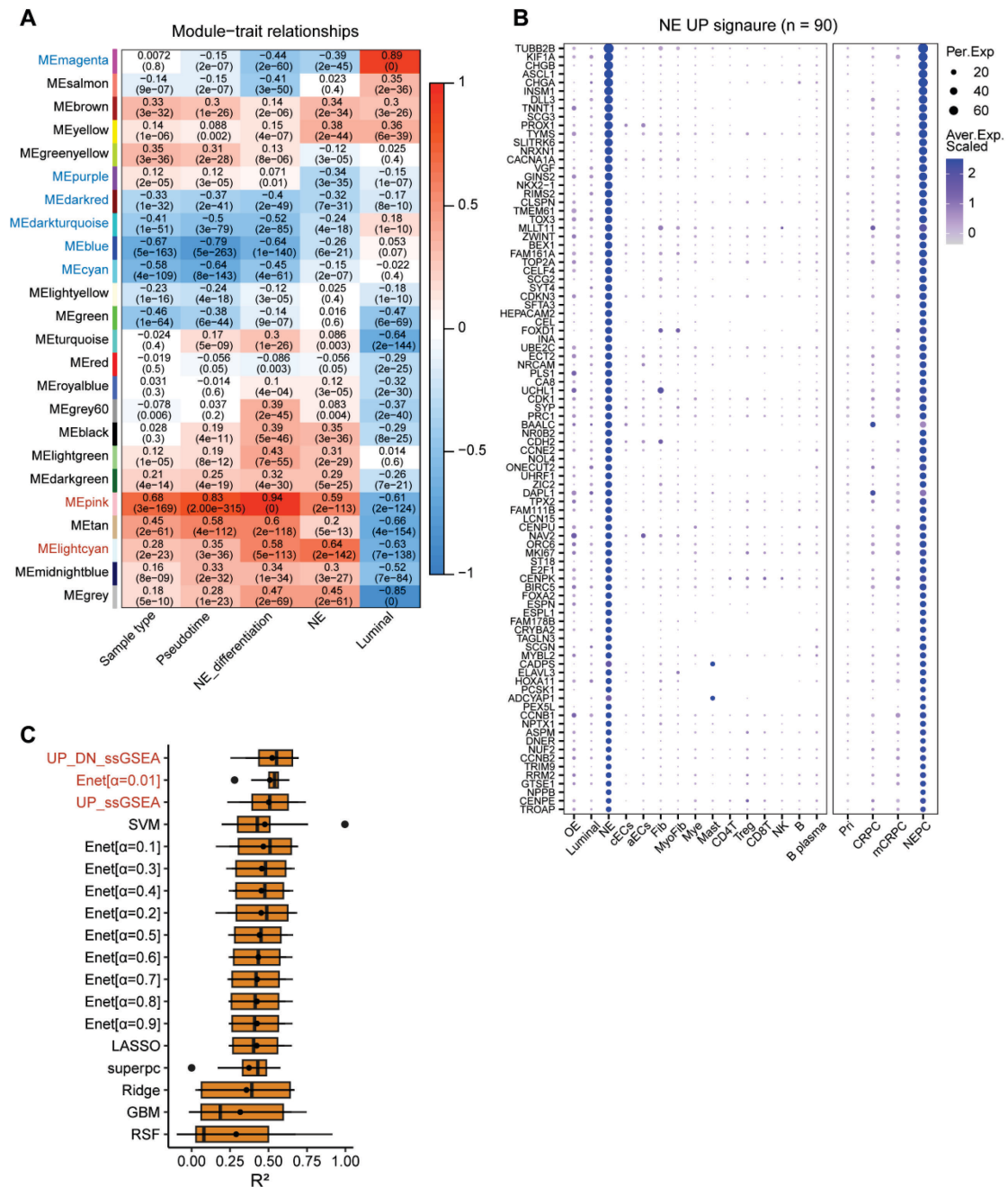
26 A. Upset plot showing the intersection of 11 literature NE gene-lists.

27 B. Heatmap showing the expression (Z-score) of 1482 published NE markers in
28 different tumor types.

29 C. AUCCell enrichment analysis comparing different NE gene sets in each cell type.

30

31 **Figure S2**



32

33 **Figure S2. Combining multiple strategies to identify NEPC feature genes based on**

34 **scRNA-seq and bulk RNA-seq meta-databases.**

35 A. Correlation analysis between module eigengenes and clinical traits by WGCNA

36 analysis.

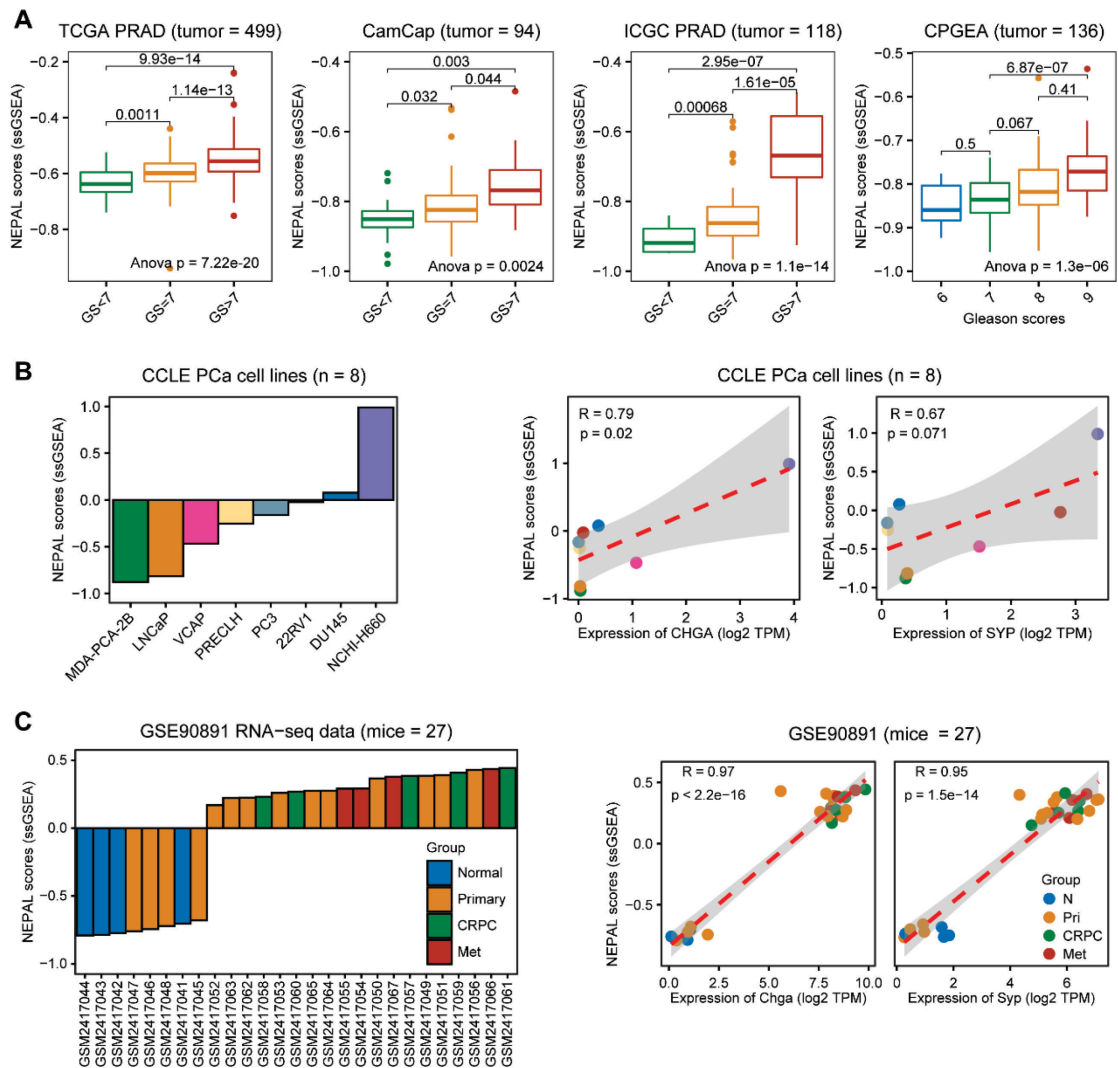
37 B. Dot plot of NE_UP signature genes (n = 90) identified by this study for each cell

38 cluster and tumor group.

39 C. The average R^2 index of 18 algorithms in the 6 testing cohorts. Error bar denote SD.

40

41 **Figure S3**



42

43 **Figure S3. Validation of NEPAL risk model in human, cell lines and mouse**
 44 **transcriptomic data.**

45 A The distribution of NEPAL risk scores among different Gleason score groups in
 46 TCGA, CamCap, ICGC and CPGEA human PCa cohorts. GS, Gleason scores. The box
 47 represents the interquartile range, the horizontal line in box is the median, and the
 48 whiskers represent 1.5 times interquartile range.

49 B. Predicting NEPAL risk scores for 8 PCa cell lines from CCLE database (left panel).

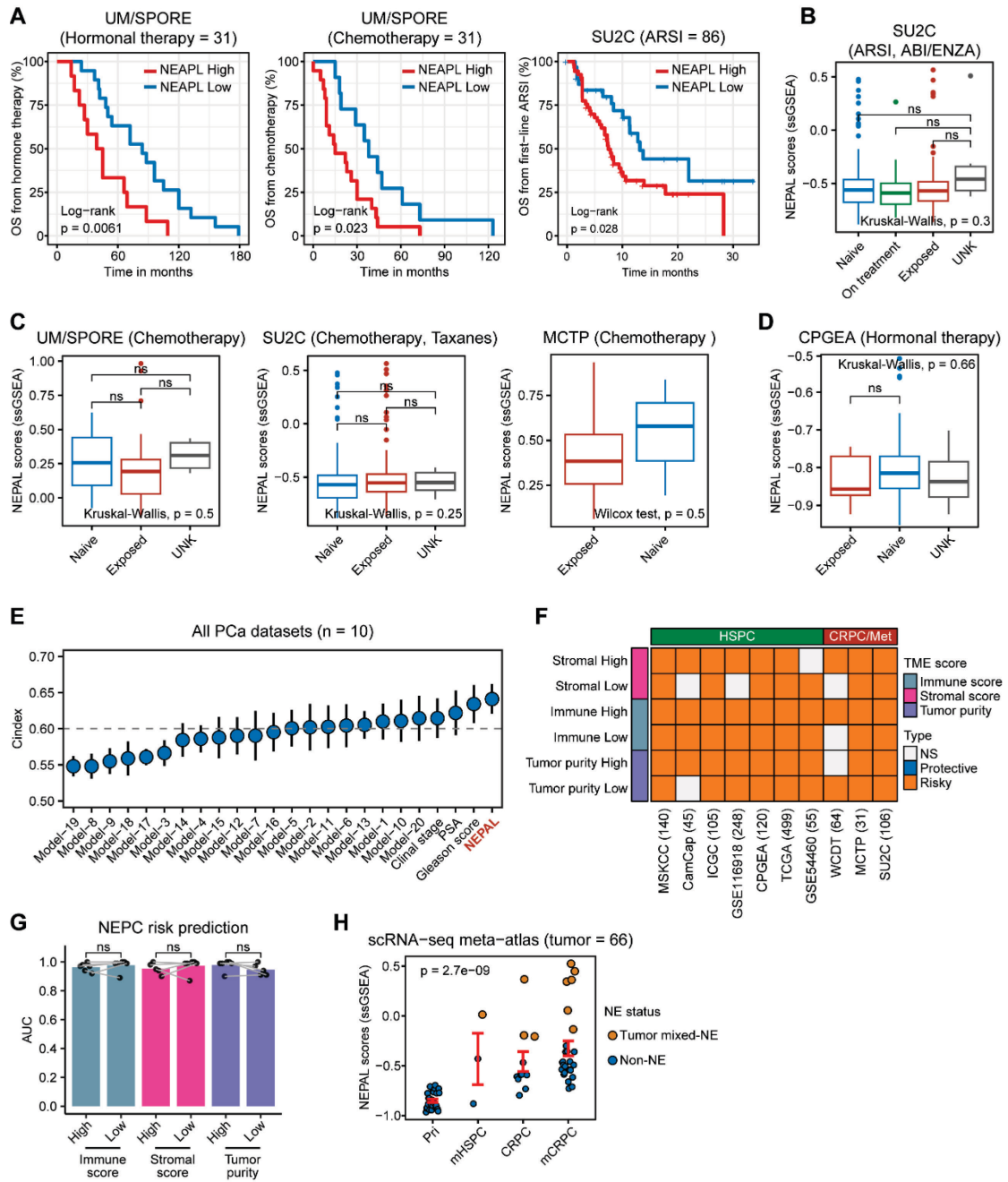
50 Pearson correlation between NEPAL risk scores and expression of *CHGA* or *SYP* in

51 PCa cell lines (right panel).

52 C. Similar analysis to GSE90891 RNA-seq data of mice with PCa (n = 27).

53

54 **Figure S4**



55

56 **Figure S4. Assessment the effects of prior treatment history, TME components**

57 **and various subtypes on the prediction accuracy of the NEPAL model.**

58 **A. Therapeutic resistance analysis by Kaplan–Meier OS curves of patients grouped by**

59 **NEPAL risk scores.**

60 **B-D. Box plots showing the distribution of NEPAL scores among different ARSI (B),**

61 chemotherapy (C), or hormonal therapy groups (D) in corresponding cohorts. The box
62 represents the interquartile range, the horizontal line in box is the median, and the
63 whiskers represent 1.5 times interquartile range.

64 E. C-indexes of NEPAL signature, 20 published machine learning prognostic models,
65 and traditional clinical parameters across 10 multicentric PCa cohorts. These cohorts
66 include 7 primary HSPC datasets (ICGC, MSKCC, CPGEA, GSE116918, CamCap,
67 TCGA and GSE54460), as well as 3 CRPC/Met datasets (WCDT, MCTP and SU2C).

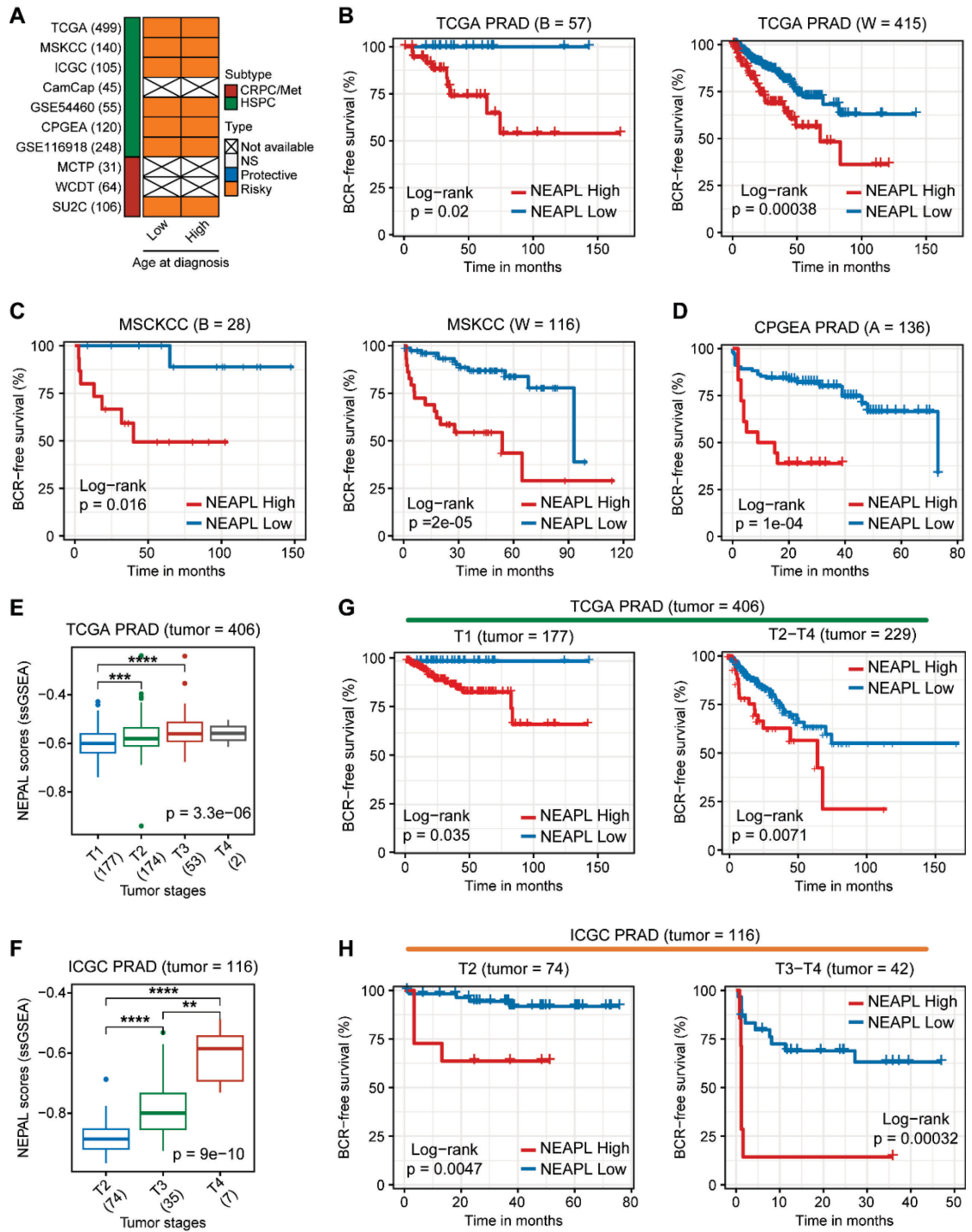
68 F-G. The stratification survival analyses between groups with high and low TME scores
69 to assess the effectiveness of the NEPAL score in predicting PCa progression (F) and
70 NEPC risk (G). Each dot represents an individual data sets.

71 H. The distribution of NEPAL scores among the various subtypes of PCa in the scRNA-
72 seq meta-atlas. Each dot represents an individual sample. Tumors without NE features
73 depicted in blue. Tumors with NE features depicted in yellow.

74 Error bar denote SD (E, G and H).

75

76 **Figure S5**



77

78 **Figure S5. Assessment the impact of patient age, race and tumor stages on the**
 79 **prediction accuracy of the NEPAL model.**

80 A. The stratification survival analyses based on patient age at diagnosis to assess the
 81 effectiveness of the NEPAL score in predicting PCa progression.

82 B-D. The stratification analysis of patient race showing the outcomes for patient groups

83 with low and high NEPAL scores in the TCGA PRAD cohorts. B, Black or African

84 American; W, White; A, Asian.

85 E-F. The distribution of NEPAL scores among patient groups with different tumor

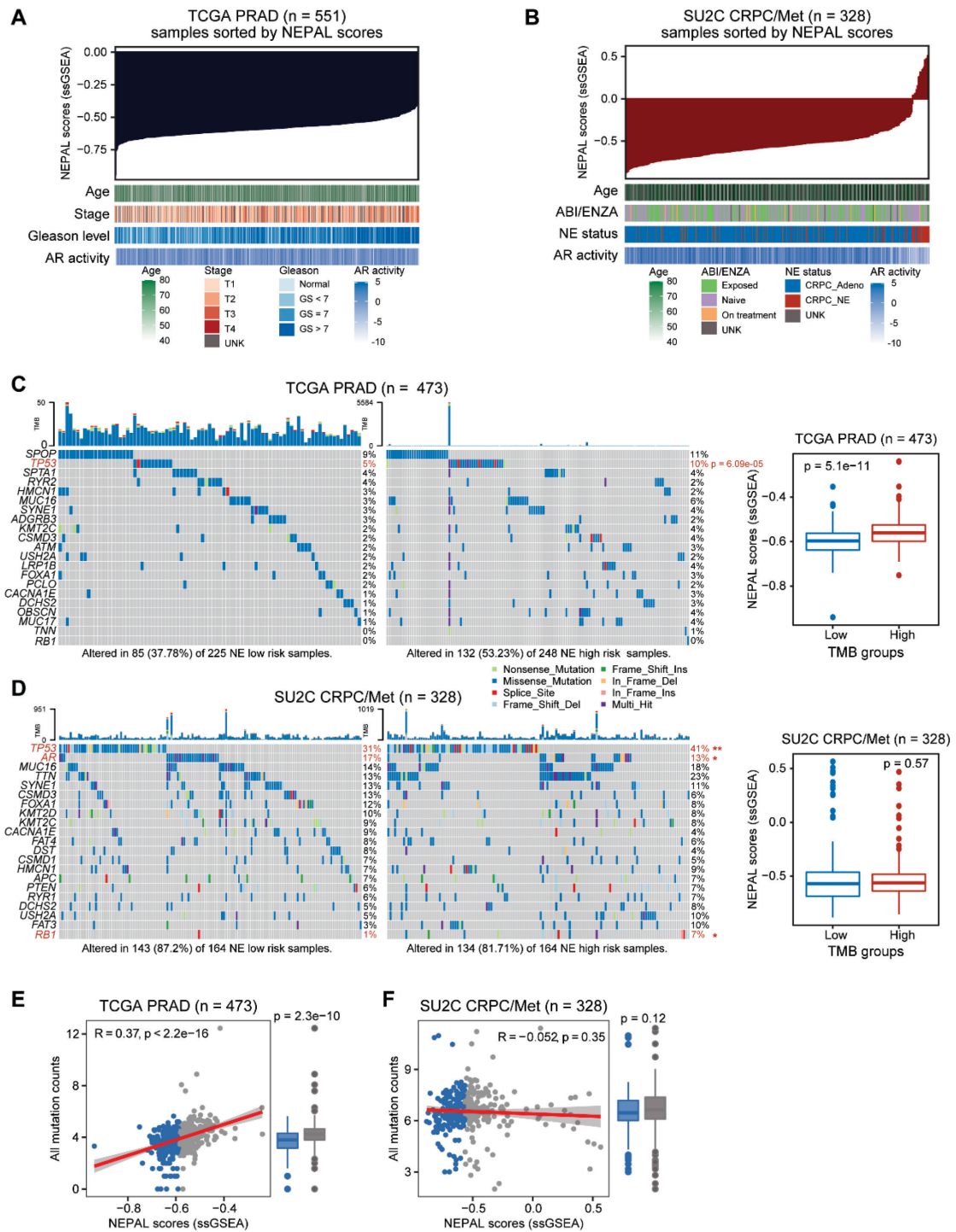
86 stages in TCGA (E) and ICGC (F) PRAD cohorts.

87 G-H. The stratification analysis of tumor stages showing the outcomes for patient

88 groups with low and high NEPAL scores in the TCGA (G) and ICGC (H) cohorts.

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90 **Figure S6**



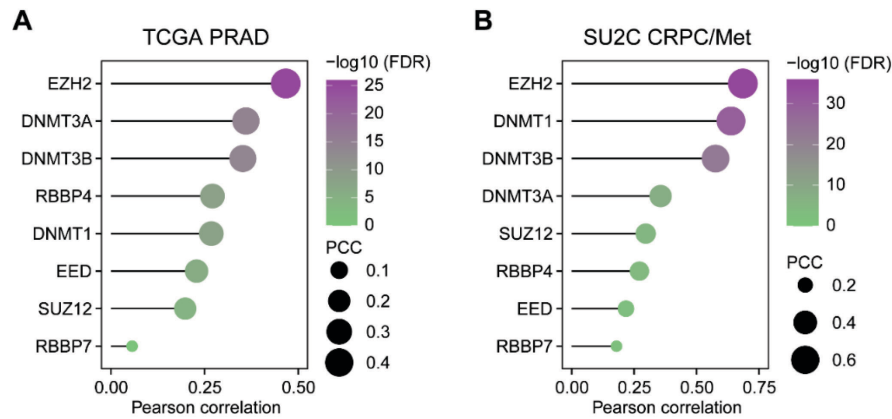
91

92 **Figure S6. Associations between the NEPAL risk scores and genetic alterations in**
 93 **human PCa databases.**

94 A-B. An overview of the association between known clinical features and NEPAL risk

95 scores in TCGA PRAD (n = 551, A) and SU2C CRPC/Met (n = 328, B) databases.
96 Columns represent samples sorted by NEPAL scores from low to high (top row). Rows
97 represent known clinical features. GS, Gleason scores.
98 C. Top 21 highly mutated genes in low- and high- NEPAL risk score groups from
99 TCGA PRAD tumors (left panel). NEPAL risk scores of different tumor mutational
100 burden (TMB) high- and low-groups (right panel).
101 D. Similar analysis to SU2C CRPC/Met cohort (n = 328). *, p <0.05; **, p <0.01.
102 E-F. Correlation analysis between NEPAL risk scores and all gene mutation counts in
103 TCGA PRAD (E) and SU2C CRPC/Met (F) cohorts. Blue representing patients with
104 low NEPAL risk scores. Gray representing patients with high NEPAL risk scores.
105

106 **Figure S7**



107

108 **Figure S7. Identification nongenetic evolution drivers for NEPC.**

109 A-B. Pearson correlation analysis between NEPAL risk scores and indicated genes in
110 TCGA PRAD (A) and SU2C CRPC/Met (B) cohorts. PCC, Pearson correlation
111 coefficient.

112

113 **Supplemental Tables**

114 **Supplemental table 1.** Cohorts and cell type markers for the scRNA-seq data used in
115 this study.

116 **Supplemental table 2.** List of published NEPC_Meta gene signatures and prognostic
117 machine learning models for PCa.

118 **Supplemental table 3.** NEPC markers and signature gene-lists in the scRNA-seq meta-
119 atlas.

120 **Supplemental table 4.** The predicting results of NEPC risk scores using multiple
121 models across six PCa cohorts.

122 **Supplemental table 5.** The correlation between gene expression or transcription

123 factors activities and the NEPAL scores in PCaProfiler dataset.