Increasing Stemness Drives Prostate Cancer Progression, Plasticity, Therapy Resistance and Poor Patient Survival

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Abstract

Background

Cancer progression is often accompanied by dedifferentiation and acquisition of stem cell-like properties

(stemness). In prostate cancer (PCa), lineage plasticity and therapy resistance remain major clinical

challenges, yet a unified quantitative transcriptomic framework connecting stemness, androgen receptor

(AR) signaling, castration resistance, and disease progression across the PCa continuum is lacking.

Methods

We performed an integrative analysis of 87,192 transcriptomic data from 27 preclinical and clinical datasets

spanning the PCa continuum—from normal prostate and treatment-naïve primary PCa (Pri-PCa) to PCa treated

with neoadjuvant ADT (nADT) and metastatic castration-resistant PCa (mCRPC). Tumor stemness was

quantified using a transcriptome-derived mRNAsi Stemness Index (Stemness for short), and a 12-gene PCa-

Stem signature was developed to capture PCa-specific stemness. Canonical AR activity (c_AR-A) and

castration-reprogrammed AR activity (cr_AR-A), *RB1*-loss, *PTEN*-loss, and MYC activity signature scores were

analyzed across cohorts, with survival assessed in multiple datasets. Functional validations included MYC

knockdown RNA-seq data analysis in LNCaP cells and siRNA-mediated depletion of representative PCa-Stem

genes in androgen-independent LAPC4 (LAPC4-AI) cells.

Results

The Stemness score and c_AR-A increased concordantly during early prostate tumorigenesis but diverged with

PCa progression: as Gleason grade increased, c_AR-A declined while Stemness continually increased.

mCRPC exhibited the highest Stemness and lowest c_AR-A, a pattern recapitulated in *Pten/Rb1/Trp53*-

deficient mouse models. Both global Stemness score and the PCa-Stem signature were enriched in aggressive

PAM50-LumB and PCS1 subtypes, associated with the proliferative and lineage plasticity programs, and

predicted poor survival. Depletion of representative PCa-Stem genes (*HMMR*, *PBK*, *AURKB*) suppressed

proliferation, invasion and organoid formation in LAPC4-AI cells. Mechanistically, MYC activity, cr_AR-A and

RB1-loss transcriptomic signature were consistently associated with and drove pervasively increasing

Stemness during PCa progression. Shared mitotic regulators linked cr_AR-A, *RB1*-loss, MYC activity, and PCa-

Stem to mitotic control and therapy-resistant proliferation.

Conclusions

The Stemness scores reported herein quantitatively capture PCa aggressiveness, plasticity, treatment

resistance and progression, and prognosticates poor patient survival. Therapy-reprogrammed AR activity

(cr_AR-A), *RB1* loss, and MYC activation together reinforce the high-Stemness state and therapy resistance in

mCRPC. Collectively, our work establishes a trajectory-integrated and scalable transcriptomic framework that

defines cancer Stemness as a quantifiable clinical determinant of PCa progression, plasticity, progression,

therapy resistance and patient survival.

Background

Malignant transformation and cancer progression are characterized by progressive loss of differentiation (or oncogenic dedifferentiation) and gain of stem cell-like traits (i.e., stemness). Poorly differentiated tumors are enriched in gene expression profiles of normal embryonic and adult stem cells and in cancer stem cells [1-5]. However, the oncogenic dedifferentiation-based stemness concept [6] that prostate cancer (PCa) represents abnormal organogenesis [7, 8] has not been systemically addressed and there lack quantitative measurements of the overall stemness-associated aggressiveness in PCa.

PCa is projected to claim the lives of >36,000 American men in 2026 [9]. PCa incidence rates increased 3% per year from 2014 - 2019 driven by advanced PCa diagnosis and the proportion of men diagnosed with metastases has doubled from 2011 to 2019 when the next generation of androgen receptor (AR) pathway inhibitors (ARPIs) such as abiraterone (Zytiga; FDA approval in 2011) and enzalutamide (Xtandi; FDA approval in 2012) were introduced to the clinic. Significant increases in diagnosis of aggressive and advanced disease and continued high PCa mortality have been linked to therapy resistance driven by intrinsic PCa cell heterogeneity (e.g., in AR expression) and treatment-induced plasticity [8].

The level of malignancy of primary PCa (Pri-PCa) has been traditionally assessed by pathologists using a combined Gleason Score (GS), which gauges histopathological differentiation pattern of prostatic glands. The higher the GS, the more undifferentiated and more malignant the Pri-PCa is. The GS system, although clinically the 'gold' standard in pinpointing PCa diagnosis, is only semi-quantitative, can be subjective (to individual pathologist's assessment), and is generally not applicable to treatment-failed tumors and distant metastases (which have mostly lost differentiated glandular structures). Notably, whether more advanced Pri-PCa (GS8-10), treatment failure and metastatic dissemination are quantitatively associated with increased cancer stemness remains unknown.

AR is the master regulator of normal prostatic epithelium differentiation and represents the therapeutic target of PCa treatments including androgen-deprivation therapy (ADT) and ARPIs. Inevitably, tumors develop resistance to ADT/ARPIs leading to the state of castration-resistant PCa (CRPC), which involves many mechanisms including genetic alterations of *AR* and key genes in AR pathway [10], lineage plasticity [8, 11, 12], and increased stemness [8, 13]. Under therapeutic pressure, AR binding shifts toward noncanonical targets (i.e., reprogramming of AR cistrome), resulting in extensive reconfiguration of the AR transcriptional program [14-17]. These observations suggest a progressive divergence of AR signaling from its canonical, pro-differentiation role during tumor evolution. Thus, quantifying canonical AR activity across disease stages should provide a tractable means to capture this adaptive trajectory. However, how such changes in AR signaling relate to global stemness and tumor aggressiveness remains unclear.

These discussions raise the need for a quantitative framework that simultaneously captures AR signaling and stemness to reveal how their dynamic interplays contribute to PCa aggressiveness, plasticity,

and therapy resistance. Here, we adapted and developed transcriptome-based gene signature scores to
quantitatively assess the canonical AR activity (c_AR-A) and oncogenic stemness levels (Stemness score;
Stemness for short) and their inter-relationship in the PCa spectrum. Specifically, we used gene expression
data collected from 87,192 samples in 27 distinct pre-clinical datasets and clinical cohorts encompassing
the PCa continuum, i.e., from normal/benign prostate to early stage and advanced PCa, to pre- and post-
therapy PCa, and, finally, metastatic CRPC (mCRPC), to systematically track the dynamic evolution of and
inter-relationship between c_AR-A and the Stemness Index. Our findings demonstrate that Stemness
quantitatively tracks PCa progression and adverse clinical outcomes, establishing a trajectory-integrated,
pan-cohort framework that links pervasively increasing Stemness as a defining hallmark of PCa
aggressiveness and therapy resistance, and poor patient prognosis.

Methods

I. PCa clinical datasets and data collection

In this study, we utilized a total of 27 published and in-house datasets, including various cohorts encompassing the evolutionary spectrum of PCa (Fig. S1A-B): normal prostate, tumor-adjacent benign tissue, treatment-naïve primary PCa (Pri-PCa) with increasing GS, PCa treated with neo-adjuvant ADT (nADT) or long-term ADT, mCRPC, and PCa cell lines, PCa patient-derived xenografts (PDX) and xenografts. Clinical information, genomic data and gene expression profiling data were downloaded and detailed information on each dataset is listed in Table S1. Dataset descriptions include dataset source references, PubMed IDs (PMIDs; RRID:SCR_004846), DOI links, sample type and source, sample sizes, data types used in the current study (clinicopathologic data, RNAseq, microarray, whole exome sequencing [WES]), and public data access portals.

Data Access and Repository Information: Data for this study were retrieved from the following public repositories and databases:

1. GTEx Portal (RRID:SCR_013042; https://gtexportal.org/)
2. Gene Expression Omnibus (GEO; RRID:SCR_005012; https://www.ncbi.nlm.nih.gov/geo/)
3. cBioPortal for Cancer Genomics (RRID:SCR_014555; https://www.cbioportal.org/)
4. Zenodo Repository (RRID:SCR_004129; https://zenodo.org/)
5. Decipher GRID Database (RRID:SCR_006552; ClinicalTrials.gov identifier: NCT02609269)
6. European Genome-Phenome Archive (EGA; RRID:SCR_004944; https://ega-archive.org/)
7. European Nucleotide Archive (ENA; RRID:SCR_006515; https://www.ebi.ac.uk/ena/browser/home)
8. UCSC Xena Functional Genomics Portal (RRID:SCR_018938; https://xenabrowser.net/)

Accession numbers and portal links for the 27 datasets described below are summarized in Table S1.

Brief Descriptions of the 27 Datasets:

1) **GTEx 2013** (PMID: 23715323; DOI: 10.1038/ng.2653) [18]: The Genotype-Tissue Expression (GTEx) Project repository collected high-throughput and clinical data of normal tissue from many organs. RNAseq data of 245 normal prostate tissue samples was downloaded from the GTEx portal (RRID:SCR_013042; https://www.gtexportal.org/, version: v8).

2) **Smith 2015** (PMID: 26460041; DOI: 10.1073/pnas.1518007112) [19]: RNAseq data of 5 prostate basal cell (Trop2$^+$CD49f^{hi}) and corresponding 5 luminal cell (Trop2$^+$CD49f^{lo}) samples FACS-purified from benign human prostate tissue in 5 PCa patients (n=5) was retrieved from the GEO database GSE82071.

3) **Liu 2016** (PMID: 27926864; DOI: 10.1016/j.celrep.2016.11.010) [20]: RNAseq data of 3 FACS-purified human prostate basal cell (CD45$^-$EpCAM$^+$CD49f^{hi}CD38^{lo}) and corresponding luminal cell (CD45$^-$

EpCAM$^+$CD49f^{lo}CD38^{hi}) and luminal progenitor cell (CD45$^-$EpCAM$^+$CD49f^{lo}CD38^{lo}) populations from

the benign prostate tissues of 3 PCa patients (n=3) was retrieved from the supplementary data of the

indicated reference. The microarray-based transcriptomic profiles of the same samples were retrieved

from the GEO database GSE89050.

4) **Zhang 2016** (PMID: 26924072; DOI: 10.1038/ncomms10798) [21]: RNAseq data of 3 human prostate

basal cell (Trop2$^+$CD49f^{hi}) with the corresponding 3 luminal cell (Trop2$^+$CD49f^{lo}) samples FACS-

purified from benign prostate tissues of 3 PCa patients (n=3) was retrieved from the GEO database

GSE67070.

5) **TCGA PRAD 2015** [22] and **Pan-Cancer Atlas 2018**: The Cancer Genome Atlas (TCGA)

(https://www.cancer.gov/tcga) repository collected high-throughput molecular and clinical data from

primary cancer and matched normal/benign samples spanning 33 human cancer types, including

prostate adenocarcinoma (PRAD). For each cancer type, TCGA published an initial "marker paper"

summarizing analyses performed. Supplemental and associated data files supporting these "marker

papers" are available through the NCI Genomic Data Commons (GDC) website

(https://gdc.cancer.gov/about-data/publications). For PCa, **TCGA PRAD 2015** [22] (PMID: 26544944;

DOI: 10.1016/j.cell.2015.10.025) is the marker paper on PCa published in 2015, which included the

dataset of 333 primary prostate adenocarcinomas (281 treatment-naïve Pri-PCa, 49 PCa with post-

surgery adjuvant ADT, and 52 matched normal/benign prostate tissue). Genomic data were obtained

from **cBioPortal for Cancer Genomics** (RRID:SCR_014555; https://www.cbioportal.org), specifically

the TCGA-PRAD Firehose Legacy study (https://www.cbioportal.org/study/summary?id=prad_tcga).

RNAseq expression data was obtained from Zhang *et al*. [23] (PMID: 32350277; DOI: 10.1038/s41467-

020-15815-7).

The expanded **TCGA PRAD 2018 (Pan-Cancer Altas)** cohort included 494 patients with Pri-PCa

(422 treatment-naïve Pri-PCa, 70 PCa with post-surgery adjuvant hormone treatment, 2 PCa with

chemotherapy) and 52 matched adjacent normal/benign prostate tissue. Clinicopathologic features

(age, Gleason scores, PSA levels, tumor stages) and genomic alterations data (mutation frequency,

copy number alterations [CNAs], structural variants [SVs], tumor mutation burden [TMB], fraction

genome altered) were retrieved from cBioPortal for Cancer Genomics PRAD PanCancer Atlas study

(https://www.cbioportal.org/study/summary?id=prad_tcga_pan_can_atlas_2018) and from the Pan-

Cancer Atlas companion site (https://www.cell.com/pb-

assets/consortium/pancanceratlas/pancani3/index.html). Survival data were obtained from Liu *et al*.

[24] (PMID: 29625055; DOI: 10.1016/j.cell.2018.02.052). Normalized RNAseq data were downloaded

via NCI GDC hub at UCSC Xena Functional Genomics Portal [25] (https://gdc.xenahubs.net, version

2019-07-20; PMID: 32444850; DOI: 10.1038/s41587-020-0546-8).

6) **Rajan 2014** (PMID: 24054872; DOI: 10.1016/j.eururo.2013.08.011) [26]: Clinicopathologic (Gleason
scores) and RNAseq data of 7 matched pre- and post-nADT PCa samples were obtained from Table
1 of the indicated reference and the GEO database GSE48403.

7) **Sharma 2018** (PMID: 30314329; DOI: 10.3390/cancers10100379) [27]: Clinicopathologic (Gleason
scores) and RNAseq data of 7 matched pre- and post-nADT PCa samples from the responder group
(also defined as "Low Impact Group" in the source reference) was obtained from supplementary Table
S1 of the indicated reference and the GEO database GSE111177.

8) **Long 2020** (PMID: 32951005; DOI: 10.1016/j.eururo.2013.08.011) [28]: RNAseq data of 6 matched pre-
and post-nADT PCa samples was obtained from the GEO database GSE82071. Additionally, RNAseq
data from 10 locally advanced PCa samples along with their paired adjacent benign prostate tissues
were obtained from the GEO database GSE82071.

9) **Nastiuk (RPCI) 2020** (PMID: 41646678; DOI: 10.64898/2026.01.10.26343859) [29]: Clinicopathologic
data (Gleason scores) and RNAseq data of 43 Pri-PCa samples from post-nADT PCa patients and 43
tumor samples from age-, stage-, clinically-matched PCa patients without nADT was obtained from
Drs. K. Nastiuk and G. Chatta at the Roswell Park Comprehensive Cancer Center.

10) **Gerhauser 2018** (PMID: 30537516; DOI: 10.1016/j.ccell.2018.10.016) [30]: RNAseq data of 118
primary tumor samples and 9 adjacent benign prostate tissue from early-onset PCa patients was
obtained from the European Genome-Phenome Archive (EGA) (https://ega-archive.org), accession
number EGAS00001002923.

11) **Wyatt 2014** (PMID: 25155515; DOI: 10.1186/s13059-014-0426-y) [31]: Clinicopathologic (Gleason
scores) and RNAseq data of 12 primary PCa samples from treatment-naïve PCa patients and 12
adjacent benign prostate tissue were obtained from supplementary Table S1 of the indicated reference
and the European Nucleotide Archive (ENA) (https://www.ebi.ac.uk/ena/browser/home), accession
number PRJEB6530.

12) **Spratt 2017** (PMID: 28358655; DOI: 10.1200/JCO.2016.70.2811) [32]: Transcriptomic profiles
(Microarray) and clinicopathologic data of 855 radical prostatectomy specimens from a multi-
institutional study of intermediate- and high-risk localized PCa patients were obtained from Veracyte
GRID (https://decipherbio.com/grid/).

13) **Tosoian 2020** (PMID: 32231245; DOI: 10.1038/s41391-020-0226-2) [33]: Transcriptomic profiles
(Microarray) and clinicopathologic data of 405 radical prostatectomy and biopsy specimens from high-
risk localized PCa patients were obtained from Veracyte GRID (https://decipherbio.com/grid/).

14) **CHAARTED correlatives 2021** (PMID: 34129855; DOI: 10.1016/j.annonc.2021.06.003) [34]:
Transcriptomic profiles (Microarray) and clinicopathologic data of 160 biopsy specimens from a Phase
3 trial of metastatic hormone-sensitive PCa patients were obtained from the NCTN Data Archive
(https://nctn-data-archive.nci.nih.gov), accession number NCT00309985-D14.

15) **Decipher GRID Biopsy** (PMID: 37060201; DOI: 10.1002/cncr.34790) [35]: Transcriptomic profiles

from 82,470 prospectively collected prostate biopsy samples were retrieved from the Decipher GRID

database   (RRID: SCR_006552;   https://decipherbio.com/grid;   ClinicalTrials.gov   identifier:

NCT02609269**;** https://clinicaltrials.gov/ct2/show/NCT02609269). Patient data were de-identified from

clinical use of the Decipher prostate genomic classifier in accordance with the Safe Harbor method

described in the HIPAA Privacy Rule 45 CFR 164.514(b) and (c) (Veracyte, San Diego, CA). The

samples, comprising a large cohort of localized PCa, were utilized to compare the distribution of

Stemness Index values across National Comprehensive Cancer Network (NCCN) risk groups.

Clinicopathologic Breakdown and Risk Group Analysis:

Detailed clinicopathologic review revealed that the majority of the cohort presents with low-grade

localized PCa. The TNM staging breakdown includes:

• **T1 stage:** Approximately 50% of samples, indicating early-stage cancer localized within

the prostate.

• **T2 stage:** Approximately 8%, representing cancer confined within the prostate but more

extensive than T1.

• **T3 and T4 stages:** Less than 1%, suggesting advanced PCa with local spread.

• **N0:** Approximately 98%, indicating no regional lymph node involvement.

• **N1:** Approximately 2%, suggesting regional lymph node involvement.

The Decipher GRID database (RRID:SCR_006552) categorizes patients into NCCN risk groups

based on TNM stage, PSA level, and Gleason score:

• **Very Low - Low Risk:** T1–T2a, N0, M0, PSA <10 ng/mL, and Gleason score ≤6; often

managed with active surveillance or less aggressive treatment.

• **Intermediate Risk – Favorable:** Typically T2b–T2c, N0, M0, PSA 10–20 ng/mL, and

Gleason score 7; managed with less aggressive treatment but closer monitoring.

• **Intermediate Risk – Unfavorable:** Similar clinical features to favorable but with higher

disease burden or adverse factors requiring careful monitoring.

• **High Risk:** Usually involves T3a, N0, M0, PSA >20 ng/mL, or Gleason score 8–10; often

managed aggressively with surgery, radiation, and/or hormonal therapy.

• **Very High Risk:** Typically includes T3b–T4, any N, M0, and high Gleason scores or PSA

levels (PSA >20 ng/mL); patients are at significant risk for metastatic progression and are treated

aggressively, often with multimodal therapies.

Observations on Disease Severity and Treatment Naïvety:

Analysis of the cohort indicates that approximately 13% of cases fall into the High and Very High-

Risk categories (8,376 + 2,399 = 10,775 samples), suggesting that the majority (approximately 87%)

are below Intermediate Risk (≤GS7). This distribution implies that most patients were treatment-naïve

and likely ADT-free due to less aggressive disease status.

16) **Bolis 2021** (PMID: 34857732; DOI: 10.1038/s41467-021-26840-5) [36]: RNAseq and clinicopathologic

data of 1,223 clinical samples from an integrated cohort consisting of normal prostate specimens

(n = 174), Pri-PCa (n = 714) and mCRPC (n = 335) was obtained from the Zenodo repository (Record

ID: 5546618; https://zenodo.org/records/5546618). This resource of PCa Transcriptome Atlas

(https://prostatecanceratlas.org) was built and integrated from the following studies/datasets: (1)

Genotype-Tissue Expression Database [18] (GTEx; PMID: 23715323); (2) The Cancer Genome Atlas

[22] (TCGA, TCGA-PRAD; PMID: 26544944); (3) Atlas of RNA-sequencing profiles of normal human

tissues [37] (GSE120795; PMID: 31015567); (4) Integrative epigenetic taxonomy of PNPCa [38]

(GSE120741; PMID: 30464211); (5) Prognostic markers in locally advanced lymph node-negative PCa

(PRJNA477449); (6) The long noncoding RNA landscape of NEPC and its clinical implications [39]

(PRJEB21092; PMID: 29757368); (7) Integrative clinical sequencing analysis of metastatic CRPC [10]

(PRJNA283922; dbGaP: phs000915; PMID: 26000489); (8) CSER—exploring precision cancer

medicine for sarcoma and rare cancers [40] (PRJNA223419; dbGaP: phs000673; PMID: 28783718);

(9) Molecular basis of NEPC [41] (Beltran 2016; PRJNA282856; dbGaP: phs000909; PMID: 26855148);

(10) Heterogeneity of androgen receptor splice variant-7 (AR-V7) protein expression and response to

therapy in CRPC [42] (GSE118435; PMID: 30334814); (11) RNAseq of human PCa cell lines and

mCRPC [43-45] (GSE14750; PMIDs: 32460015; 33658518; 34244513 | GSE171729; PMID:

34244513); and (12) Molecular profiling stratifies diverse phenotypes of treatment-refractory metastatic

CRPC [46] (PRJNA520923; GEO: GSE126078; PMID: 31361600).

17) **Taylor 2010** (PMID: 20579941; DOI: 10.1016/j.ccr.2010.05.026) [47]: Transcriptomic profiles

(Microarray) and clinicopathologic (recurrence-free survival) data of 29 adjacent benign prostate tissue,

131 Pri-PCa, and 19 mPCa were obtained from the GEO database GSE21034 and the cBioPortal for

Cancer   Genomics   PRAD   MSKCC   2010   study

(https://www.cbioportal.org/study/summary?id=prad_mskcc).

18) **SU2C 2015** (PMID: 26000489; DOI: 10.1016/j.cell.2015.05.001) [10]: Clinical and genomic data of 150

mCRPC samples were obtained from the cBioPortal for Cancer Genomics PRAD SU2C 2015 study

(https://www.cbioportal.org/study/summary?id=prad_su2c_2015). RNAseq data of 98 mCRPC

samples was retrieved from Zhang *et al.* [23] (PMID: 32350277; DOI: 10.1038/s41467-020-15815-7).

19) **SU2C 2019** (PMID: 31061129; DOI: 10.1073/pnas.1902651116) [48]: This dataset includes

clinicopathologic and genomic data for 444 mCRPC samples. RNAseq data of 266 mCRPC samples

(prepared by using poly(A) enrichment for RNAseq library construction) were obtained from the

cBioPortal   for   Cancer   Genomics   PRAD   SU2C   2019   study

(https://www.cbioportal.org/study/summary?id=prad_su2c_2019). In parallel with TCGA-PRAD,

clinicopathologic features (age, Gleason scores, PSA levels), genomic alterations (mutation frequency,

CNAs, SVs, TMB, fraction genome altered), and patient outcome data (overall survival) were also

retrieved from cBioPortal (RRID:SCR_014555). These datasets were used for comparative analysis

between Stemness-high and Stemness-low groups, and to explore genomic drivers and clinical
associations as described in the Methods.

20) **Labrecque 2019** (PMID: 31361600; DOI: 10.1172/JCI128212) [46]: RNAseq data of 98 mCRPC
samples and 39 PDX-LuCaP was obtained from the GEO database GSE126078.

21) **Alumkal 2020** (PMID: 32424106; DOI: 10.1073/pnas.1922207117) [13]: RNAseq data of 25 mCRPC
samples before treatment with enzalutamide was obtained from Supplementary dataset S01 of the
indicated reference.

22) **Westbrook 2022** (PMID: 36109521; DOI: 10.1038/s41467-022-32701-6) [12]: RNAseq data of 42
mCRPC samples consisting of 21 matched pre/post Enzalutamide treatment samples was retrieved
from of the indicated reference.

23) **Beltran 2016** (PMID: 26855148; DOI: 10.1038/nm.4045) [41]: RNAseq data of mCRPC samples,
including 34 castration-resistant adenocarcinoma (mCRPC-Adeno) and 15 mCRPC with
neuroendocrine histologies (mCRPC-NEPC), was obtained from cBioPortal for the Cancer Genomics
(https://www.cbioportal.org/study/summary?id=nepc_wcm_2016).

24) **Goodrich 2017** (PMID: 28059767; DOI: 10.1126/science.aah4199) [49]: RNAseq data of murine
prostate tumors from genetically engineered mouse models (GEMMs) of PCa of different genotypes,
including 4 SKO (single knockout: PBCre4;$Pten^{f/f}$), 13 DKO (double knockout PBCre4;$Pten^{f/f}$:$Rb1^{f/f}$),
and 6 TKO (PBCre4;$Pten^{f/f}$:$Rb1^{f/f}$:$Trp53^{f/f}$) was obtained from the GEO database GSE90891 (*f* = a
floxed allele of the indicated genes).

25) **CCLE 2018** (PMID: 22460905; DOI: 10.1038/nature11003) [50]: RNAseq data of 1,019 human cell
lines were obtained from the Xena Functional Genomics Portal [25] (https://xenabrowser.net, version:
2018-05-30). Among them, eight PCa cell lines — DU145 (RRID:CVCL_0105), LNCaP clone FGC
(RRID:CVCL_1379), MDA PCa 2b (RRID:CVCL_4745), NCI-H660 (RRID:CVCL_0459), PC-3
(RRID:CVCL_0035), VCaP (RRID:CVCL_2235), 22Rv1 (RRID:CVCL_1045), and PRECLH (PrEC LH;
RRID:CVCL_V626) — were included for analysis.

26) **XG-LNCaP** and **XG-LAPC9** (PMID: 30190514; DOI: 10.1038/s41467-018-06067-7) [51]: RNAseq data
of 12 LNCaP xenografts (XG-LNCaP) and 10 LAPC9 xenografts (XG-LAPC9) was obtained from the
GEO database GSE88752.

27) **LNCaP (MYC knockdown series)** (PMID: 32681068; DOI: 10.1038/s41388-020-01389-7) [52]:
RNAseq data for the LNCaP MYC-knockdown system were obtained from the GEO database
(GSE135942). This dataset included non-targeting control samples (n=3) and MYC-knockdown
samples (n=6) generated using two shMYC constructs (shMYC-512 and shMYC-637) targeting the
MYC open reading frame (ORF), each performed in triplicate. The shMYC-627 construct, which targets
the 3′UTR, was excluded from analysis.

Sex as a biological variable:

All clinical datasets analyzed in this study consisted exclusively of male patients, consistent with the male-

specific nature of PCa. Preclinical models, including xenografts, patient-derived xenografts, and GEMMs

were also male-derived. All PCa cell lines analyzed in the study were of male origin, with the exception of

Figure S5A, where a broader cohort of 1,019 cell lines from the CCLE, comprising both male- and female-

derived samples across multiple cancer types, was analyzed. Analyses of CCLE data in Figure S5A were

performed without stratification by sex.

II. Transcriptomic data normalization and transcriptome-based signature quantification

To ensure consistency across diverse transcriptomic datasets, all data acquisition and normalization, and

signature quantification (scoring) were performed using methods tailored to data type and analytical scope.

All analyses were conducted within each dataset, thereby avoiding inter-study batch effects. For

comparisons across pathological stages (e.g., normal/benign → Pri-PCa → mCRPC), we used only

harmonized, pre-integrated transcriptomic datasets, including the PCa Transcriptome Atlas (Bolis 2021)

[36] and Taylor 2010 [47], which provide variance-stabilized, library size–adjusted expression matrices

normalized across disease stages.

In this project, we adopted, derived, and utilized multiple transcriptomic gene signatures

representing PCa differentiation, stemness, oncogenic signaling, and tumor-suppressor loss. Signatures

analyzed included: (1) the Stemness Index, (2) Canonical AR activity (c_AR-A; 10 genes), (3) MYC

signaling activity (MYC-sig; 58 genes), (4) the PCa-Stem Signature (12 genes), (5) castration-

reprogrammed AR activity (cr_AR-A; 63 genes), (6) cr_AR-Growth_Wang (8 genes), (7) *RB1*-loss

signature (158 genes), and (8) *PTEN*-loss signature (45 genes).

Transcriptome-based quantitative measurement of oncogenic stemness (the Stemness Index):

We adapted mRNA-based **Stemness Index** (mRNAsi) [6] to determine the degree of oncogenic

dedifferentiation and to quantify the aggressiveness in PCa. Briefly, we computed Spearman correlations

between the stemness model's weight vector and the transcriptome expression profile of the queried

samples. Spearman correlation calculations were performed using the 'stats' package in R (version 4.3.3;

RRID:SCR_001905). The resulting correlation coefficients were then linearly transformed to scale the

mRNAsi scores between 0 and 1 using the following formula: Stemness Index = (Spearman correlation +

0.2619) /0.4151. Spearman correlation was adopted for calculating the Stemness Index because of its

robustness to non-normal expression distributions and its reduced susceptibility to cross-dataset batch

effects inherent in large-scale integrative analyses.

Canonical AR activity and MYC activity:

Canonical AR activity (**c_AR-A**) was determined by RNA-seq based measurements of AR-regulated

transcripts under intact androgen/AR signaling conditions. Similarly, the MYC signaling (**MYC-sig**) activity

was determined by MYC-regulated transcripts. We employed Z-score normalization [53] to quantify c_AR-

A and MYC-sig. Briefly, the numeric AR or MYC activity score was calculated based on a linear
combination of expression values (Z-scores) of experimentally validated AR target genes (10 genes) [54]
or MYC target genes (58 genes; GSEA Molecular Signature Database 2022.1 version, MSigDB) [55]. The
target gene lists were detailed in Table S2. The expression value for each AR or MYC target gene was
converted to Z-score by $Z = (x − μ)/σ$, where x is the expression value of the target gene in a specific sample,
μ is the mean and σ is the standard deviation across all samples of a gene. Finally, the combined Z-scores
were summed across all genes to represent the expression score of canonical AR or MYC target genes.
All Z-score analyses were confined to individual datasets to avoid cross-study normalization artifacts.

For cross-stage analyses using harmonized datasets (e.g., the PCa Transcriptome Atlas; ref. [36]),
c_AR-A and MYC-sig were additionally quantified using single-sample gene set enrichment analysis
(ssGSEA) to enable direct comparison with other gene set–based signatures.

PCa-Stem Signature (the 12-gene PCa-specific stemness signature):

A PCa–specific stemness signature was constructed by identifying genes consistently enriched in high-
stemness tumors across distinct disease states. Differential expression analysis compared the top 33%
(Stemness-high) versus bottom 33% (Stemness-low) samples in treatment-naïve Pri-PCa (TCGA-PRAD)
and mCRPC (SU2C 2019) cohorts. Genes upregulated in both cohorts (fold change ⩾ 2, FDR < 0.05;
Table S3) were intersected to generate the 12-gene **PCa-Stem signature** (Table S2). Per-sample
enrichment scores were quantified by ssGSEA.

Castration reprogrammed AR activity (cr_AR-A) signatures:

The 63-gene **cr_AR-A** (Table S2) signature was derived by integrating differential chromatin analyses of
AR and H3K27ac ChIP-seq performed in CRPC versus Pri-PCa samples (GSE130408) [16] with
differential transcriptional analysis comparing CRPC and Pri-PCa samples (GSE21032) [47], thereby
identifying genes exhibiting concordant CRPC-enriched AR binding, enhancer activation, and
transcriptional up-regulation.

The **cr_AR-Growth_Wang** (8 genes; Table S2) signature was adopted from Wang *et al*. [14] and
consists of AR-bound, enhancer-validated growth regulators identified in androgen-independent LNCaP-
abl cells, representing a proliferation-oriented, castration-reprogrammed AR transcriptional program. Both
AR-reprogrammed signatures were quantified by ssGSEA.

Tumor-suppressor-loss signatures:

Transcriptional signatures reflecting functional loss of key tumor suppressors were analyzed using
previously validated gene sets. The ***RB1*-loss signature** (158 genes; Table S2), derived from Ertel *et al.*
[56], captures E2F-driven transcriptional deregulation associated with RB1 pathway inactivation. The
***PTEN*-loss signature** (45 genes; Table S2), derived from Liu *et al.* [57], represents transcriptional
consequences of *PTEN* loss. Both signatures were quantified using ssGSEA.

ssGSEA implementation:

ssGSEA was performed using the Gene Set Variation Analysis (GSVA) [58] package (version 1.50.5;
RRID:SCR_021058) in R (version 4.3.3; RRID:SCR_001905) to quantify per-sample enrichment scores.
All ssGSEA analyses were conducted within individual datasets, using rank-based enrichment to minimize
sensitivity to expression scale differences. For analyses spanning disease stages, ssGSEA was applied
to the harmonized transcriptomic datasets to minimize batch effects. All gene sets are provided in Table
S2.

III. Integrative analysis of genomic alterations in Pri-PCa (TCGA) and mCRPC (SU2C)

To explore molecular and clinical features associated with the PCa stemness, we performed integrative
analysis of genomic, transcriptomic, clinicopathologic, and outcome data using cBioPortal for Cancer
Genomics (RRID:SCR_014555), which provides interactive access to multidimensional cancer genomics
datasets and integrated visualization tools [59]. Specifically, we analyzed data from Pri-PCa (TCGA-PRAD
2018, Pan-Cancer Atlas) and mCRPC (SU2C 2019) cohorts. Clinicopathologic variables (e.g., age,
Gleason scores, PSA levels, tumor stage), genomic alterations (e.g., mutation frequency, TMB, fraction
genome altered, CNAs, and SVs), and patient outcome data (e.g., overall survival, progression-free
survival) were retrieved from cBioPortal (RRID:SCR_014555) as described in the "PCa clinical datasets
and data collection" section. Transcriptomic data used for the Stemness Score calculation were obtained
as described in the same section. For comparative analysis, mCRPC samples were stratified into top and
bottom 33% by the Stemness Scores. In TCGA, only treatment-naïve Pri-PCa samples were used for a
similar 33% stratification, excluding 70 patients who received adjuvant (post-surgery) hormone therapy to
reflect spontaneous disease progression. Differential expression analysis was conducted using DESeq2
[60] (version 1.42.1; RRID:SCR_015687), and gene-level and genome-wide alteration frequencies were
assessed across stratified groups and disease stages (e.g., Pri-PCa vs. mCRPC) using OncoPrint
visualizations, bar plots, and correlation analysis. Associations with clinical outcomes were evaluated as
described in the "Statistical analysis" section.

IV. Functional characterization of representative PCa-Stem signature genes in castration-resistant
LAPC4-AI cells

Cell culture:

The androgen-independent (AI) LAPC4 (LAPC4-AI) cells were derived as described [61] and cultured at
37°C with 5% CO_2 in IMDM (Thermo Fisher, Cat# 21056023) supplemented with charcoal-stripped serum
and 1× penicillin/streptomycin. Cells were routinely passaged to maintain exponential growth and
confirmed to be mycoplasma-free prior to experimentation.

siRNA transfection:

LAPC4-AI cells at ~70% confluence were transfected with Accell SMARTpool siRNAs targeting *HMMR*,
AURKB, or *PBK*, or a non-targeting control (NTC) siRNA (Horizon Discovery). The following reagents were

used: Accell Human *HMMR* siRNA SMARTpool (E-010409-00-0005); Accell Human *PBK* siRNA

SMARTpool (E-005390-00-0005); Accell Human *AURKB* siRNA SMARTpool (E-003326-00-0005). siRNA

complexes were prepared in serum-free medium and added to cells at 1 µM final concentration per

manufacturer's protocol. Media were replaced with complete medium after incubation for 24 h. Knockdown

efficiency and functional assays were performed at the indicated time points.

RNA isolation and qRT-PCR:

Total RNA was isolated 48 h post-transfection using the PicoPure RNA Isolation Kit (Applied Biosystems,

Cat# KIT0204). RNA (1 µg) was reverse-transcribed using SuperScript™ VILO™ Master Mix (Invitrogen,

Cat# 11755050). Quantitative real-time PCR (qRT-PCR) was performed using TaqMan probe-based

assays on a QuantStudio™ Real-Time PCR System (Applied Biosystems). Relative expression levels were

calculated using the ΔΔCt method and normalized to GAPDH, with values expressed relative to NTC

controls. Data were presented as mean ± SD from technical triplicates.

Trans-well Matrigel invasion assays:

At 48 h post-transfection, cells were harvested and equal numbers were seeded into Matrigel-coated trans-

well inserts (Corning, Cat# 354480) in serum-free medium. Medium containing serum was placed in the

lower chamber as a chemoattractant. After 24 h, non-invading cells were removed, and invaded cells on

the underside of the membrane were fixed and stained with DAPI. Images were acquired using a Keyence

microscope. Invaded cells were quantified by counting nuclei in multiple non-overlapping fields per insert.

Data were presented as mean ± SD from technical replicates.

Colony formation assays:

At 24 h post-transfection, LAPC4-AI cells were replated at clonal density (500 cells per well in 6-well plates)

and cultured for 14 days. Colonies were fixed and stained with crystal violet with representative images

shown. Where indicated, colonies were quantified using a consistent size threshold across conditions.

Organoid formation and real-time cytotoxicity assays:

At 24 h after siRNA transfection, LAPC4-AI cells were seeded for 3D culture in organoid medium

supplemented with 5% Matrigel [61]. Real-time cytotoxicity assays were initiated 24 h later and monitored

for 72 h using a cell-impermeant dead-cell dye (Thermo Fisher, Cat# L7013). Fluorescence was recorded

at defined intervals to assess cell death kinetics. Fluorescent signals were background-corrected using

cell-free wells. Data were presented as mean ± SD from technical triplicates.

V. Statistical analyses

Statistical analyses were performed using GraphPad Prism software (version 10.4.1 (532);

RRID:SCR_002798) and R (version 4.3.3; RRID:SCR_001095).

For comparisons between two groups, independent sample or paired *t*-tests were used to compare

group means, assuming normality and equal variance. For multi-group comparisons, Tukey's range test

was employed following one-way ANOVA (adjusted p-values listed in Table S4). The Wilcoxon rank-sum

test was applied for comparisons of altered genome fraction, TMB, or age between two groups. For
differential expression analyses and comparisons involving multiple hypotheses (e.g., RNAseq-based
gene comparisons), p-values were further adjusted using the false discovery rate (FDR) method to control
for multiple testing.

Pearson's correlation coefficient was used to evaluate linear associations between two continuous
variables, assuming normally distributed paired observations. Linear regression modeling was applied to
examine the relationship between two continuous variables, with the slope of the best-fit regression line
reported where applicable. Spearman's rank correlation was employed to assess monotonic relationships
between continuous or ordinal variables, assuming paired observations and monotonic trends without
significant outliers.

The Jonckheere-Terpstra (J-T) trend test was used to assess monotonic association between an
ordinal variable and a continuous variable. For analyses involving proportions across ordered disease
categories, the Cochran–Armitage trend test was used to test for a linear trend in alteration proportions
across GS6, GS9–10, Pri-PCa/ADT, and mCRPC. Chi-square test or Fisher's exact test was performed to
evaluate the associations between categorical variables.

For the analysis of patient progression-free survival (PFS), recurrence-free survival (RFS) and
overall survival (OS), the standard Kaplan-Meier method was used for the estimation of survival fractions
and log-rank tests were used for group comparisons. Cox proportional hazards models were used for
multivariable analysis and for assessing the prognostic significance of gene signatures (the Stemness
Index, PCa-Stem signature, etc). For the mRNA-based gene signatures (the Stemness Index, PCa-Stem
signature, c_AR-A), patients were stratified into high and low signature groups based on median split in
cohorts including Spratt 2017 (Fig. 4A), Tosoian 2020 (Fig. 4B), SU2C 2019 (Fig. S6A), and Taylor 2010
(Fig. S6D-E). For some analyses, including CHAARTED 2021 (Fig. 4C) and SU2C 2019 (Fig. S6B),
patients were alternatively stratified by comparing the top 25% versus the bottom 75% of signature scores
to assess whether patients with very high Stemness levels exhibited a higher risk of disease progression.

For the receiver operating characteristic (ROC) analysis, ROC curves and corresponding area
under the curve (AUC) values were computed to evaluate the discriminative performance of the 12-gene
PCa-Stem signature and the general Stemness Index. ROC analyses were performed using the pROC
package in R (version 4.3.3), with AUC estimated by the non-parametric DeLong method. Classifications
included (i) high-grade (GS > 7) versus low-grade (GS $\leqslant$ 7) Pri-PCa, and (ii) mCRPC versus treatment-
naïve Pri-PCa. All ROC analyses were performed within the PCa Transcriptome Atlas to avoid inter-dataset
batch effects.

All statistical tests were two-sided, and *P* < 0.05 was considered statistically significant.

VI. Data and Code Availability

Data availability: All datasets analyzed in this study are publicly available from repositories including GEO (RRID:SCR_005012), cBioPortal (RRID:SCR_014555), the NCI GDC Portal, the UCSC Xena Functional Genomics Portal (RRID:SCR_018938), EGA (RRID:SCR_004944), ENA (RRID:SCR_006515), and Zenodo (RRID:SCR_004129), as detailed in Table S1. No new sequencing or genomic data were generated.

Code availability: All custom R scripts used for quantification of Stemness Score (i.e., mRNAsi), PCa-Stem signature ssGSEA scoring, Jonckheere–Terpstra trend testing, multivariable Cox modeling, and regression analysis are available on GitHub: https://github.com/DaltonLiu2026/ProstateCancer-Stemness-Scripts. A permanently archived, citable version of this repository has been deposited in Zenodo: https://zenodo.org/records/15620990. The GitHub/Zenodo repository includes all scripts, example input/output files, a README, dependency list, and a code-reproducibility overview.

Results

Adapting and developing the stemness and c_AR-A index scores for PCa analysis.

To determine the global and dynamic changes of and inter-relationship between the degree of malignancy (oncogenic dedifferentiation) and level of (luminal) differentiation during PCa development and progression (Fig. S1A-B), we employed transcriptome-based algorithms to annotate 27 datasets of 3,111 bulk RNA-seq and 84,081 microarray samples encompassing the PCa continuum (Fig. S1B; Table S1). In our studies, we focused on and compared three progressive stages: from normal prostate to localized Pri-PCa, from low-grade to high-grade Pri-PCa, and from treatment-naïve Pri-PCa to CRPC/mCRPC (Fig. S1A). We defined "progression" as stages beyond Pri-PCa and as disease entities that are more aggressive in a comparative manner. Specifically, we adapted the Stemness Index [6] (mRNAsi; **Stemness** for short) (Fig. S1C) to gauge the degree of malignancy (or aggressiveness) and employed the Z-score normalized canonical AR activity or **c_AR-A** (Fig. S1D) to measure the level of differentiation. Canonical c_AR-A can be determined by quantifying AR-regulated transcripts under intact androgen/AR signaling conditions, and there are several such AR-regulated gene lists [22, 23, 54, 62, 63] (Fig. S2A-B). We validated the c_AR-A list based on their enrichment in prostatic epithelium differentiation, correlation of individual gene expression with c_AR-A signatures in clinical datasets, and overall consistency in correlation among the AR-A scores (Fig. S2B-D). Given that Bluemn's c_AR-A score [54] correlated well with other scores (Fig. S2E-G) and the 10 genes in this signature consistently represented AR targets in multiple clinical datasets (Fig. S2D; Table S2), we decided to use this AR-regulated gene list for our c_AR-A quantification.

Normal prostate epithelium shows a negative correlation between Stemness and c_AR-A.

The normal human prostate (NHP) comprises 2 major epithelial types: basal and luminal cells (Fig. S3A). We annotated two studies that profiled FACS-purified NHP luminal and basal cell populations [19, 21] and observed that the luminal cell population (Trop2$^+$CD49f^{lo}) possessed higher *AR* mRNA levels and c_AR-A but lower Stemness compared to basal cells (Trop2$^+$CD49f^{hi}) and, in both datasets, c_AR-A negatively correlated with Stemness (Fig. S3B-C). These results support that the NHP basal cell compartment harbors primitive stem cells [7, 19, 21, 64, 65] and that c_AR-A measures the level of prostate epithelial differentiation.

Pri-PCa exhibits concordantly increased Stemness and c_AR-A, and neoadjuvant ADT (nADT) decreases both Stemness and c_AR-A.

In analyzing c_AR-A and the Stemness in matched pairs of prostate tumor (T) and normal (N; tumor-adjacent benign) tissues in the TCGA-PRAD [22] (n=51 pairs), Wyatt 2014 [31] (n=12 pairs), and Long 2020 [28] (n=10 pairs) cohorts, we observed concordantly increased c_AR-A and Stemness (Fig. 1A-C).

Accompanying elevated c_AR-A, *AR* mRNA levels were also increased in Pri-PCa compared to benign

tissue (Fig. 1A-C; note that increase in *AR* mRNA levels in the Long 2020 cohort approached statistical

significance). The paired T/N comparisons (Fig. 1A-C) suggest that early PCa growth is characterized by

concordantly increased Stemness and c_AR-A. To test whether c_AR-A might causally drive increased

Stemness during early prostate tumorigenesis, we investigated 4 PCa nADT (i.e., ~2-6 months of ADT

before prostatectomy or radiation) cohorts [26-28]. In the first 3 cohorts with matched pairs of pre- and

post-nADT samples (from same patients), nADT concordantly downregulated c_AR-A (without decreasing

AR mRNA levels) as well as the Stemness (Fig. 1D-F). In the Nastiuk cohort with non-paired post-nADT

and no-nADT samples (i.e., from different patients but matched for ages and tumor grades and stages),

nADT increased *AR* mRNA levels (Fig. S4A) but reduced both c_AR-A and Stemness (Fig. S4B-C).

Pri-PCa progression is accompanied by reduced c_AR-A but continually increasing Stemness.

We next assessed the dynamic changes of Stemness and c_AR-A during *spontaneous* (i.e., therapy-free)

Pri-PCa progression (Fig. 2). To this end, we sorted out treatment-naïve tumors in TCGA-PRAD by

excluding samples from patients who received adjuvant (post-surgery) hormone therapy (i.e., Pri-PCa/ADT

or Tx; n=70) (Fig. 2A) and grouped the Pri-PCa samples according to increasing GS (Fig. 2B-D). When

compared with the 52 benign (N) samples, all the four GS groups from Pri-PCa (GS6, GS7, GS8, and

GS9/10 combined) showed higher c_AR-A and Stemness (Fig. 2C-D), consistent with the results in

pairwise T/N comparisons (Fig. 1A-C). However, when compared to GS6 PCa, the three higher GS groups

showed increasing *AR* mRNA levels (Fig. 2B) but decreasing c_AR-A (Fig. 2C) and increasing Stemness

(Fig. 2D). Jonckheere-Terpstra's (J-T) trend test validated a gradual reduction in canonical AR signaling

but an increasing trend of Stemness with Pri-PCa progression (Fig. 2C-D). Notably, although we observed

a modest positive correlation between c_AR-A and Stemness in pooled Pri-PCa samples (Pearson's

r=0.27; Fig. 2E), this positive correlation gradually diminished with PCa progression when we categorized

the samples by tumor grade (Fig. 2F). The linear regression analysis confirmed that the interaction

between Stemness and c_AR-A significantly depended on tumor grade (*P*=0.0003), with a linear decrease

in the slope of the correlation as GS increased (Fig. 2G).

Collectively, these results indicate that, in contrast to early tumorigenesis, *spontaneous PCa*

progression (i.e., with increasing GS and tumor grade) is marked by a divergence between oncogenic

Stemness and pro-differentiation c_AR-A.

Therapies and metastatic progression drive further divergence between attenuated c_AR-A and

increased Stemness.

Next, we asked how clinical treatment and metastatic progression may impact the Stemness and c_AR-A

by querying untreated Pri-PCa and Pri-PCa/ADT from TCGA and mCRPC in SU2C [10] (Fig. 3A-C). c_AR-

A was elevated in Pri-PCa compared to adjacent benign tissue (N) but reduced in more aggressive Pri-

PCa/ADT samples, while the Stemness, in contrast, continually and persistently increased from N → Pri-

PCa → Pri-PCa/ADT (Fig. 3B-C). Strikingly, mCRPC, despite markedly upregulating *AR* mRNA (Fig. 3A),

showed the lowest c_AR-A but highest Stemness (Fig. 3B-C), *indicating a shift from a positive correlation*

between c_*AR-A and Stemness in Pri-PCa to a negative association in mCRPC* (Fig. 3D).

By employing normalized RNAseq data from the Bolis 2021 PCa transcriptome atlas [36], which

included normal prostate specimens (n = 174), Pri-PCa (n = 714) and mCRPC (n = 335), we tracked the

Stemness and c_AR-A across the PCa spectrum (Fig. 3E). c_AR-A increased from benign to Pri-PCa but

declined in Pri-PCa/ADT and continued to decrease in mCRPC, reaching its lowest in mCRPC-NE [41] as

supported by J-T test (Fig. 3E). In contrast, the Stemness exhibited a continually increasing trajectory

across the PCa spectrum encompassing Normal/Benign → treatment-naïve Pri-PCa → Pri-PCa/ADT →

(m)CRPC (*P*<0.0001, J-T Trend test; Fig. 3F; Fig. S5A). Notably, the 3 subtypes of mCRPC, i.e., AR-

positive (ARPC), CRPC-NEPC and AR⁻/NE⁻ double-negative PCa (DNPC) all showed higher Stemness

than Pri-PCa and displayed increasing Stemness among the 3 subtypes (Fig. S5B). Unexpectedly, tumor-

adjacent benign prostate tissues showed much higher Stemness than normal prostate in the Genotype-

Tissue Expression Project (GTEx) [18] (Fig. 3F; Fig. S5A), which were all obtained from cancer-free organ

donors. This surprising finding suggests that the transcriptomes of adjacent benign tissues have apparently

skewed towards those of cancer samples, consistent with previous observations that adjacent benign

tissues represent an intermediate state between healthy and tumor tissues [66]. Also of interest, the

Cancer Cell Line Encyclopedia (CCLE) [50, 67] cell lines including PCa cell lines, and PCa-derived PDX

[46] and xenografts (XG) [51] exhibited the highest Stemness (Fig. 3F; Fig. S5A), supporting that cancer

cell lines and xenografts are clonally derived from and highly enriched in cancer stem cells (CSCs).

As in our early dissection of the relationship between c_AR-A and Stemness during spontaneous Pri-

PCa progression (Fig. 2F-G), analysis of the Bolis 2021 PCa transcriptome atlas [36] revealed a similar

change from a positive correlation between c_AR-A and Stemness in Pri-PCa (blue line; Pearson's r=0.32,

P<0.0001; Fig. 3G) to a negative correlation between the two in mCRPC (green line; Pearson's r=-0.15,

P=0.005; Fig. 3G). We further extended our Stemness and c_AR-A interrogation to include microarray-

derived transcriptomic datasets [35, 47], allowing us to access data from PCa cohorts generated before

the next-generation sequencing (NGS) era. Analyzing the GRID database of over 82,000 prospectively

collected biopsy samples of localized PCa from clinical use of the Veracyte Decipher test [35], we

systematically quantified the Stemness across the NCCN Risk Groups and observed increasing Stemness

along the NCCN Risk trajectory (Fig. 3H). Likewise, in the Taylor dataset [47], we observed that c_AR-A

was the highest in Pri-PCa but significantly decreased in metastatic PCa (mPCa) (Fig. 3I) while the

Stemness increased progressively from benign to Pri-PCa and reached the highest levels in mPCa (Fig.

3J). Linear regression analysis confirmed a gradual loss of positive correlation between c_AR-A and

Stemness during PCa progression, as illustrated by distinct regression lines for each stage (Fig. 3K-M).

Finally, we analyzed the changes of Stemness and c_AR-A in genetically engineered mouse models
(GEMMs) of PCa with increasing aggressiveness due to individual or combined deletion of 3 tumor
suppressor genes, *Pten*, *Rb1* and *Trp53* [49] (Fig. S5C-H). Briefly, *Pten$^{-/-}$* single knockout (SKO) prostate
tumors develop around 9 weeks, and mice rarely develop metastasis with a median lifespan of 48 weeks.
In contrast, the *Pten$^{-/-}$;Rb1$^{-/-}$* double knockout (DKO) mice develop highly metastatic PCa that shortens
median survival to ~38 weeks whereas the triple KO (TKO; *Pten$^{-/-}$;Rb1$^{-/-}$;Trp53$^{-/-}$*) tumors are exclusively
AR$^-$ NEPC and castration-resistant *de novo* with high metastatic rate and lifespan of ~16 weeks [49]. We
found that the c_AR-A was the highest in SKO tumors but much reduced in aggressive DKO and TKO
tumors (Fig. S5C). In contrast, Stemness was the lowest in SKO but significantly increased in DKO and
TKO (Fig. S5D). Correlation analyses revealed a positive correlation between c_AR-A and Stemness in
SKO that turned negative in both DKO and TKO tumors (Fig. S5E-H).

The above results, collectively, indicate that *hormone therapy and metastatic progression further*
drive marked increases in Stemness with concomitant decreases in c_AR-A.

The general Stemness score is prognostic of poor survival in PCa patients.
We investigated global Stemness and its prognostic significance, and observed that high Stemness
consistently correlated with worse patient survival across various cohorts including the Spratt 2017 [32]
(Fig. 4A), Tosoian 2020 [33] (Fig. 4B), CHAARTED 2021 [34] (Fig. 4C), and the mCRPC (SU2C 2019 [48];
Fig. S6A-B) as well as Taylor 2010 [47] (Fig. S6C-D). Notably, the CHAARTED cohorts displayed the
highest mean Stemness compared to Tosoian and Spratt cohorts, and the highest median Decipher
Prostate Genomic Classifier [32-34] among the three cohorts (Fig. 4D). Interestingly, like high Stemness,
low c_AR-A was correlated with poor patient survival in the Taylor dataset (Fig. S6E).

Stemness-high PCa are associated with aggressive molecular subtypes and a new 12-gene PCa-
Stem signature prognosticates poor patient survival.
To identify key determinants of Stemness and explore differences between tumors with high versus low
Stemness scores, we stratified Pri-PCa (TCGA-PRAD) and mCRPC (SU2C 2019) samples separately
based on Stemness scores (Fig. 5A). Differential gene expression (DEG) analyses revealed significant
differences between the top 33% (Stemness-high) and the bottom 33% (Stemness-low) PCa samples in
both treatment-naïve Pri-PCa (Fig. 5B) and treatment-failed mCRPC (Fig. 5C), resulting in 12 shared
genes that we considered as the "**PCa-Stem signature**" (Fig. 5D; Table S2; see Methods).

Gene set enrichment analysis (GSEA) revealed that Stemness-high PCa samples were enriched in
gene sets associated with embryonic stem cells (ESC) as well as aggressive cancer phenotypes such as
undifferentiated cancer and metastasis in both Pri-PCa and mCRPC whereas Stemness-low PCa samples
were enriched in gene signatures linked to lower aggressiveness and inflammatory pathways (Fig. 5E-F).
Additionally, hallmark pathways such as E2F targets, MYC targets, mTORC1 signaling, and DNA repair

were upregulated in Stemness-high PCa (Fig. 5F), while TGF-β signaling, TNF-α signaling, and IFN-γ

responses were prominent in Stemness-low PCa (Fig. 5E).

The aggressive PAM50-LumB molecular subtype [68-70] was significantly more prevalent in

Stemness-high PCa, accounting for 74% in Pri-PCa (compared to 15% in Stemness-low PCa; Fig. 5G)

and 43% in mCRPC (compared to 4% in Stemness-low PCa; Fig. 5H). The PAM50-Basal subtype [68, 69]

was also increased in Stemness-high mCRPC but not in Pri-PCa (Fig. 5G-H), aligning with the

characteristics of mCRPC, which involves lineage plasticity and acquisition of basal, mesenchymal, neural

and stem-like phenotypes when developing ARPI resistance [7, 70, 71]. The PCS1 subtype [72, 73], known

for its association with ADT resistance and the highest risk of progression to advanced disease in

comparison with PCS2 or PCS3, was enriched in both Stemness-high Pri-PCa and mCRPC whereas

PCS3 signature was enriched in Stemness-low Pri-PCa and mCRPC (Fig. 5I-L). Moreover, in PCa

subtypes epigenetically stratified by chromatin accessibility [74], Stemness-high samples remained largely

AR-dependent in Pri-PCa (Fig. 5M) but transitioned to AR-independent NE subtype in mCRPC (Fig. 5N).

Of interest, Stemness-high PCa was characterized by high proliferation in both Pri-PCa and mCRPC as

evidenced by their enrichment in a 31-gene cell-cycle progression signature [70] (Fig. 5O-P; Table S5).

Finally, we examined the association between Stemness and a signature of lineage plasticity risk in

mCRPC after Enza treatment [12] and found that Stemness-high tumors was at risk for this virulent form

of treatment resistance (Fig. 5Q-R).

To further assess the clinical relevance of Stemness, we analyzed the prognostic impact of our newly

developed **12-gene PCa-Stem signature** (Fig. 5D). We observed that higher PCa-Stem signature

correlated with worse patient survival in both Pri-PCa ($P<0.0001$, log-rank; Fig. 5S-T) and mCRPC

($P<0.0001$, log-rank; Fig. 5U-V) patients. Multivariate analysis, adjusted for clinicopathologic parameters

such as age, GS and stage, showed that patients with high PCa-Stem signature had significantly worse

independent prognosis compared to those with low PCa-Stem signature. This was demonstrated by worse

progression-free survival (PFS) in Pri-PCa (multivariable-adjusted HR=1.636 (1.014 – 2.64), P=0.0438;

Fig. 5T) and overall survival (OS) in mCRPC (multivariable-adjusted HR=4.712 (2.011 – 11.04), P<0.001;

Fig. 5V), respectively. Furthermore, the PCa-Stem signature steadily and continually increased across the

PCa evolutionary spectrum and correlated with PCa disease progression scores as supported by trajectory

inference analysis of the Bolis PCa transcriptome atlas [36] (Pearson's r=0.72; Fig. S7A-B). Strikingly,

gene expression analysis revealed that 11 of the 12 genes (except *KLK12*) in the PCa-Stem signature

significantly correlated with the PCa disease progression (Fig. S7C). In contrast, among the genes

commonly downregulated in Stemness-high PCa samples in both Pri-PCa and mCRPC (Table S3), some

(e.g., *PTGDS*, *SPARCL1*, *CLU*, *GJA1* and *S100A4*) were involved in regulating prostate-specific glandular

structures and luminal functions while others (e.g., *FBLN1*, *SFRP1*, *IGFBP6*, *GAS1* and *TIMP2*) played

general roles in epithelial differentiation (Fig. S7D).

We further compared the 12-gene PCa-Stem signature with the general Stemness Score using ROC
analysis and observed that PCa-Stem signature demonstrated enhanced discriminative power in
distinguishing high-grade (GS > 7) from low-grade (GS ≤ 7) primary tumors (AUC = 0.662; Fig. S7E) and
mCRPC versus treatment-naïve Pri-PCa (AUC = 0.865; Fig. S7F). These findings indicate that while the
global Stemness Score effectively captures tumor dedifferentiation and plasticity, the PCa-Stem signature
provides added PCa–specific sensitivity for identifying aggressive and advanced disease states.

Finally, we employed siRNAs to knock down 3 representative genes of the PCa-Stem signature, i.e.,
HMMR (encoding hyaluronan-mediated motility receptor), *AURKB* (encoding Aurora Kinase B), and *PBK*
(encoding PDZ-binding kinase) (Fig. S8A) and analyzed their impact on the aggressiveness and stemness
(Fig. S8B–F) in androgen-independent LAPC4 (LAPC4-AI) cells [51, 61]. The results revealed that
knockdown of all 3 genes inhibited cell invasion (Fig. S8B–C) and single cell-based colony formation (Fig.
S8D) whereas knockdown of AURKB and PBK, two mitotic kinases, significantly inhibited the
establishment of live, stemness-associated organoids (Fig. S8E–F).

Taken together, these findings indicate that *PCa with high Stemness exhibit increased*
aggressiveness, lineage plasticity, and therapy resistance, and is associated with poor patient survival.
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Stemness-high PCa have high tumor mutation burden (TMB) and unique genomic features.
To explore potential genomic differences between Stemness-high and Stemness-low prostate tumors, we
first compared global genomic instability and found that mCRPC exhibited a greater fraction of altered
genome (Fig. 6A) and higher TMB (Fig. 6B) than Pri-PCa. Furthermore, within both Pri-PCa and mCRPC,
the Stemness-high tumors displayed a significantly higher fraction of altered genome (Fig. 6A) and TMB
(Fig. 6B) than Stemness-low tumors, despite no differences in patient age between the groups (Fig. 6C).
These findings support a strong association between oncogenic Stemness and genomic instability. We
next examined the distribution of recurrent cancer-associated alterations in Stemness-defined subgroups
across disease states (Fig. 6D–E). In treatment-naïve Pri-PCa, Stemness-high tumors were enriched for
tumor-suppressor lesions (including *PTEN* and *RB1* deletions (DEL) and *TP53* mutations (MUT)), and
alterations in known PCa drivers such as *SPOP* and *FOXA1* MUT and focal *MYC* amplification (AMP) (Fig.
6D). In contrast, the Stemness-high mCRPC exhibited markedly increased frequencies of therapy-selected
drivers such as AR alterations (*AR* MUT, *AR* AMP; Fig. 6F). Furthermore, PI3K-pathway lesions, including
PIK3C2B AMP (Fig. 6E), were enriched in Stemness-high mCRPC in contrast to their low prevalence in
Pri-PCa. Several additional amplified loci—including *ELK4*, *RECQL4*, *SLC45A3*, and *ELOC*—were present
in both disease states but showed substantially higher frequencies in mCRPC (Fig. 6D-E). Notably, copy-
number gain of *SLC45A3*, an androgen-regulated gene, was enriched in Stemness-high tumors and
increased in frequency in mCRPC (Fig. 6E). These results support selective amplification of prostate
lineage–associated loci under ARPI treatment and during progression to mCRPC.

Globally, both Pri-PCa and mCRPC exhibited mutations in more than a dozen genes although most
of these alterations were <10% (Fig. S9A; green symbols), consistent with reports that PCa is genomically
heterogeneous with a broad spectrum of genomic alternations of low penetrance [75, 76]. On the other
hand, homozygous deletion (HOMDEL) events, particularly, loss of *PTEN* and *RB1*, occurred frequently in
both Pri-PCa and mCRPC (Fig. S9A; blue symbols) whereas AMP events in oncogenes such as *MYC*
were more prevalent in mCRPC (Fig. S9A; red symbols). Nevertheless, *PTEN* and *RB1* HOMDEL
represented among the most prevalent alterations in early-stage (GS6) PCa (Fig. S9B-D). Analysis of
genetic alterations across the spectrum of PCa progression revealed that among the 3 tumor suppressors
(*RB1, PTEN* and *TP53*), while *RB1* HOMDEL remained relatively constant at 13%, 6%, 10% and 10% in
low-grade (GS6), high-grade (GS9/10), Pri-PCa/ADT and mCRPC, respectively, *PTEN* HOMDEL (9%,
23%, 30% and 26%) and *TP53* MUT (0%, 21%, 27% and 37%) continued to increase along this
progression (Fig. S9B-D). Among the 3 oncogenic events analyzed, while high levels of *TMPRSS2* fusions
(~40%) remained unchanged from low-grade Pri-PCa to mCRPC, *MYC* (2%, 12%, 19% and 24%) and *AR*
(0%, 1%, 6% and 49%) AMP continued to increase along the progression trajectory (Fig. S9B-C, E). In
fact, prevalent *AR* MUT (11%) were observed only in the most aggressive and Stemness-highest mCRPC
(Fig. S9B-C). Analyzing these major genomic alterations in association with PCa Stemness, we observed
that *RB1* HOMDEL, *FOXA1* (together with *SPOP*, *IDH1*, and *CHD1*) MUT, and especially *MYC* AMP were
significantly associated with increased Stemness in Pri-PCa (Fig. S9F) whereas in mCRPC, only *RB1*
HOMDEL exhibited a statistically significant association with higher Stemness (Fig. S9G).

MYC drives Stemness during PCa progression.
The above studies (Fig. 6; Fig. S9) provided genomic correlates of PCa stemness. *In following studies, we*
explored 1) MYC signaling, 2) noncanonical (i.e., castration-induced) AR activity, and 3) tumor suppressor
loss as potential drivers of persistently increasing Stemness during PCa progression. We showed that
during early PCa growth, increased c_AR-A may drive elevated Stemness (Fig. 1D-F); however, treatment-
naïve Pri-PCa displayed continually increasing Stemness but decreasing c_AR-A (Fig. 2). As *AR* AMP and
MUT are exclusively treatment-induced and there were virtually no *AR* genomic alterations in treatment-
naïve Pri-PCa (Fig. S9B-C, E), what could be driving high Stemness during Pri-PCa progression? We
found that Stemness-high Pri-PCa, compared to Stemness-low Pri-PCa, were enriched in MSigDB
Hallmark MYC_TARGETS (Fig. 5F) and had more prevalent *MYC* AMP (Fig. 6D and 6F). High-grade
(GS9/10) Pri-PCa also had more *MYC* AMP events than low-grade (GS6) Pri-PCa, and in fact, *MYC* AMP
continued to increase along the PCa continuum (Fig. S9B-C, E) and was associated with increased
Stemness in Pri-PCa (Fig. S9F). These observations led us to hypothesize that MYC may represent a
critical Stemness driver during both spontaneous Pri-PCa progression and mCRPC transition. To test this
hypothesis, we quantified MYC signaling activity [55] (**MYC-sig**; See Methods and Table S2 for gene
signature information) across the PCa progression spectrum. We observed that: 1) both *MYC* mRNA and

MYC-sig increased in Pri-PCa compared to matched benign samples (Fig. 7A-B); 2) MYC-sig continued to go up during Pri-PCa progression (Fig. 7C); 3) unlike nADT-induced concomitant decline in both c_AR-A and Stemness (Fig. 1D-F; Fig. S4), nADT showed no discernible effect on MYC-sig (Fig. S10A-D); and 4) MYC-sig continued to increase across the disease spectrum with mCRPC exhibiting the highest MYC activity (Fig. 7D-E) and with MYC-sig positively correlated with the Stemness (Fig. 7F-H).

To further test whether MYC functionally promotes stemness, we examined an independent RNA-seq dataset generated in LNCaP cells with MYC knockdown (KD) (GSE135942) [52]. Silencing MYC using two ORF-targeting shMYC constructs led to a marked reduction in MYC-sig (Fig. S10E), confirming effective suppression of the MYC transcriptional output. Importantly, MYC-KD significantly reduced the Stemness score (Fig. S10F), thus supporting a direct role for MYC in maintaining the stem-like transcriptional state. Strikingly, MYC-KD also increased c_AR-A (Fig. S10G), consistent with the reported inverse relationship between pro-differentiation AR signaling and oncogenic MYC activity [77, 78].

These results, together, support MYC as a Stemness driver during PCa progression.

Castration-reprogrammed AR activity (cr_AR-A) significantly rises and aligns with stem-like programs during PCa progression.

Having established MYC as a driver of Stemness during PCa progression, we next asked how therapeutic pressure remodels AR signaling to sustain or amplify the stem-like programs. Androgen deprivation and AR-pathway inhibition remodel the AR cistrome and redirect AR toward non-canonical survival/plasticity programs [14-17]. To capture this shift, we derived the **cr_AR-A** by integrating AR and H3K27ac ChIP-seq data from Pomerantz *et al.* (GSE130408; [16]) with mRNA profiling data from Taylor *et al.* (GSE21032; [47]) (Fig. S11A; Table S2). We intersected genes that exhibited CRPC-enriched AR binding, enhancer activation, and transcriptional up-regulation to obtain a 63-gene set representing AR-regulated outputs preferentially active in mCRPC (Fig. S11A; Table S6).

As expected, cr_AR-A increased sharply in androgen-independent (AI) versus androgen-dependent (AD) LNCaP xenografts, whereas the canonical AR program (c_AR-A) declined (Fig. S11B). Genome-browser views confirmed that enhancer-level reprogramming [16] for *AR*, *UBE2C*, *CDK1*, *MELK*, *BIRC5*, and many other oncogenic and proliferation-associated genes displayed stronger AR and H3K27ac peaks in CRPC than in Pri-PCa (Fig. S11C; data not shown), while *CNN1* and *TNS1* showed the opposite pattern (Fig. S11D). To further benchmark the cr_AR-A, we compared it with the Wang "**cr_AR-Growth**" 8-gene set [14] curated from AR-bound, enhancer-validated and AI LNCaP-abl growth drivers (e.g., *UBE2C*, *CDK1*, *CDC20*) (Fig. S11E). Despite distinct derivations, the two signatures, with only one overlapped gene (i.e., *CDK1*), were highly concordant (r = 0.93, *P* < 0.0001; Fig. S11F–H) and both increased from normal/benign to Pri-PCa to mCRPC (Fig. 8A; S11I), underscoring a shared transcriptional logic linking therapy-reprogrammed AR signaling with stemness-associated proliferative activity.

804   Together, these data reveal a state-dependent bifurcation of AR programs: the c_AR-A tracks
805 differentiation in androgen-intact contexts whereas the cr_AR-A couples AR signaling to stem-like
806 aggressiveness under therapeutic pressure, establishing cr_AR-A as a transcriptomic bridge between AR
807 adaptation and PCa evolution.
808

RB1 and PTEN losses differentially associate with Stemness along the disease continuum.
Finally, we examined whether transcriptomic signatures associated with tumor suppressor losses may also
reinforce therapy-driven Stemness. Prior genomic analyses (Fig. 6; Fig. S9) showed that, in Pri-PCa, *RB1*
DEL, *FOXA1* MUT, and especially *MYC* AMP associate with elevated Stemness whereas *PTEN* loss is
prevalent early and persists into advanced disease and that in mCRPC, *RB1* DEL significantly correlated
with high Stemness. To further assess these trends transcriptionally, we quantified the *RB1*-loss and
PTEN-loss gene signatures described by Ertel *et al.* [56] and Liu *et al.* [57], respectively. We found that
the *RB1*-loss signature increased progressively from benign to Pri-PCa to mCRPC (Fig. 8B) whereas the
PTEN-loss signature rose sharply from normal prostate to Pri-PCa but plateaued thereafter, peaking in
aggressive Pri-PCa/ADT and remaining high in mCRPC (Fig. 8C). These analyses suggest that *PTEN* loss
might function as an early and persistent driver of spontaneous progression whereas *RB1* loss represents
a more prominent contributor to Stemness and proliferative reprogramming in therapy-resistant disease.
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Convergence of cr_AR-A, RB1-loss, and MYC signaling with PCa-Stem and global Stemness score
Building on the above analyses showing progressive increase in cr_AR-A (Fig. 8A) and distinct dynamics
of *RB1*- and *PTEN*-loss signatures (Fig. 8B-C), we next examined how these programs relate quantitatively
to the general Stemness score and PCa-Stem signature (Fig. 8D-P). Consistent with its progressive rise
across disease states, the PCa-Stem score increased from normal prostate and Pri-PCa to mCRPC (Fig.
8D), broadly tracking the trajectory of cr_AR-A and *RB1*-loss (Fig. 8A-B). Across the Bolis integrated cohort
(n = 1,223), the cr_AR-A correlated strongly with both general Stemness (Fig. 8E; see Fig. 8L for symbol
definitions) and the PCa-Stem (Fig. 8I). In parallel, the LNCaP-abl-derived cr_AR-Growth_Wang signature
also correlated with the two Stemness indices (Fig. S11J-K). Similarly, the *RB1*-loss signature correlated
with the global Stemness (r = 0.74, *P* < 0.0001; Fig. 8F) and even more strongly with PCa-Stem (r = 0.91,
P < 0.0001; Fig. 8J) whereas the *PTEN*-loss signature exhibited a more modest association with the two
Stemness indices (Fig. 8G, K).

We next integrated MYC signaling into this framework. Consistent with our earlier MYC analyses
(Fig. 7), MYC-sig increased along the PCa evolution continuum in the Bolis integrated PCa cohort (Fig.
S11M) and correlated strongly with both the global Stemness (Fig. S11N) and PCa-Stem (Fig. S11O). Of
interest, despite this strong transcriptional convergence, the MYC-sig and PCa-Stem showed no direct
gene overlap (Fig. S11P), indicative of their convergence at the level of coordinated downstream
proliferative programs rather than shared gene membership.

Across the same cohort, PCa-Stem displayed the strongest positive correlation with the general
Stemness (Fig. 8H), consistent with the PCa-Stem being derived from Stemness-stratified DEGs (Fig. 5B-
D). Gene-overlap analyses further supported convergence among these programs. The PCa-Stem shared
MELK with the 63-gene cr_AR-A signature (Fig. 8M) and shared *UBE2C* with the 8-gene cr_AR-
Growth_Wang (Fig. S11L). PCa-Stem also showed broader overlap with the *RB1*-loss signature (Fig. 8N),
including *AURKB*, *BIRC5*, *CENPA*, *DLGAP5*, and *NEK2*, genes largely involved in cell-cycle progression
and mitotic regulation. In contrast, no direct gene overlap was observed between *PTEN*-loss and PCa-
Stem (Fig. 8O). When signatures were integrated (Fig. 8P), the proliferative core was most evident
between cr_AR-A and the *RB1*-loss signature (i.e., *ANLN*, *RRM2*, *MCM4*, *TYMS*, *PLK1*, *CCNE2*, and
CCNB1), supporting convergent selection for cell-cycle machinery characteristic of stem-like, self-
renewing tumor cells.

Discussion

The current project was undertaken to quantitatively co-analyze the global changes of and interrelationship between cancer stemness and canonical AR signaling activity during PCa evolution. By employing gene expression-based general Stemness and c_AR-A signature scores and through developing a new 12-gene PCa-Stem signature, we show that while differentiation-associated c_AR-A steadily declines in the PCa continuum, progressively increasing Stemness quantitatively tracks PCa aggressiveness, plasticity and progression, and represents a poor prognosticator for patient outcomes. Stemness-high PCa possess unique genomic features including elevated TMBs and are transcriptionally enriched in aggressive molecular subtypes such as PAM50-LumB [68-70] and PCS1 [72, 73]. Our data further suggest that elevated Stemness in early PCa is causally associated with increased c_AR-A while castration-reprogrammed AR-A (cr_AR-A), MYC activation and tumor suppressor alterations (especially *RB1* loss) likely propagate the markedly increased Stemness observed in mCRPC (where c_AR-A is suppressed).

Early studies reported that AR-regulated genes decline in high-grade Pri-PCa [79, 80] and inhibition of AR signaling promotes stem-like phenotypes [8, 51, 81, 82]. However, global pro-differentiation AR activity and oncogenic stemness have not been systematically and quantitatively co-analyzed across the PCa continuum. By integrating 27 transcriptomic datasets encompassing normal prostate, tumor-adjacent benign tissues, treatment-naïve Pri-PCa, nADT-treated tumors, (m)CRPC subtypes and model systems, we demonstrate that PCa progression is accompanied by continual increase in Stemness and progressive decline in canonical c_AR-A, with the two inversely correlated (Fig. S12). Importantly, both the global Stemness and PCa-Stem signature prognosticate poor patient survival, establishing Stemness as a quantifiable and clinically relevant indicator of PCa progression. To our knowledge, this is the first comprehensive study to simultaneously quantify the oncogenic stemness and c_AR-A across the PCa continuum. Our pan-cohort approach enables signature validation in rare archival biopsy samples and cross-platform integration — a translational advantage not addressed by other studies.

The normal prostatic epithelium consists of AR$^+$ secretory luminal cells and AR$^-$ basal cells. We find that NHP luminal cells have higher c_AR-A whereas basal cells display higher Stemness, consistent with earlier findings from our lab [21] and others [19, 20, 64, 65] showing stem/progenitor cell properties within the basal compartment. Compared to adjacent benign tissue, Pri-PCa exhibit elevated Stemness, which is associated with and likely driven by increased c_AR-A. Early genomic alterations including *PTEN* and *RB1* loss in GS6 tumors (9% and 13%, respectively; Fig. S9D) may further contribute to this initial rise in Stemness. Strikingly, tumor-adjacent benign tissues, the so-called 'normal' tissues used in most comparative studies, displayed higher Stemness than the true normal prostate obtained from cancer-free organ donors in GTEx, indicating that the commonly used "benign" controls may already exhibit transcriptional shifts toward cancer-associated programs.

Our studies suggest that the drivers of increased Stemness may differ between spontaneous Pri-
PCa progression and mCRPC transition. In treatment-naïve Pri-PCa, where tumor progression is
characterized by a gradual decline in c_AR-A while Stemness shows a continual elevation (Fig. S12),
increased Stemness may likely be driven by oncogenic events such as *MYC* amplification and activation,
with additional contributions from early loss of tumor-suppressors such as *PTEN* and *RB1*. On the other
hand, in mCRPC, which develops under sustained therapeutic pressure from long-term ADT and ARPI
treatment, the c_AR-A is further suppressed while Stemness reaches its highest levels, This paradoxical
increase in Stemness despite reduced c_AR-A coincides with emergence of the cr_AR-A, which is
enriched for cell-cycle and proliferation-associated genes and correlates tightly with *RB1* loss and MYC
activation (Fig. S12). Thus, unlike in Pri-PCa, the high Stemness in mCRPC appears to be reinforced by
AR functional reprogramming that cooperates with genomic instability to sustain aggressive, proliferative
and therapy-resistant stem-like states.

What biological correlates do our Stemness metrics measure? ***First***, it measures transcriptional
features and relative abundance of stem cells and CSCs. Therefore, the NHP basal/stem cells display
higher Stemness than luminal cells (consistent with literature [19, 21, 64, 65]); ARPI treatment, while
shutting down the c_AR-A, enriches CSCs [7, 51, 81, 82] and upregulates Stemness (this study); and PCa
cell lines, xenografts and PDX, known to be clonally derived from cancer stem/progenitor cells,
demonstrate the highest Stemness. ***Second***, it measures cellular and lineage plasticity [8] induced by
treatment and genetic alterations. Thus, mCRPC, which harbor more abundant treatment-reprogrammed
AR$^{-/lo}$ cells and PCa cells with stem-like features or in an AR-indifferent state [8, 12, 13, 23, 46, 54, 71, 74],
manifests the highest Stemness. Our analysis further substantiates the aggressive nature of (AR$^{-/lo}$) CRPC-
NEPC and DNPC compared to ARPC, as evidenced by their elevated Stemness scores (Fig. S5B). This
suggests a shift in the phenotypic landscape of mCRPC towards more stem-like and aggressive forms.
Likewise, aggressive DKO and TKO murine prostate tumors have undergone lineage transformation and
exhibit higher Stemness than indolent SKO tumors. ***Third***, the Stemness metrics likely report the high
proliferative status of advanced PCa and mCRPC, as Pri-PCa and mCRPC with high global Stemness
both are enriched in "Cell-cycle progression" signature (Fig. 5O-P) while the majority of PCa-Stem genes
encode mitotic regulators (Fig. 5D). ***Finally***, the Stemness metrics quantitatively measure PCa
aggressiveness as high Stemness correlates not only with more advanced and aggressive stages of PCa
but also with aggressive molecular subtypes and poor survival.

A key implication of our analysis is that stemness in PCa represents a dynamic cell-state continuum
rather than a fixed CSC population. Studies in normal adult tissues have demonstrated that regenerative
capacity is maintained through the coexistence of quiescent reserve stem cells and fast-cycling active stem
cells, with cells reversibly transitioning between these states in response to stress or injury [83]. Applying
this framework to PCa, our data suggest that both the general Stemness Index and PCa-Stem signature
preferentially reflect a fast-cycling, proliferation-enriched stem-like state. This framework explains why

Stemness progressively increases despite declining c_AR-A associated with cellular maturation:
therapeutic pressure and accumulating genomic alterations select for proliferating and plastic cell states
rather than a static CSC compartment. Our functional validation provides support for this proliferation-
driven cancer stemness - depletion of mitotic kinases *AURKB* and *PBK* markedly suppressed invasion,
clonogenic growth, and 3D organoid viability (Fig. S8). Notably, this proliferative stem-like state mirrors
transcriptional programs captured by cr_AR-A and cr_AR-growth signatures, both enriched for cell-cycle
genes and strongly correlated with global Stemness and PCa-Stem scores. Together, these data support
convergence on a fast-cycling, therapy-adapted stem-like state in aggressive PCa, consistent with recently
reported convergence of CSC states across tumor types [84].

Of clinical significance, both the general Stemness Index and the 12-gene PCa-Stem signature
correlate with poor patient survival, suggesting the possibility of developing the Stemness metrics into a
predictive biomarker to distinguish aggressive from indolent primary tumors and a prognostic indicator of
unfavorable clinical outcomes in mCRPC patients. Notably, 11 of the 12 PCa-Stem genes correlate with
PCa progression (Fig. S7C), implicating their individual contributions to the increased Stemness in
advanced Pri-PCa and mCRPC. Analysis using data from The Human Protein Atlas (www.proteinatlas.org)
reveals that these 11 genes are also recognized as unfavorable prognostic markers in PCa and several
other cancers (Liu X and Tang, unpublished), raising the potential utility of the PCa-Stem signature as a
prognostic marker not only for PCa but also for other malignancies. Coupled with earlier studies linking
increased Stemness with aggressive breast and brain cancer subtypes [6], our findings herein underscore
the increased Stemness as a 'universal' and fundamental characteristic of cancer progression and
aggressiveness. Beyond its ability to track tumor dedifferentiation and lineage plasticity across the PCa
continuum, the PCa-Stem signature demonstrated improved disease-focused classification compared with
the pan-cancer Stemness Index (Fig. S7E-F). This does not diminish the biological value of the general
Stemness Index; rather, PCa-Stem complements it by providing increased PCa–specific sensitivity.

In recent years, several studies [36, 85-88] have proposed stemness-based PCa classifications or
prognostic models using either single-cell RNA-seq (scRNA-seq), bulk RNA-seq or integrative analyses.
These studies reinforce the biological relevance of stemness and highlight oncogenic pathways such as
MYC activation, *RB1*/*PTEN* loss, and lineage plasticity in PCa progression. However, to our knowledge,
none has established quantitative, clinically validated Stemness metrics across a pan-cohort framework
as comprehensive as ours. Of note, our 12-gene PCa-Stem signature, derived from bulk transcriptomic
stratification, shows strong biological overlap with the lineage plasticity signature (LPSig) reported by Zhao
et al. using scRNA-seq [87]. Among the shared genes, *HMMR* emerges as a critical node of convergence
as it has been shown that *HMMR* promotes NE differentiation and aggressive behavior in CRPC models
[87]. The presence of *HMMR*, along with *DLGAP5*, *AURKB*, and *BIRC5* in our PCa-Stem signature,
highlights the translational potential of this gene set in targeting NEPC and other plasticity-driven CRPC
subtypes. Supporting this, Zheng *et al*. used multi-omics integration and machine learning to define three

stemness-based PCa subtypes and constructed a nine-gene prognostic signature [85] that also included

HMMR and *DLGAP5*. *KLK12*, another PCa-Stem gene, was recently identified as a unique marker for

SOX9^{High} stem-like luminal epithelial cells enriched following androgen deprivation [89]. Additionally, our

findings that *MYC* amplification, *RB1* deletion, and *PTEN* loss are enriched in Stemness-high tumors are

consistent with the previously reported chromatin accessibility (ATAC-seq) patterns [74] and multi-omics

spatial data [89]. It is worth noting that although our PCa-Stem signature was initially designed for risk

stratification in mCRPC, the analytical framework is inherently flexible as the same platform can be

extended to derive subtype-specific signatures.

We recognize that the Stemness algorithm utilized in our studies was not developed specifically for

PCa and therefore, its sensitivity to distinguish subtle intra-group differences remains to be fully validated.

The bulk RNA-seq data used to derive Stemness, c_AR-A and other signature scores was not from pure

epithelial cancer cells, a technical issue that can be potentially mitigated by scRNA-seq analysis and other

Stemness pipelines such as the CytoTRACE [90, 91] and by using cancer-specific genomic features

derived, for example, from cell-free DNA [92].

In conclusion, we establish transcriptome-based signature scores to assess pro-differentiation AR

activity, MYC signaling, and oncogenic stemness across the PCa continuum. Stemness progressively

increases during spontaneous PCa progression and becomes much heightened in mCRPC through AR

reprogramming, *RB1*-loss associated transcriptional programs, and MYC activation. These findings

provide a quantitative framework linking PCa progression, oncogenic dedifferentiation, proliferative

reprogramming, lineage plasticity and therapy resistance, and identify stemness-associated transcriptional

programs as potential clinical vulnerabilities. The signature scores reported herein have the potential to

serve as clinical classifiers and aid in the identification of patients who may benefit from stemness-targeting

therapies.

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Ethics declarations

Competing interests

All authors declare no competing interests relative to this work.

Figure Legends

Figure 1. *Pri-PCa shows concordant increases of c_AR-A and Stemness and both are decreased by nADT.*

A-C, PCa has increased c_AR-A as well as the Stemness compared to matched benign tissues. Pairwise
comparisons of *AR* mRNA levels, canonical c_AR-A, and Stemness scores showing significant increases
in primary tumors (T) as compared to the matched adjacent benign prostate tissues (N) from the same
individual in TCGA-PRAD cohort (n=51; **A**), and Wyatt 2014 cohort (n=12; **B**). In the Long 2020 cohort
(n=10; **C**), increases in c_AR-A and Stemness reached statistical significance whereas the increase in
AR mRNA levels approached statistical significance (P = 0.06).

D-F, nADT decreases both c_AR-A and Stemness. Pairwise comparison of *AR* mRNA levels, c_AR-A, and
Stemness showing significant decrease of both c_AR-A and Stemness after nADT (Post-nADT) as
compared to the matched samples before nADT (Pre-nADT) from the same individual (**D**, Rajan 2014
cohort; **E**, Sharma 2018 cohort; **F**, Long 2020 cohort).

In all plots, sample sizes are indicated (see also Table S1 for cohort and RNA-seq data access information).
Within the plots, results are shown as the mean ± SD and pairs are linked with a grey line. Significance
was calculated by two-tailed paired Student's *t*-test (ns, not significant; *, $P < 0.05$; **, $P < 0.01$; ***, $P <$
0.001; ****, $P < 0.0001$).

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Figure 2. *Continual increases in Stemness with declining c_AR-A during spontaneous PCa progression.*

A, The pie chart showing sample sizes in different Gleason grades in the TCGA untreated Pri-PCa cohort.
B-D, Progression of treatment-naïve Pri-PCa is accompanied by decreasing c_AR-A but increasing
Stemness. Data is presented as mean ± SD. Shown on top are the Jonckheere-Terpstra's trend (J-T)
test results (wedges).

E-F, Progression in Pri-PCa is accompanied by a gradual loss of the positive correlation between canonical
c_AR-A and Stemness. Scatter plots illustrating the correlation between c_AR-A and Stemness in (**E**)
combined Pri-PCa cases in TCGA with an overall linear regression model and (**F**) individual GS grades
with corresponding linear regressions showing decreasing slopes from low to high GS grades by J-T test.
The slopes of best-fit regression line are also shown.

G, Merged scatter plot showing the correlation between c_AR-A and Stemness across the 4 GS PCa with
each GS represented by a distinct color. The correlation becomes progressively weaker from GS6 to
GS9/10, transitioning from positive to nearly zero. The correlation coefficients (r) and p-values for each
GS are as follows: GS6 (r = 0.56, $P < 0.0001$), GS7 (r = 0.37, $P < 0.0001$), GS8 (r = 0.48, P = 0.022),
and GS9/10 (r = -0.02, P = 0.89). Linear regression lines are overlaid for each GS, demonstrating the
decline in the correlation co-efficiency as the GS increases.

All statistical analyses were performed using R and statistical significance was assessed using one-way
analysis of variance followed by Tukey's multiple-comparison test (B-D). J-T trend test in B-D and F was

used to calculate the statistical significance of the trend across different groups. *, $P < 0.05$; **, $P < 0.01$;
***, $P < 0.001$; ****, $P < 0.0001$; ns, not significant.

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Figure 3. *Therapies and metastatic progression drive further divergence between Stemness and canonical*
c_AR-A with mCRPC showing the highest Stemness but the lowest c_AR-A.

A-D, Hormonal treatment further drives down c_AR-A but significantly upregulates Stemness. **A-C**,
mCRPC displays the lowest pro-differentiation c_AR-A but highest Stemness. Shown are *AR* mRNA
levels (**A**), c_AR-A (**B**) and Stemness (**C**) in tumor-adjacent benign tissues (N), treatment-naïve Pri-PCa
and advanced Pri-PCa with post-surgery adjuvant ADT (Tx) in TCGA, and mCRPC (SU2C 2015).
Sample sizes are indicated in parentheses. Shown on top are the Jonckheere-Terpstra's (J-T) trend test
results (wedges). **D,** Stemness inversely correlates with c_AR-A in mCRPC**.** Shown are scatter plots with
best-fit linear regression lines illustrating the correlation between c_AR-A and Stemness with Pearson
correlation coefficient (r), the slopes of lines and J-T test results of slopes indicated below.

E-F, PCa progression is accompanied by loss of c_AR-A (**E**) but gain of Stemness (**F**) across PCa states.
Shown are samples representing the spectrum of PCa development and progression, from normal (organ
donors in GTEx) to (tumor-adjacent) benign tissues, to (treatment-naïve) Pri-PCa, aggressive Pri-PCa
treated with adjuvant ADT (Pri-PCa/ADT), mCRPC, and, finally, to (clonally-derived) PCa models
including PDX, xenografts (XG) and cells lines. From Left to right: Normal (n=116): Normal prostates
from GTEx; Benign (n=52): tumor-adjacent benign tissue from TCGA-PRAD; Pri-PCa (n=422):
treatment-naïve localized PCa from TCGA-PRAD; Pri-PCa/ADT (n=70): advanced Pri-PCa treated with
adjuvant hormone therapy from TCGA-PRAD; mCRPC (n=59): mCRPC from GSE126078; mCRPC
(n=135): mCRPC from SU2C 2015 cohort; mCRPC-Adeno (n=34): adenocarcinoma mCRPC from
Beltran 2016 cohort; mCRPC-NE (n=15): neuroendocrine mCRPC from Beltran 2016 cohort; mCRPC
(n=42): mCRPC from Westbrook 2022; mCRPC (n=25): mCRPC from Alumkal 2020; PDX-LuCaP (n=39):
PCa PDXs from GSE126078; PCa cell lines (n=8): PCa cell lines from CCLE; XG-LAPC9 (n=10) and
XG-LNCaP (n=12): PCa xenografts from GSE88752. Statistical significances between groups were
shown in inverted pyramid grid plot as indicated by different colors. Student's *t*-test was used to compare
each group and adjusted p-value for multiple comparisons was done by Tukey's range test. See Table
S4 for the summary of statistical comparisons. J-T trend test was used to assess the statistical
significance of the trend across groups. See also Table S1 for cohort and RNA-seq data access
information.

G, Scatter plots in the Bolis 2021 integrated cohort (normal n=174, Pri-PCa n=714, mCRPC n=335)
showing the changing correlation between c_AR-A and Stemness across disease stages: positive in
normal to weaker correlations in Pri-PCa to negative correlations in mCRPC. Regression lines are color-
coded, and the slope of the best-fit regression line and Pearson's r are provided: yellow for normal

(Pearson's r=0.42, *P* <0.0001; slope: 43.87, 95%CI, 29.57 to 58.18); blue for Pri-PCa (r=0.32, *P* <0.0001;

slope: 15.04, 95%CI, 11.76 to 18.32); and green for mCRPC (r=-0.15, *P* = 0.005; slope: -17.25, 95%CI,

-29.24 to -5.26).

H, Violin plot showing increasing Stemness among the NCCN Risk Groups containing 82470 microarray

samples with localized disease in GRID. J-T trend test was used to assess the statistical significance of

the trend across groups.

I-M, Increasing Stemness during PCa progression in the Taylor 2010 cohort consisting of tumor-adjacent

benign tissue (Normal; n=29), Pri-PCa (n=131) and metastatic mPCa (n=19). The c_AR-A significantly

increased in Pri-PCa vs. Normal and significantly decreased in mPCa compared to Pri-PCa (**I**) whereas

the Stemness continued to increase from Benign to Pri-PCa to mPCa (**J**). **K-M**, Scatter plots illustrating

the correlations between c_AR-A and Stemness in different contexts with corresponding linear

regression lines: **K,** Positive correlation in normal (Pearson's r=0.69, *P* <0.0001); **L,** a gradual loss of

positive correlation between Stemness and c_AR-A during PCa progression (Pearson's r=0.18, *P* =

0.043); **M,** a loss of positive correlation between the Stemness and c_AR-A at more advanced mPCa

stage (Pearson's r=0.18, *P* =0.47).

All data in dot plots and violin plots are shown as mean ± SD. Statistical significance was determined using

one-way analysis of variance (ANOVA) followed by Tukey's multiple-comparison test. Jonckheere-

Terpstra's trend (J-T) test was used to calculate the statistical significance of the trend across different

groups. Pearson correlation coefficients (Pearson's r) were used to calculate the correlations between the

Stemness and c_AR-A. Note: ns, not significant; *, *P* < 0.05; **, *P* < 0.01; ***, *P* < 0.001; ****, *P* < 0.0001.

1380

Figure 4. *High Stemness is associated with poor patient overall survival.*

A-C, Kaplan-Meier plots showing that high Stemness associates with worse overall survival in PCa patients

from Spratt 2017 (**A**), Tosoian 2020 (**B**), and CHAARTED 2021 (**C**) cohorts. *P* value was determined

using the log-rank test.

D, Stemness increases across patient groups with higher Decipher genomic classifier scores. The three

cohorts were arranged by their median Decipher genomic classifier scores, and the J-T trend test was

used to assess statistical significance of this trend.

1388

Figure 5. *Stemness-high PCa are associated with aggressive molecular subtypes and a newly developed*

12-gene PCa-Stem signature prognosticates poor patient survival.

A, Schematic illustrating the profiling strategy used to assess associations between Stemness and

molecular features in PCa. Patients were ranked by Stemness score and stratified into Stemness-high

(top 33%) and Stemness-low (bottom 33%) groups for downstream analyses. Genome-wide functional

analyses were performed using transcriptomic, genomic, and clinical data.

B-C, Volcano plots showing differentially expressed genes (DEGs) between Stemness-high and

Stemness-low groups in Pri-PCa (**B**) and mCRPC (**C**) cohorts. Red and blue indicate upregulated and

downregulated DEGs, respectively. Genes with FDR > 0.05 are shown in gray. Sample sizes (n) of each

group are indicated. See Table S3 for complete DEG lists.

D, Venn diagram showing the 12-gene "PCa-Stem signature" derived from commonly upregulated DEGs

(FC ≥ 2, FDR < 0.05) in Pri-PCa and mCRPC.

E-F, GSEA showing low Stemness is associated with immune signaling and inflammatory response (**E**)

while high Stemness in both cohorts is enriched for embryonic stem cell traits, aggressiveness, DNA

repair, MYC activation, and mTORC1 signaling (**F**). All enrichments are significant ($P < 0.05$, FDR <

0.05).

G-H, PAM50 subtyping showing a higher frequency of aggressive LumB subtype in Stemness-high versus

Stemness-low samples in Pri-PCa (**G**) and mCRPC (**H**). (****, $P < 0.0001$, χ^2 test).

I-L, GSEA showing enrichment of the aggressive PCS1 signature in Stemness-high groups and the less

aggressive PCS3 signature in Stemness-low groups in Pri-PCa (**I**, **K**) and mCRPC (**J**, **L**). The Prostate

Cancer Subtype (PCS) classification system (45,46) stratifies tumors into three molecular subtypes

based on transcriptomic features: PCS1 (most aggressive), PCS2 (intermediate), and PCS3 (least

aggressive). See Table S2 for PCS gene signature.

M-R, GSEA showing AR signature enrichment in Pri-PCa Stemness-high (**M**), NEPC signature enrichment

in mCRPC Stemness-high (**N**), and shared enrichment of cell cycle (**O**, **P**) and lineage plasticity (**Q**, **R**)

programs in both cohorts. See Table S5 for gene sets.

S-V, Kaplan-Meier analyses showing that the 12-gene PCa-Stem signature predicts worse progression-

free survival (PFS) in TCGA Pri-PCa (**S**) and worse overall survival (OS) in SU2C mCRPC (**U**).

Multivariable Cox models adjusting for clinicopathologic variables confirm the high PCa-Stem signature

score as an independent prognostic for PFS (**T**) and OS (**V**).

1419

Figure 6. *Stemness-high PCa is associated with higher genomic instability.*

A-C, Box plots showing that Stemness-high subgroup in both Pri-PCa (n = 141) and mCRPC (n = 89)

displays a higher fraction of altered genome (**A**) and higher TMB (**B**), but no age difference (**C**) compared

to Stemness-low cases. Wilcoxon rank-sum test was used to determine significance (****, $P < 0.0001$;

ns, not significant). Box plots represent the median, interquartile range (IQR), and whiskers extending to

1.5× the IQR.

D-F, Comparisons of genomic alteration frequencies (Alt. Freq) in cancer-associated genes between
Stemness-high and Stemness-low subgroups in TCGA Pri-PCa (**D**, **F**) and SU2C mCRPC (**E**, **F**) cohorts.
Statistical significance was determined by two-sided Fisher's Exact test (*, $P < 0.05$).

1429

Figure 7. *MYC activation contributes to increased Stemness during spontaneous PCa progression.*

A-B, Pairwise comparisons showing increased *MYC* mRNA levels and MYC signaling activity (MYC-sig)
in primary tumors (T) versus matched adjacent benign tissues (N) in TCGA-PRAD cohort (n=51; **A**) and
Wyatt (n=12; **B**) cohorts. Data is shown as mean ± SD; paired samples are linked by grey lines.
Significance was determined using two-tailed paired Student's *t*-test (****, $P < 0.0001$).

C-H, MYC activity increases during PCa progression, peaking in mCRPC. In treatment-naïve Pri-PCa (**C**),
MYC-sig is significantly increased in all-grade (GS) tumors as compared to tumor-adjacent benign
tissues (N) with the most advanced GS9/10 tumors exhibiting the highest MYC-sig. In **D**, MYC-sig
increases from normal to treatment-naïve Pri-PCa and further in advanced Pri-PCa treated with adjuvant
ADT (Tx) in TCGA-PRAD, while mCRPC shows the highest MYC-sig in both SU2C 2015 (**D**) and Taylor
2010 (**E**) cohorts. Data is presented as mean ± SD. Statistical significance was assessed by one-way
ANOVA with Tukey's multiple-comparison test (**C-E**). J-T trend test was used in (C, D) to assess the
significance of progressive increase. **, $P < 0.01$; ***, $P < 0.001$; ****, $P < 0.0001$; ns, not significant. **F-**
H, Scatter plots showing positive correlations between MYC activity and Stemness in the Taylor 2010
cohort across different stages. Pearson's r and P-values are indicated.

1445

Figure 8. *Castration-reprogrammed AR activity (cr_AR-A) and RB1-loss signature contribute to increased*
Stemness in mCRPC.
A–D, The cr_AR-A and genomic *RB1*-loss signature increase progressively from normal and Pri-PCa to
mCRPC. Shown are cr_AR-A (**A**) and *RB1*-loss (**B**), *PTEN*-loss (**C**) and PCa-Stem (**D**) signature scores
across the disease spectrum using the Bolis integrated PCa cohort: normal prostates (GTEx, n=116),
tumor-adjacent benign tissues (TCGA-PRAD, n=52), treatment-naïve Pri-PCa (TCGA-PRAD, n=422),
aggressive Pri-PCa treated with adjuvant ADT (Pri-PCa/ADT) (n=70), and two mCRPC cohorts including
GSE126078 mCRPC (n=59) and SU2C 2015 (n=135). Sample sizes are indicated in parentheses.
Shown at the bottom are Jonckheere–Terpstra (J-T) trend-test results (wedges).
E–H, Scatter plots illustrating correlations between cr_AR-A (**E**), *RB1*-loss (**F**), *PTEN*-loss (**G**), PCa-Stem
(**H**) scores with Stemness across Bolis integrated cohort (total n=1,223; including normal (n=174), Pri-
PCa (n=714), and mCRPC (n=335)). Pearson's correlation coefficients (*r*) and *P* values are shown.
Details of symbol colors and shapes are shown in (**L**).
I–L, Inter-signature relationships among cr_AR-A, *RB1*-loss, *PTEN*-loss, and PCa-Stem signatures in the
Bolis integrated cohort (total n=1,223, normal n=174, Pri-PCa n=714, mCRPC n=335). Correlation plots

demonstrate strong positive correlations between cr_AR-A and PCa-Stem (**I**), and between *RB1*-loss

and PCa-Stem (**J**), and a moderate but significant correlation between *PTEN*-loss and PCa-Stem (**K**).

Details of symbol colors and shapes are shown in (**L**).

M-P, Venn diagrams showing overlapping genes among cr_AR-A (**M, P**), *RB1*-loss (**N, P**), *PTEN*-loss (**O**),

and PCa-Stem signatures, highlighting shared components (e.g., *AURKB, BIRC5, CENPA, PLK1, ANLN)*

involved mitotic regulation and the self-renewing proliferation typical of stem-like tumor cells.

All dot plots data are shown as mean ± SD. Statistical significance among groups was determined using

one-way ANOVA followed by Tukey's multiple-comparison test, and J-T trend tests were used to assess

significance across disease states. Pearson correlation coefficients (*r*) were calculated for all pairwise

associations. *ns*, not significant; *, $P < 0.05$; **, $P < 0.01$; ***, $P < 0.001$; ****, $P < 0.0001$. See Table S4 for

full statistical summaries and data sources.

Fig. 1

A Paired prostate tumor (T) and adjacent benign (N) (TCGA-PRAD)

B Paired prostate tumor (T) and adjacent benign (N) (Wyatt, 2014)

C Paired prostate tumor (T) and adjacent benign (N) (Long, 2020)

D Paired Pre- and Post-nADT PCa (Rajan, 2014)

E Paired Pre- and Post-nADT PCa (Sharma, 2018)

F Paired Pre- and Post-nADT PCa (Long, 2020)

Fig. 2

Fig. 3

Fig. 4

A

Spratt 2017 (855)

P = 0.001
(log-rank)

Strata
- Stemness-low (427)
- Stemness-high (428)

Number at risk

Stemness	0	30	60	90	120
high	428	391	326	211	130
low	427	405	352	253	177

B

Tosoian 2020 (405)

P = 0.014
(log-rank)

Strata
- Stemness-low (202)
- Stemness-high (203)

Number at risk

Stemness	0	30	60	90	120
high	203	163	126	74	37
low	202	174	130	79	45

C

CHAARTED 2021 (160)

P = 0.006
(log-rank)

Strata
- Stemness-low (120)
- Stemness-high (40)

Number at risk

Stemness	0	25	50	75	100
high	40	25	6	0	0
low	120	85	35	7	1

D

P < 0.01
(J-T trend test)

Dataset: # Patients:	Spratt 2017 (855)	Tosoian 2020 (405)	CHAARTED 2021 (160)
Decipher Genomic Classifier	Median 0.37	0.48	0.72
	Q1 0.24	0.30	0.57
	Q3 0.54	0.65	0.83

Fig. 5

Fig. 6

Fig. 7

A Paired samples: Pri-PCa (TCGA)

B Paired samples: Pri-PCa (Wyatt 2014)

C TCGA-PRAD (Pan-Cancer 2018)

D TCGA, Cell 2015 / SU2C 2015

E, F, G, H Taylor 2010 (179)

F: Normal (29), r = 0.32, P = 0.0002

G: Pri-PCa (131), r = 0.44, P = 0.06

H: mPCa (19), r = 0.76, P < 0.0001

Fig. 8