Recurrent mechanisms of biallelic epigenetic inactivation reveal new putative tumour suppressor genes in prostate cancer

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Abstract

The inactivation of tumour suppressor genes is a key step in cancer development, and is usually achieved by homozygous loss. In prostate cancer, however, large genomic regions are often hemizygously lost, which complicates the identification of putative tumour suppressors in these regions. Here, we developed Epi2Hit, an integrative computational method that leverages whole genome sequencing, epigenomic profiling and gene expression to identify biallelic inactivation of tumour suppressor genes involving DNA methylation of promoter and enhancer regions of one allele and genomic loss of the other allele. We apply Epi2Hit to a cohort of 2,021 prostate cancers to discover tumour suppressor genes. In particular, we identify epigenetic biallelic inactivation of *ZFHX3* at a recurrence level similar to *TP53*. Biallelic inactivation of *ZFHX3*, a transcriptional repressor, leads to upregulation of oncogenes, including *MYC* and a shorter time to metastasis. Finally, we provide evidence that epigenetic silencing as 2nd hit is particularly enriched in regions with nearby essential genes, precluding homozygous loss.

Introduction

Prostate cancer is the second most frequent type of cancer in men worldwide[1,2]. The disease is highly heterogeneous at the molecular level, with a paucity of somatic single nucleotide variant (SNVs) drivers but frequent structural variations (SVs), which commonly cause copy number losses[3]. Approximately 10% of the prostate cancer genome is recurrently lost in more than 20% of prostate cancer tumours, but only a subset of these harbour known prostate cancer driver genes[4–7].

Tumour suppressor genes (TSG) often undergo biallelic inactivation in various cancer types including prostate cancer[8–11]. The landmark Two-Hit hypothesis posited by Knudson forms the cornerstone of our understanding of TSGs. It suggests that the path towards malignancy is often paved by the sequential inactivation of both alleles of a gene[12]. This is true for prostate cancer, where TSGs such as *PTEN*, *TP53*, *CHD1* and *BRCA1/2* are frequently biallelically inactivated by a combination of copy number loss and SNVs[13–15]. Biallelic inactivation can, however, be highly complex, involving different inactivating germline and somatic events.

Epigenetic silencing by e.g. hypermethylation of promoter and enhancer regions of TSGs is an alternative mechanism of inactivation, often coinciding with genomic inactivation of the other allele. Biallelic inactivation involving copy number loss of one allele and epigenetic silencing of the other allele remains poorly explored except for a few prominent examples including *MLH1* (in colorectal cancer and endometrial cancer)[16,17], *BRCA1* (breast and ovarian cancer)[18–20], *MGMT* (glioma)[21,22] and *APC* (various cancers including prostate cancer)[23–26]. Several of these examples represent established prognostic or predictive biomarkers. Despite its recognised significance, a comprehensive methodology to elucidate the multifaceted nature of biallelic inactivation within this context has remained elusive, constraining our insights into disease progression and the implicated genes, as previous studies were limited to smaller gene panels, low-resolution methodologies, or lack of systematic integration of genomic alterations, DNA methylation, and expression[27,28].

To discover and explore the spectrum and magnitude of epigenetic biallelic inactivation in prostate cancer, we develop and apply a computational methodology, Epi2Hit, which integrates hemizygous genomic disruptions with hypermethylation at regulatory CpG sites to identify biallelic inactivation in TSGs. By leveraging information from somatic alterations with HM450 methylation array, ATAC-sequencing, Hi-C and RNA-sequencing, our approach provides complementary support for the discovery of TSGs inactivated by genomic and epigenetic biallelic inactivation.

Results

Methodology to discover Epi2Hit in prostate cancer

Pan Prostate Cancer Group (PPCG) has assembled multiomics data from a clinically well-annotated and diverse collection of prostate cancers taken from 2,021 patients. The sequence data has been analysed with standardised pipelines to identify whole-genome sequencing (WGS)-based single nucleotide variants (SNVs), insertions and deletions (indels), copy number alterations (CNAs), structural variations (SVs), 450K array-based methylation patterns, and RNA-seq-based gene expression profiles[29]. Here we selected data from 991 primary prostate cancers, from which WGS data was available, to investigate genomic regions recurrently subjected to copy number loss (altered in at least 10% of the cohort). Consistently with previous findings, our analysis revealed several well-described genomic regions that exhibit high

frequencies of homozygous loss, with particular enrichment on chromosomes 5, 10,13 and 17[30,31] (representing 0.2% of the genome, dark blue, **Fig. 1a**). In contrast, we identified 8% of the genome being recurrent and almost exclusively hemizygously lost (light blue, **Fig. 1a**), in particular on chromosomes 2, 3, 5, 8 and 16[32,33,34] (**Fig. 1a,b,** Supplementary Table 1, Supplementary Data 1), suggesting that additional (epi)mutational processes could contribute to biallelic inactivation of putative TSG candidates in these otherwise hemizygously deleted regions.

Hypermethylation of regulatory CpG regions can cause transcriptional repression of TSGs including *MLH1*[35], *APC*[23] and *BRCA1*[20]. Motivated by these seminal findings, we asked whether any of the genes recurrently affected by hemizygous loss also exhibit an increase in promoter or enhancer methylation. To this end, we analysed methylation in regulatory regions associated with these genes using data obtained from the Illumina HumanMethylation450 BeadChip array for 1,268 samples from the PPCG cohort, representing 318 donors with genomic, transcriptomic and methylation data (**Supplementary Fig. 1a,** methods). We assessed differential methylation by examining the distribution of β-values at each CpG site. Specifically, we considered a site to exhibit differential methylation if the distribution of β-values showed evidence of multimodality, characterised by two or more distinct peaks, using a KDE-optimization approach (**Supplementary Fig. 2a-d,** methods). This approach allowed us to identify regions where methylation levels varied significantly across the sample set. We identified 22% (*n*=1,187) of the genes undergoing recurrent hemizygous loss (*n*=5,492) to also display differential methylation (**Fig. 1c**), representing candidate genes for biallelic inactivation through a combination of genetic and epigenetic mechanisms.

CpG regions that regulate transcription tend to be located in open chromatin, which we confirmed using available orthogonal ATAC-seq data from an independent cohort of primary prostate cancer samples (GSE188797)[36] (**Fig. 1d**), suggesting a more robust regulatory influence of CpGs in these regions. We confirmed a transcriptional repressive role of CpG hypermethylation using linear regression for key TSGs such as *APC*, *PTEN*, and *NOTCH1* (negative coefficients demonstrating anti-correlation between CpG methylation in open chromatin and transcription) (**Fig. 1e)**.

To systematically discover and characterise known and poorly characterised TSGs undergoing biallelic inactivation involving hemizygous loss of one allele and CpG hypermethylation of the other allele in the PPCG cohort, we developed a computational integrative methodology, encompassing genomic, transcriptomic and epigenomic data with associated clinical annotations (from hereon termed “Epi2Hit”, **Fig. 2a,** methods). We excluded CpG sites that correlated with stromal and immune cell content in the tumours, as well as those affected by global demethylation in partially methylated domains (PMDs) (**Supplementary Fig. 1b**). We further prioritised CpG sites located in open chromatin regions (using external ATAC-seq peak data). Regions were also annotated with external Hi-C based chromatin loops (GSE164347)[37], enhancer and promoter regions based on prostate-specific ChromHMM[38], to identify regulatory CpG, sites with a likely gene regulatory function (**Fig. 2b, Supplementary Fig. 1c-d, Supplementary Fig. 2e**). We regressed RNA-seq based gene expression on these regulatory CpGs to identify expression CpG sites whose methylation levels were significantly and negatively correlated with gene expression, and restricted our analysis to CpG sites displaying multimodal distribution, to select CpGs with differential methylation levels in prostate cancer epithelial cells across the cohort (eCpGs, *n*=300, **Supplementary Fig. 2c-d**). These associations were stable when adjusting the model for tumour purity and fraction genome altered (FGA) (**Supplementary Fig. 1e-f,** Supplementary Table 2, methods). Finally, we integrated methylation levels of eCpGs with copy number losses from the same tumour, requiring the CpG site to overlap the copy number loss, to identify Epi2Hit candidate genes

(*n*=155, **Fig. 2b, Supplementary Fig. 1c-d**) and investigate their biological and clinical relevance in prostate cancer.

Epi2Hit-based discovery of tumour suppressors with epigenetic inactivation mechanisms

We systematically identified genomic-based biallelic inactivation events in our companion paper[39] including prostate cancer-specific TSGs from an external database[40] to discover known and poorly characterised TSGs also subjected to epigenetic-based inactivation. Among the TSGs that are inactivated in more than 2% of the PPCG cohort, we identified numerous TSGs with known and previously published tumour-suppressor function as Epi2Hit candidates (**Fig. 3a** som.loss/methyl), including *PSD3*[41] (*n*=48, 5%), *ZFHX3*[42,43] (*n*=47, 5%), *RBPMS*[44,45] (*n*=41, 4%), *APC*[46,47] (n=30, 3%), *PDE4D*[48–50] (*n*=20, 2%) and *KLF5*[51,52] (*n*=17, 2%). Consistent with a tumour-suppressive role, DepMap CRISPR dependency data (CERES scores) support that these genes are generally non-essential across cancer cell lines, including prostate cancer lines (Score > (-1), Supplementary Table 3). To assess the transcriptional consequences of Epi2Hit, we compared gene expression levels between wild-type, hemizygous loss, and Epi2Hit samples (**Fig. 3b**), and identified a significant reduction in expression in Epi2Hit samples. We found a high frequency of hemizygous loss across multiple genes located on the chromosome 8p arm (**Supplementary Fig. 3b**). Chromosome 8p is deleted in more than 60% of prostate cancers[39,53,54], but the actual TSG(s) have remained elusive due to the absence of recurrent homozygous losses. Although rare, we observed recurrent epigenetic inactivation of several genes including *NKX3-1* (1%), previously recognized as a candidate TSG in chr8p[55], suggesting that several TSGs in this region may contribute to tumour suppression through Epi2Hit.

APC is a known TSG, often subjected to promoter hypermethylation and gene expression downregulation[26]. The *APC* locus includes two promoters, promoter 1A and promoter 1B, which regulate distinct transcripts and show different methylation patterns in normal and cancer tissue[23]. Promoter 1B generates three transcript isoforms that are predominant in normal colonic mucosa, whereas promoter 1A, produces transcript 1A and is more frequently methylated in cancer. In gastrointestinal malignancies, promoter 1A is often hypermethylated while promoter 1B remains unmethylated, a pattern associated with reduced *APC* expression. The *APC* locus contains 12 regulatory CpGs (**Fig. 3d**), four of which we identified as eCpG (CpGs9-12) coinciding with promoter 1A, which we found to display strong methylation correlation (**Fig. 3c-e**). Indeed, we found no correlation with gene expression when inspecting methylation levels of each of the first eight CpG sites associated with promoter 1B, whereas the methylation level of the eCpG identified by Epi2Hit pipeline (CpG9-12) displayed a strong anti-correlation with *APC* gene expression (*P*=0.01) (**Fig. 3f-g**), confirming these as bona fide eCpGs and validating the general approach in our methodology. This finding also supports that *APC* is mediated predominantly through methylation of promoter 1A in prostate cancer as in other malignancies, whereas promoter 1B remains unaffected.

We next tested the extent to which biallelic inactivated genes tended to be inactivated by hemizygous loss, methylation or both (Epi2Hit) at the sample level. For each gene, we plotted the percentage of samples with hemizygous loss and eCpG hypermethylation-based inactivation (**Fig. 3h**), with genes at the diagonal representing exclusively the Epi2Hit mechanism. While several TSGs displayed exclusive hemizygous loss (**Fig. 3h**) as well another genomic second hit (**Fig. 3a**), such as *PTEN* and *TP53*, we found several genes with frequent Epi2Hit including *PDE4D,* a gene with established suppressor function in prostate cancer[56,57],

and *KLF5*, previously shown to be inactivated in prostate cancer by copy-number loss and epigenetic silencing[14](**Supplementary Fig. 2f, Supplementary Fig. 3a**).

To assess the reproducibility of our findings, we performed two levels of analysis. First, we observed robust concordance with MethylMix[58], a multi-state model that identifies differential methylation states predictive of gene expression. This analysis confirmed the presence of regulatory CpGs near *APC, KLF5* and *ZFHX3*. Next, we performed external validation by applying Epi2Hit to TCGA-PRAD[13] (n = 493 tumours) using matched methylation, RNA-seq, CNAs and SVs. This analysis confirmed our Epi2Hit discovery genes in the PPCG cohort, with 6 of the 7 top Epi2Hit TSGs among the top most frequently altered genes in the TCGA-PRAD cohort (**Supplementary Fig. 3c**, Supplementary Tables 4-5). Reassuringly, Epi2Hit confirmed the key candidates including *APC, KLF5* and *ZFHX3* (**Supplementary Fig. 3d**, methods).

Biallelic inactivation of *ZFHX3* drives *MYC* expression and is linked with more aggressive prostate cancer

One of the genes we identified as frequently inactivated as an Epi2Hit is *ZFHX3. ZFHX3* is a zinc finger homeobox transcriptional repressor, known to bind and repress the transcription of numerous genes[59–63]. It was previously reported to be a putative TSG in prostate cancers with downregulation of the gene associated with higher proliferation, cell migration and aggressiveness[42,64–66]. The biallelic inactivation encompassed a copy number loss of one allele and eCpG hypermethylation of the other allele, located in the gene's promoter region. Tumours with hemizygous loss showed higher eCpG methylation levels compared to tumours with copy-number neutral states (**Supplementary Fig. 4a-b**), confirming the observed co-occurrence of copy number loss and hypermethylation at the Epi2Hit genes.

To investigate the identified eCpGs at the *ZFHX3* locus and validate the biallelic inactivation, we took advantage of Oxford Nanopore-based long-read sequencing of six prostate cancer samples with and without biallelic inactivation of *ZFHX3*. Using phased allele-specific copy number and methylation-based analyses, we identified in Epi2Hit prostate cancer examples (*n*=3, Supplementary Table 6) allele 1 to be lost (green dashed line, **Fig. 4a** top) and a concomitant strong allele-specific hypermethylation (5mC) at the eCpG (cg16563255) of allele 2 (yellow line, respectively, **Fig. 4a** top), with beta values ranging from 0.82-0.9. In contrast, we found no allele-specific differences at the copy number and methylation level of control prostate cancer cases (*n*=3) without *ZFHX3* Epi2Hit (**Fig. 4a** bottom). We found the eCpG region of *ZFHX3* to form long-range loops to several other proximal regions including a hypomethylated promoter region of *ZFHX3*, suggesting that this eCpG could represent a critical enhancer element in regulating the transcription of *ZFHX3*. To further explore the epigenetic state of the *ZFHX3* locus, we extended the analysis to 5-hydroxymethylcytosine (5hmC), DNA modification associated with dynamic and transcriptionally permissive state[67,68]. In Epi2Hit tumours, the retained allele exhibited high 5mC and absence of 5hmC, consistent with stable transcriptional silencing. In contrast, Epi2Hit-WT tumours exhibited intermediate 5mC together with low 5hmC across both alleles, suggesting a more dynamic regulatory configuration (**Supplementary Fig. 4c**).

We further investigated whether inactivation of *ZFHX3* co-occurs with other frequent genetic alterations known to drive prostate cancer progression. We identified co-occurrence of *ZFHX3* inactivation with loss of *PTEN* (q = 0.007) or loss of *TP53* (q < 0.0001, Supplementary Table 7), in keeping with a cooperative role[69,70]. *MYC* gain exhibited a striking interaction with *ZFHX3* inactivation (odds ratio = 6, q < 0.0001, Supplementary Table 7), with significant upregulation of *MYC* in prostate cancer samples harbouring *ZFHX3* Epi2Hit (p = 0.03, **Fig. 4b**), suggesting that *ZFHX3* inactivation contributes to *MYC* overexpression. To further contextualize its evolutionary

role, we used the mutational exclusivity metric (Gerhauser et al., 2018[14], **Supplementary Fig. 4d,** methods). This analysis showed that *ZFHX3* displays a higher exclusivity score, indicating that its inactivation tends to occur as an early event in prostate cancer.
To explore the mechanistic basis of this regulation, we examined ZFHX3 binding within the *MYC* locus using orthogonal chromatin data from colon adenocarcinoma and neural stem cell[71,72], together with prostate adenocarcinoma cell[43]. *ZFHX3* binds to a specific site within a prostate-specific promoter region at the *MYC* locus (**Fig. 4c, Supplementary Fig. 4e**), marked by active chromatin (H3K4me3), in keeping with *ZFHX3* to act as transcriptional repressor of *MYC* expression by binding to regulatory elements of *MYC*[43].
We identified 11 additional prostate cancer-related genes with ZFHX3 binding sites near their promoter, and therefore likely to be direct targets of ZFHX3. We found genes associated with tumour-suppressive functions such as *CDH1* and *MUTYH*[73–79] to be downregulated in *ZFHX3* Epi2Hit tumours and genes that drive oncogenic processes (e.g. *SF3B1*, *PLEC*)[80–85] showed higher expression levels in *ZFHX3* Epi2Hit cancers **(Fig. 4d,** methods**)**. These observations suggest a key transcriptional regulatory impact upon *ZFHX3* inactivation in driving prostate cancers.
Indeed, *ZFHX3* inactivation was significantly enriched in patients with high Gleason grade group (GG3-5) compared to low Gleason grade group (GG1-2) (Chi-square test: *P*=0.0004) (**Fig. 4e**). Moreover, patients with *ZFHX3* inactivation displayed shorter time to metastasis (log-rank test *P*=0.0007, **Fig. 4f**), suggesting that *ZFHX3* inactivation is driving more aggressive disease, potentially through transcriptional upregulation of *MYC*.
Interestingly, in a companion study, we identify *ZFHX3* inactivation in a subgroup of prostate cancer patients characterised by losses of several key TSGs including *TP53, PTEN* and *FANCA*, and by shorter metastasis-free survival[39], but it was not identified as an independent prognostic factor in multivariable Cox models (**Supplementary Fig. 5f**), suggesting that *ZFHX3* is correlated with other markers of aggressive disease.

Proximity of essential genes influences tumour suppressor gene inactivation mechanisms

We sought to understand the difference in inactivating mechanisms observed in TSGs, such as *PTEN*, which frequently undergoes biallelic loss, compared to Epi2Hit genes such as *KLF5* and *ZFHX3* that exhibit loss of one allele and epigenetic silencing of the other allele. A previous study has suggested that TSGs subjected to biallelic loss are often located away from genes essential for cell survival[86]. We hypothesised that Epi2Hit genes would be less impacted by this constraint, since methylation of the wild-type allele would not affect the neighbouring genes compared to homozygous losses, which often encompass multiple neighbouring genes.
In contrast to homozygously deleted genes, we found Epi2Hit TSGs such as *KLF5* and *ZFHX3* indeed positioned in close proximity to common essential genes (**Fig. 5a,** methods). This proximity likely prevents their complete inactivation through double loss, favouring hemizygous deletion and hypermethylation as alternative inactivation mechanism. To further explore the enrichment of essential genes near TSGs undergoing Epi2Hit, we expanded our analysis to a broader list of genes identified by Epi2Hit. We observed a significant enrichment of essential genes near these TSGs (Chi-square test, *P*=0.006, **Fig. 5b**), confirming that essential genes are more frequently located close to TSGs inactivated by Epi2Hits rather than by homozygous loss.
To corroborate this finding, we quantitatively assessed the genomic distance between each TSG and the closest essential gene. In support, Epi2Hit genes were significantly closer to essential genes than homozygous deleted TSGs (**Fig. 5c,d**). This association remained significant after adjusting for gene length and local gene density (**Supplementary Fig. 5a-d,**

Supplementary Table 8-9, methods). Finally, to investigate whether expression differences might reflect selective constraints, we compared average expression levels between essential genes and TSGs. Essential genes showed significantly higher expression than TSGs **(Fig. 5e)**, supporting the notion that preserving their expression may prevent adjacent homozygous loss. These findings underscores the importance of considering methylation as a second hit in the inactivation of TSGs, particularly those that are located in close proximity to essential genes. Moreover, it supports a model where proximity of essential genes constrain homozygous losses and favour alternative epigenetic mechanisms of inactivation, thereby avoiding the complete loss of function that could compromise tumour cell survival.

Discussion

Our study presents an integrative computational methodology to systematically identify biallelic inactivation of TSGs in cancer, integrating both genetic and epigenetic mechanisms - Epi2Hit. This workflow provides an orthogonal approach to deepen our understanding of prostate cancer initiation and progression by revealing how hemizygous deletions and hypermethylation of cis-regulatory regions cooperate to inactivate TSGs. Oncogenic mutational processes shaping prostate cancer genomes play a pivotal role[87]. In contrast, the impact of epigenetics is poorly understood. While previous studies have highlighted the role of hypermethylation and copy number loss in gene silencing, our approach identifies both previously known and understudied TSGs undergoing this complex inactivation process.

The strength of our methodology lies in its ability to identify putative Epi2Hit TSGs by leveraging CpG sites that are directly associated with gene expression changes, distinguishing them from non-functional CpGs. Our analysis of *APC* in prostate cancer further illustrates this principle: consistent with observations in other malignancies, epigenetic inactivation was driven predominantly by methylation of promoter 1A, while promoter 1B remained unaffected[23], underscoring the importance of promoter-specific regulation in tumour suppressor gene silencing. This precise identification of eCpGs, in conjunction with data from large cohorts, enables the detection of TSGs that are biallelically inactivated through hemizygous loss and hypermethylation, broadening our catalogue of potential cancer drivers. Notably, we identified known and understudied TSGs including *PSD3, PDE4D*, *RBPMS*, *APC* and *ZFHX3*, as undergoing Epi2Hit, emphasising the versatility of our approach in uncovering TSGs. *ZFHX3* Epi2Hit displayed a surprising recurrence, making it the fifth most frequent biallelic inactivated TSG in our analysis of primary prostate cancers across 1,001 donors, superseding established TSGs such as *BRCA2* and *APC*. Our findings confirm and extend prior reports, showing a pervasive role in transcriptional regulation, with *ZFHX3* inactivation leading to relief of oncogene transcriptional repression such as *MYC*[43,88]. In support of an important and early driver role **(**methods**, Supplementary Fig. 3d**), we identified frequent early gains of *MYC* and loss of *ZFHX3* in an evolutionary Ordering-III, associated with a shorter time to metastasis in our companion paper[89].

While several prior studies have explored biallelic inactivation through combined deletion and hypermethylation[27,28], they focused on small cohorts, targeted methylation panels, or preselected TSGs. In contrast, Epi2Hit performs genome-wide discovery, integrating gene expression and regulatory annotation (ATAC-sequencing, Hi-C loops) to systematically prioritize functionally relevant CpG sites. A methodological comparison (Supplementary Table 10) highlights how Epi2Hit advances previous efforts by providing a modular tool applicable across different cancer types, and by leveraging regulatory and transcriptional data to improve specificity and biological interpretability of epigenetic hits.

The applicability of the Epi2Hit approach is not limited to prostate cancer. The principles

underlying our methodology can be extended to other tumour types, where similar interactions between genetic deletions and epigenetic silencing may play a pivotal role in cancer progression[27,90,91]. Epi2Hit is compatible with large-scale, multi-omic datasets such as those generated by The Cancer Genome Atlas (TCGA), and could be applied to these cohorts to further validate its utility across diverse malignancies. We anticipate that our methodology will also enable the discovery of TSGs in other cancer types, and develop a more comprehensive understanding of the cancer genome landscape across various malignancies.

The identification of epigenetic silenced genes also opens up avenues for targeted treatments. Specifically, the methylation component of biallelic inactivation presents an attractive target for epigenetic therapies. Preclinical studies in prostate cancer cells have shown that treatment with the DNA-demethylating agent decitabine, particularly in combination with S-adenosylmethionine (SAM), exerts synergistic anti-tumour effects by reducing proliferation and invasion while promoting reactivation of silenced tumour suppressor pathways[92]. In clinical settings, azacitidine has been associated with reduced PSA doubling time and decreased *LINE-1* methylation levels in men with chemo-naïve castration-resistant prostate cancer, suggesting systemic demethylation and a favourable safety profile[93]. A systematic review by Linnekamp et al. further highlights the therapeutic relevance of demethylating agents across a broad range of solid tumours, including prostate, colorectal, and lung cancers, with early-phase clinical trials showing clinical responses in subsets of patients[94]. Notably, in prostate cancer, PSA decline was associated with gene-specific demethylation such as reduced *GADD45A* methylation observed in responders[95]. Beyond systemic agents, a locus-specific demethylation strategy using a TALE–TET1 fusion protein was shown to reactivate a tumour suppressor gene and inhibit metastatic progression in prostate cancer models, underscoring the promise of targeted epigenetic editing approaches[96]. Together, these findings highlight the translational potential of reversing methylation-mediated silencing as a therapeutic avenue in prostate cancer and beyond.

Our methodology also paves the way for more sophisticated analyses using long-read sequencing technologies. While the 450k array provides valuable insights into methylation patterns, its probe design is biased toward CpG islands and promoter regions, potentially missing key regulatory elements such as enhancers, including super-enhancers[97], which are often located in open sea or intergenic regions[98] and tend to have a stronger regulatory effect on transcription than promoter elements alone[99]. As a result, some epigenetically silenced TSGs may go undetected in our analysis, representing a source for future studies.

In contrast, unbiased methods such as whole genome bisulphite or nanopore sequencing allow the investigation of all eCpGs outside the predefined regions. Moreover, since the array platform does not allow different haplotypes to be distinguished, we were not able to detect methylation in combination with small variants (SNVs and indels) or SV breakpoints. Long-read sequencing can capture these events more accurately, enabling the detection of intricate allele-specific epigenetic landscapes in conjunction with genomic alterations on the same DNA fragment that are missed by traditional short-read technologies. Future studies applying WGBS or long-read methylation profiling in large tumour cohorts will likely identify additional functionally silenced TSGs that remain undetected in 450K-based analyses.

Prostate cancer is characterized by frequent and recurrent copy number losses. We find that homozygous losses are depleted near essential genes compared to Epi2Hit events, suggesting that these losses are constrained by the proximity of essential genes, where Epi2Hit mechanisms tend to be favoured. This model further implies that additional TSGs inactivated by Epi2Hit may be located near essential genes.

In summary, the Epi2Hit workflow enabled us to discover TSG inactivation mechanisms including *ZFHX3*, a key regulator of *MYC*, and enables a more systematic investigation of

epigenetics as a tumour-promoting mechanism in cancer. Its applications in other cancer types, potential therapeutic implications, and future integration with long-read sequencing underscore its value as a versatile and powerful approach in cancer genomics.

Methods

We used data from the PPCG consortium of primary prostate cancer samples from a total of 1,001 prostate cancer donors. Informed written ethical consent was obtained at clinical follow-up, and was consistent with local research ethics and International Cancer Genome Consortium (ICGC) guidelines (https://icgc.org/). Ethical approval was obtained from local research ethical committees.

The full list of approving boards/committees:
Human Research Ethics Committee at Melbourne Health (HREC 2006.073; HREC 2011.009; HREC 2012.275; HREC 2012.220; HREC 2016.087) (Australia)
University Health Network Research Ethics Board and CHU de Québec–Université Laval Research Ethics Board (UHN 06- 0822- CE; UHN 11- 0024- CE; CHUQc- UL 2012- 913:H12- 03- 192) (Canada)
UBC Clinical Research Ethics Board (UBC REB H21- 03722) (Canada)
The National Committee on Health Research Ethics (reference no. 1302791) and notification to the Danish Data Agency (no. 1- 16- 02- 330- 13) (Denmark)
CPP Ile de France IV Institutional Review Board (IRB 00003835) (France)
Ethik- Kommission der Ärztekammer Hamburg (PV3552; PV4445; PV4679) (Germany)
NHS East of England–Cambridge Research Ethics Committee (REC 3/0180) (UK)
NHS East Midlands Research Ethics Committee (01/4/061) (UK)
NHS London Research Ethics Committee (CCR 2075) (UK)
University of Pretoria Human Research Ethics Committee (FWA00002567; IRB00002235; IORG0001762; approval #43/2010) (South Africa)
St Vincent's Hospital Human Research Ethics Committee (#SVH/12/231; #SVH/15/227) (Australia)
Human Research Protection Office, US Army Medical Research and Development Command (approvals E02371 and E03280 for genomic interrogation of SAPCS samples) (USA)

Dataset

The study leverages data from the Pan-Prostate Cancer Group (PPCG) cohort, a harmonized, clinically annotated dataset comprising 2,021 prostate cancer donors across seven countries. Multi-modal molecular profiling includes whole genome sequencing (WGS), 450K DNA methylation arrays, RNA-seq, and where available, long-read Oxford Nanopore Technologies (ONT) sequencing. Detailed clinical annotations including Gleason Grade Group, PSA levels, treatment, and survival outcomes are described in Jakobsdottir et al.[29]
Of the 2021 donors, 1001 had WGS (1209 samples), 1490 had 450K methylation arrays (1928 samples), and 1292 had RNA-seq (1594 samples) available after quality control.
The details of the PPCG cohort are described in the accompanying marker resource paper[29].

WGS data and variant calling

Whole-genome sequencing (WGS) data were generated across multiple international centers as part of the PPCG consortium and processed using standardized, containerized pipelines to

ensure reproducibility and harmonization across sites. Two centralized workflows for somatic and germline variant calling were applied uniformly, as described in Jakobsdottir et al.[29]

Allele-specific somatic copy number alterations (CNAs) were inferred using the Battenberg algorithm (v2.2.9, https://github.com/Wedge-lab/battenberg), which phases heterozygous SNPs using the 1000 Genomes Project reference panel. B-allele frequency (BAF) and logR ratios were then jointly modelled to identify clonal and subclonal CNAs. The method incorporates statistical testing to assess clonality and estimates cancer cell fraction (CCF), tumour purity, and ploidy for each sample.

CNA profiles were generated for all tumour–normal WGS pairs. CNA call sets were manually reviewed by two analysts and samples were classified as satisfactory (n = 1128), unsatisfactory (n = 24), over-fragmented (n = 13), or samples without detectable copy-number alterations (n = 301). Only high-confidence CNA profiles (satisfactory samples) were retained for downstream analyses in Epi2Hit.

Hemizygous loss on autosomes were defined as segments with total copy number = 1 and CCF ≥ 0.9, ensuring high-confidence clonal deletion events. These calls rely on Battenberg's allele-specific modelling and purity/ploidy-aware segmentation, providing robust and consistent annotation of deletion events for integration with methylation and gene expression data.

Further processing and harmonisation of the PPCG WGS data are described in detail in the accompanying marker resource paper[29]

DNA methylation

450K array-based methylation data were processed using a standardized and publicly available RnBeads-based workflow[100,101] (https://github.com/panprostate/PPCG_DNA_methylation), which integrates preprocessing, normalization, and QC steps designed to harmonize large multi-cohort data, as described in Jakobsdottir et al.[29] Briefly, Raw IDAT files were imported and preprocessed using RnBeads v2.15.1 with background subtraction, dye-bias correction, and bead count-based filtering. Low-quality samples (median bead count <3 or high probe-wise detection p-values >0.05) were flagged and excluded. Probes were filtered out if they overlapped known SNPs (MAF >0.05), were known to be cross-reactive[102], or had detection p-values ≥0.05 in ≥1% of samples. Methylation data were normalized using a single-sample approach implemented via the SeSAMe method[103], re-implemented in the RnBeads framework. Background correction was performed using the "noobsb" method, which fits a sample-specific background distribution based on out-of-band signal intensities from Type I probes and regresses this from foreground intensities. Dye-bias correction was conducted using internal channel scaling. This normalization strategy enabled robust cross-cohort comparison without requiring batch metadata. Technical consistency across countries and cohorts was evaluated using density plots of 65 SNP-tagging CpG probes. Additionally, beta-value distributions were visually inspected, and principal component analysis (PCA) of normalized values confirmed that primary axes of variation reflected biological rather than technical differences. To further mitigate population structure effects, genotype-derived SNP principal components were included in downstream analyses.

Reference methylation data for major immune and stromal cell types were compiled from public datasets and in-house FACS-sorted prostate epithelial populations. To distinguish among 11 major cell types, the 200 most differentially methylated CpG sites per cell type (100 hypermethylated and 100 hypomethylated), along with CpGs within 50 bp, were selected [104], resulting in a set of 2851 CpGs. Cell-type proportions were then estimated using the Houseman algorithm[105,106] as implemented in RnBeads, and normalized to sum to 100% per sample for downstream adjustment in methylation-expression analyses. Estimated cell-type proportions were used as covariates in downstream methylation-expression modelling within the Epi2Hit framework.

Further processing and harmonisation of the PPCG Methylation data are described in detail in the accompanying marker resource paper[29].

Principal component analysis is shown in **Supplementary Fig. 1a**

RNA sequencing data

RNA-seq data were uniformly processed across samples using a harmonized pipeline based on STAR for alignment to the GRCh37 reference genome, followed by transcript-level quantification with Salmon (v1.4.0) using GENCODE v19 annotations (https://github.com/panprostate/RNA).
RNA-seq data from the PPCG cohort, generated across several centers using diverse chemistries and platforms, underwent a multi-step normalization strategy to correct for both known and unknown sources of technical variation. Lowly expressed genes were filtered, retaining 22760 transcripts for downstream analysis. Tumour purity was estimated using ESTIMATE[107,108] and singscore methods.
Normalization was performed using the RUV-III method[109] with pseudo-replicates of pseudo-samples (PRPS), implemented in both supervised and unsupervised modes. In the supervised approach, known biological covariates (ERG status, tumour purity) guided the selection of negative control genes. In the unsupervised approach, mutual nearest neighbours (MNN) and KNN-based algorithms were used to generate pseudo-replicates and identify control genes based on low biological variability and high association with technical noise. RUV-III-PRPS outperformed other tested methods (CPM, TMM, upper-quartile, VST, ComBat) in preserving biological signals while removing technical artefacts. All normalization code is publicly available at https://github.com/RMolania/RUVprps**.**

Further processing and harmonisation of the PPCG RNA data are described in detail in Jakobsdottir et al.[29]

Principal component analysis is shown in **Supplementary Fig. 1a**

Multi-omic data integration strategy

Due to the sparsity data representation, a stepwise integration strategy was employed to maximize the use of available data while minimizing loss of statistical power. First, regulatory CpGs were identified using the full set of available DNA methylation profiles (*n*=1,268) together with ATAC-seq data from an independent cohort (GSE188797) and further annotated with external Hi-C-based chromatin loops (GSE164347). Next, expression-correlated CpGs (eCpGs) were determined within the subset of samples for which both methylation and RNA-seq data were available (*n*=1,292). Finally, candidate biallelic inactivation events were evaluated by integrating methylation data with WGS-derived copy number profiles (*n*=1,001). This modular approach enabled robust cross-modal analysis without restricting the study to only the samples profiled in all three data types.

Hi-C data

Hi-C data from prostate cancer were retrieved from the Gene Expression Omnibus (GEO) from data sets GSE164347[37].

For integration with Oxford Nanopore (ONT) long-read sequencing data, which was processed using the hg38 genome build, we performed liftover of the relevant Hi-C loop regions from hg19 to hg38 using **pyliftover v0.4.1** to enable visualisation and plotting in the hg38 coordinate space.

ChIP-seq data

Processed ChIP-seq data for ZFHX3 was obtained from the Gene Expression Omnibus (GEO) (GSE49402, GSM1208743; Yan et al., 2013)[72] and from human neural stem cells (Pérez Baca et al., 2024)[71,72]. To provide prostate-specific evidence, we additionally used published ChIP-PCR data in C4-2B prostate cancer cells (Hu et al., 2019)[42,43], where primers targeting three regions of the MYC promoter (Regions A–C) were designed. These primer sequences were validated in silico using the UCSC isPcr tool against the hg38 assembly, which confirmed single, specific amplicons within the MYC promoter (chr8:127,735,377–127,735,930). The identified regions overlapped with ZFHX3 binding peaks detected in neural stem cells and colon cells, confirming promoter-proximal binding across distinct cellular contexts.

liftover from hg18 to hg19 and from hg19 to hg38 was performed using pyliftover 0.4.1.

Epigenetic marks (H3K4me3, H3K27ac) and CTCF binding sites at the loci were derived for prostate cancer cells (PC-3, C4-2B) from the ENCODE project [110]

ATAC sequencing data

To identify CpG sites located within open chromatin regions, processed ATAC-seq data generated from human tumour samples was retrieved from the Gene Expression Omnibus (GEO) from data set GSE188797[36]

Long-read sequencing

Tumour and matched normal genomic DNA from six prostate cancer donors were prepared for Oxford Nanopore long-read whole-genome sequencing using the Ligation Sequencing Kit V14

kit (SQK-LSK114). The libraries were sequenced on a PromethION P24 instrument with R10.4.1 flow cells (FLO-PRO114M). Average library sequencing depth was 30x and 18x, range 19.5x-48.6x and 6.0x-48.0x, for tumor and normals, respectively. Basecalling was performed with Dorado v1.0.0 with model hac@v5.2.0, while 5mC and 5hmC modifications were called concurrently with model sup@v5.2.0_5mC_5hmC@v1. The data was then aligned to hg38 and phased with the epi2me-labs wf-human-variation workflow v2.7.1, performing genome-wide allele specific CpG methylation calling (5mC and 5hmC) with modkit v0.3.3**.**

For *ZFHX3*, phased haplotypes allowed us to distinguish the deleted allele (allele 1, copy number = 0) from the retained allele (allele 2). The expected pattern for biallelic inactivation is (i) absence of methylation signal on the deleted allele and (ii) strong hypermethylation on the retained allele.

Identification of Regulatory CpG Sites (eCpGs)

DNA methylation data

Methylation data was obtained from the 450k array methylation dataset provided by the PPCG. The data included β-values corresponding to the methylation levels at various CpG sites across multiple samples. Samples that failed quality control were excluded from the analysis. The remaining 1268 primary tumour samples were used for the analysis.

Annotation of CpG sites with gene Information

Each site was annotated with the nearest gene(s) using the hg19 reference genome. This annotation was performed using the pybedtools package and the 'closest' function. The reference gene annotations were retrieved from the GENCODE v19 database. The CpG sites were matched to the closest genes, considering both strand orientation and distance. The output included all potential gene associations for each CpG site, facilitating further exploration of gene-specific methylation patterns.

Filtering based on methylation correlations

The dataset was subjected to a series of filtering steps to prioritise CpG sites with specific methylation patterns:

- **Correlation with immune and stromal components:** CpG sites were filtered based on their correlation with immune and stromal cells abundance. Pearson correlation coefficients were calculated for each site using methylation beta-values against a methylation-derived estimation of stromal and immune cell type proportions (described in detail in Jakobsdottir et al.[29] Sites showing low correlation (correlation coefficient < 0.4) with these components were retained, ensuring that the selected CpG sites primarily reflect methylation changes in tumour cells rather than in the surrounding stromal or immune cells.
- **Correlation with global loss of methylation:** Additionally, CpG sites were filtered based on their correlation with global loss of methylation estimated by the EpiCMIT-hypo score[111] (as described in Jakobsdottir et al.[29]), reflecting epigenetically-determined Cumulative MIToses which result in stochastic loss of methylation and the formation of 'partially methylated domains (PMDs).

ChromHMM annotation for regulatory elements

Filtered CpG sites were annotated with chromatin states using prostate-specific ChromHMM data from Pomerantz et al[38]. ChromHMM annotations were intersected with CpG sites using pybedtools, and states were mapped to corresponding categories (e.g., Active Prostate

Lineage-Specific Promoter). This step identified CpG sites within enhancer and promoter regions.

Merging CpG sites by methylation correlation

CpG sites annotated within the same regulatory region were merged if their methylation levels exhibited a Pearson correlation coefficient above 0.6. Merged sites were represented by the average methylation value and spanned the combined genomic coordinates of the individual CpG sites.

Hi-C data integration for chromatin loops

Hi-C data from prostate cancer (GEO; GSE164347) was used to annotate regulatory CpG sites with chromatin loop information. CpG sites overlapping loop anchor regions were identified, and corresponding loop IDs were assigned to these sites. Sites associated with loops were indicated by a 'Ls_' prefix in their identifiers.

Linear regression analysis to identify expression-associated CpG sites.

We performed linear regression to identify CpG sites associated with gene expression (eCpGs) by regressing methylation levels against RNA-seq-based gene expression from the PPCG group.

- **Regression modelling:** Ordinary Least Squares (OLS) regression was performed using the statsmodels package, treating methylation as the independent variable and gene expression as the dependent variable. Regression coefficients, p-values, confidence intervals, and R-squared values were extracted.
- **Multiple testing correction:** P-values were adjusted for multiple comparisons using the Benjamini-Hochberg False Discovery Rate (FDR) method from the statsmodels package (Ruiz-Arenas *et al.*, 2022[112]; Advani *et al.*, *Nat Commun* 2024[113]; Ando *et al.*, *Nat Commun* 2019[114]), Supplementary Data 2.
- **eCpG identification:** CpG sites with significant negative associations (adjusted p-value < 0.05) were classified as eCpGs. To ensure biological relevance, we further applied a regression coefficient threshold of < -0.4, which corresponds to an approximate 25% reduction in gene expression across the methylation range. Since gene expression was modelled as $\log_2$(TPM+1), a coefficient of -0.4 implies a moderate-to-strong transcriptional repression effect per unit increase in methylation. This level of effect size is consistent with enhancer and promoter methylation–expression associations previously reported in cancer cohorts[99] (Supplementary Data 2)

Sensitivity analyses for tumour purity and global genomic instability

Purity-adjusted methylation–expression regression

To assess the robustness of methylation-expression associations to tumour purity, we re-fit the regression models used to define eCpGs. In the baseline analysis, for each CpG–gene pair we modelled gene expression as a function of methylation using ordinary least squares (OLS):

$$(1)\ expression = \alpha + \beta \cdot methylation + \varepsilon$$

$$(2)\ expression = \alpha + \beta \cdot methylation + \gamma \cdot purity + \varepsilon$$

For all CpG-gene pairs considered in the main analysis we extracted the methylation coefficients (β) and R2 values from both models and compared their distributions. The direction of the methylation effect was preserved and the association remained significant after Benjamini–

Hochberg false discovery rate (BH-FDR) correction (q < 0.05). Genome-wide concordance of methylation effect sizes between baseline and purity-adjusted models was summarised using Pearson and Spearman correlations (Pearson r = 0.996, Spearman ρ = 0.996) **(Supplementary Fig. 1e)**.

To further account for global genomic instability, we additionally fit a two-covariate model including both tumour purity and fraction genome altered (FGA):

$$(3)\ expression = \alpha + \beta \cdot methylation + \gamma \cdot purity + \delta \cdot FGA + \varepsilon$$

Methylation coefficients from this model were compared to the baseline model in the same way (Pearson r = 0.969, Spearman ρ = 0.964) **(Supplementary Fig. 1f)**.

For loci highlighted in **Fig. 3a** (*ZFHX3, PDE4D, PSD3, KLF5, NAT1, APC* and *RBPMS*), we report locus-level regression results with and without purity adjustment, including methylation coefficients, p-values, FDR-adjusted q-values and R2 (Supplementary Table 2), to illustrate the stability of effect direction and magnitude at key Epi2Hit loci.

Categorization of methylation Levels

Methylation levels for each feature were categorised into three groups: 'Not/Low_methyl', 'Medium_methyl', and 'Highly_methyl'. The classification was based on predefined thresholds (down_threshold=0.2 and up_threshold=0.7)[115–118] and the distribution of methylation values. Features with all values below the down_threshold were categorised as 'Not/Low_methyl', while those with values above the up_threshold were labelled 'Highly_methyl'. Features with methylation values spanning these thresholds were further analysed using kernel density estimation (KDE) and peak detection to identify potential multimodal distributions.

For features with intermediate methylation levels, a Gaussian kernel density estimation (KDE) was applied to estimate the probability density function (PDF) of the methylation values.

The KDE was performed using the scipy.stats.gaussian_kde function.

Peaks in the KDE were identified using the scipy.signal.find_peaks function. Depending on the number of detected peaks, the feature's methylation values were categorised accordingly:

To ensure reproducibility and robustness, we conducted a sensitivity analysis across three key KDE parameters: distance, height, and prominence, which define the minimum distance between peaks, the KDE height threshold, and the peak prominence threshold respectively.

A total of 305 CpG sites were selected from the prostate cancer cohort, each visually confirmed to exhibit bimodal or trimodal methylation distributions. We then systematically evaluated 125000 parameter combinations generated from a three-dimensional grid (50 linearly spaced values from 0.01–0.5 for each parameter; see Supplementary Data 3).

Performance was measured by the number of CpGs for which the algorithm correctly detected 2–3 peaks. The optimal parameter range was defined as:

- distance_frac: 0.01–0.11
- height_quantile: 0.01–0.33
- prominence_frac: consistently optimal at 0.01

The midpoint values (distance_frac=0.06, height_quantile=0.17, prominence_frac=0.01) were selected as defaults for downstream analyses and recovered 94% (287/305) of the benchmark regions.
Pairwise KDE parameter performance is visualized in **Supplementary Fig. 2d**, where warmer (red) regions indicate higher peak detection accuracy across the parameter grid.

This parameter configuration was further validated on an independent luminal breast cancer cohort (TCGA-BRCA[119]), where an additional 450 manually selected CpG sites were analysed. Using the same settings, the KDE algorithm correctly identified 1, 2 or 3 peaks in 443/450 (98.4%) regions, confirming the sensitivity of the approach (Supplementary Data 4-5).
Depending on the number of detected peaks, the feature's methylation values were categorised accordingly:

- Single Peak: A Gaussian Mixture Model (GMM) with three components was fitted to the methylation values using sklearn.mixture.GaussianMixture(https://scikit-learn.org/stable/modules/generated/sklearn.mixture.GaussianMixture.html). The resulting clusters were used to assign methylation categories based on the cluster means, with thresholds calculated from the median and minimum of these means.

We chose GMM for unimodal distributions based on its successful use in prior studies[116], where it stratified promoter methylation into binary states. In contrast, our method applies GMM at the CpG level and partitions the distribution into three states: 'Not/Low_methyl', 'Medium_methyl', and 'Highly_methyl', capturing partial methylation patterns frequently observed in cancer. GMM is only used when KDE fails to detect more than one peak, ensuring method selection is driven by the distributional shape.
A visual overview of the KDE vs. GMM logic, is shown in **Supplementary Fig. 2a.**

- Two Peaks: Features displaying a bimodal distribution were manually reviewed, with the lower and upper peak values serving as thresholds for categorising the methylation levels into *'Not/Low_methyl'*, *'Medium_methyl'*, and *'Highly_methyl'*.
- Three Peaks: Features with a trimodal distribution were also manually reviewed, using the median and minimum of the peak values as thresholds for classification.

If no peaks were detected or distributions were ambiguous, conservative fallback quantile thresholds (quant_low=0.3, quant_high=0.7) were used.

To identify genes that are biallelic inactivated we used our previously published methodology[14,39,120], expanding it to DNA methylation data.
Loss/Methylation: A heterozygous loss combined with high methylation (som_loss/methyl).

Validation of Epi2Hit in TCGA-PRAD

TCGA-PRAD data acquisition and preprocessing

For external validation, we applied Epi2Hit to an independent prostate cancer cohort from TCGA-PRAD. DNA methylation (450k array β-values), RNA-seq expression, and copy-number alteration (CNA) profiles for primary tumours (n = 493) were downloaded from cBioPortal(https://www.cbioportal.org/), and structural variant (SV) calls were obtained from TCGA-PRAD whole-genome sequencing samples in the NCI Genomic Data Commons (GDC(https://portal.gdc.cancer.gov/); accessed 22 July 2025). Only samples with matched

methylation, expression and CNA data were retained. Gene expression values were transformed to $\log_2$(TPM+1).

Re-implementation of the Epi2Hit workflow in TCGA

We re-implemented the complete Epi2Hit pipeline on TCGA-PRAD using the same parameter settings as for PPCG. Briefly, CpG sites were annotated to genes, filtered (removal of CpGs correlated with immune/stromal estimates or global PMD-associated hypomethylation, restriction to prostate ChromHMM promoters/enhancers, intersection with prostate tumour ATAC-seq peaks, and prioritisation of CpGs at Hi-C loop anchors), and tested for association with gene expression to define eCpGs. CpG-level p-values were adjusted using the BH-FDR, and within-gene multiplicity was controlled using Simes-based aggregation[121] of eCpG p-values to obtain per-gene q-values. For each gene, methylation distributions at eCpGs were then modelled with KDE/GMM as described above to obtain discrete methylation states, which were integrated with CNAs and SVs to call Epi2Hit events (heterozygous loss plus hypermethylation).

Comparison of biallelic inactivation patterns across cohorts

For the most frequently disrupted tumour suppressor genes (TSGs), we quantified the number of samples in each cohort harbouring genomic biallelic hits versus Epi2Hit events These counts were summarised as bar plots for TCGA-PRAD and PPCG (**Supplementary Fig. 3c,** Supplementary Table 4-5).

MethylMix validation

Construction of gene-level methylation profiles

To compare Epi2Hit with a MethylMix framework for methylation-driven genes, we used the pre-eCpG set defined in the PPCG discovery cohort (prior to KDE/GMM-based peak detection).

Gene-level methylation and expression matrices were analysed with the MethylMix algorithm (R package MethylMix 2.0(https://bioconductor.org/packages/release/bioc/html/MethylMix.html)) using recommended settings.

Overlap with Epi2Hit and visualisation of methylation states

To quantify concordance, we intersected the list of methylation-driven genes with the set of genes harbouring Epi2Hit events in PPCG. Overall, 47% of methylation-driven genes were also identified by Epi2Hit, including key tumour suppressors such as *APC, KLF5, NAT1* and *ZFHX3*. For these four genes, we visualised the MethylMix beta mixture models as density curves overlaid on β-value histograms (**Supplementary Fig. 3d**), illustrating the presence of 2–3 distinct methylation states per gene.

Standardized mean difference analysis (Cohen's *d*)

We first used publicly available ChIP-seq data (GSE49402) to identify genes with ZFHX3 binding sites located within ±2 kb of their annotated transcription start sites, representing putative promoter-proximal targets of *ZFHX3*. From this list, we selected genes previously

reported in the literature to have tumour-suppressive or oncogenic functions in prostate cancer. This final set of genes was used for expression analysis.

To quantify the differences in gene expression between *ZFHX3* wild-type (WT) and epigenetic biallelic inactivation (Epi2Hit) prostate cancer samples, we computed the standardized mean difference (Cohen's *d*) for the preselected genes. For each gene, we calculated the mean expression in the WT and Epi2Hit groups and divided their difference by the pooled standard deviation across the two groups. This approach allows comparison of expression differences across genes on a standardized scale, independent of absolute expression values.

The pooled standard deviation (s_p) was computed as:

$$(4)\ s_p = \sqrt{\frac{(n_1 - 1)\, s_1^2 \ + (n_2 - 1)\, s_2^2}{n_1 + n_2 - 2}}$$

where n_1 and n_2 are the sample sizes of the WT and Epi2Hit groups, respectively, and s_1 and s_2 are their respective standard deviations.

Cohen's *d* is then:

$$(5)\ d = \frac{\bar{x}_1 - \bar{x}_2}{s_p}$$

Positive values of *d* indicate higher expression in the WT group, and negative values indicate higher expression in the Epi2Hit group.

Essential genes analysis

To investigate the association between essential genes and tumour suppressor genes (TSGs) that are rarely or never inactivated by bi-allelic loss, we utilised data from the DepMap(https://depmap.org/portal/) database. Genes with scores below this threshold (<−1.2) were considered essential.

Calculation of Proximity to Essential Genes

The distance between each TSG and the closest essential gene was calculated as the absolute genomic distance in megabases (Mb), considering both upstream (5′) and downstream (3′) directions. For each TSG, the minimum of the two distances (5′ or 3′) to the nearest essential gene was used. The presence of an essential gene near a TSG was annotated as True if the distance between the TSG and the nearest essential gene was less than the first quantile (Q1) of the mean distance (dTSG <Q1) across all TSGs. This criterion was used to assess the pattern of essential genes in relation to TSGs that are rarely or never inactivated by biallelic loss.

For comparative analyses, we included only TSGs affected by Epi2Hit or homozygous deletion in more than two tumour samples. Differences in the distance to essential genes between these groups were assessed using the two-sided Mann–Whitney U test.

To explore functional consequences, we also compared average gene expression ($\log_2$(TPM + 1)) between essential genes and TSGs using RNA-seq data from the same cohort. Statistical significance was evaluated using the Mann–Whitney U test **(Fig. 5e)**.

Structural covariates and multivariable models

To assess whether the proximity signal could be explained by structural genomic features and to address potential confounding, we assembled a unified gene-level dataset for all TSGs that included:

- **Gene length** (bp, converted to kb),
- **Local gene density** in a ±250 kb window (gene_density_500kb),
- **Distance to the centromere** (dist_to_centromere, in kb),
- **Proximity to essential genes** at several DepMap CERES thresholds.

For each DepMap essentiality cutoff $X \in \{CERES<-0.2, <-0.5, <-0.7, <-1.0, <-1.2, <-1.5\}$, we computed:

- dist_CERES_X: distance (kb) to the nearest essential gene,
- count_CERES_X: number of essential genes within 500 kb,
- has_dist_CERES_X_within_500kb: indicator of ≥1 essential neighbour within 500 kb.

All distance-like variables were rescaled to kilobases for interpretability. These variables were used as predictors in multivariable logistic regression models with outcome Epi2Hit vs homozygous loss for each CERES threshold. Each model included gene length, local gene density, distance to centromere, number of nearby essential genes (count_CERES_X), distance to the nearest essential gene (dist_CERES_X) and the 500 kb proximity indicator. Odds ratios (ORs) and 95% confidence intervals are summarised in **Supplementary Fig. 5a-b** and Supplementary Table 8. At the main common-essential threshold (CERES < –1), both the number of essential neighbours and, to a lesser extent, their proximity remained significantly associated with Epi2Hit status after adjustment for gene length, gene density and chromosomal context.

Prostate-specific essentiality

To evaluate whether these patterns hold in a prostate-specific context, we repeated the analysis using only prostate cancer cell lines (22RV1, LNCaP, DU145) from DepMap. Essentiality scores were recalculated across the same CERES thresholds, and prostate-specific proximity measures (count_CERES_X, dist_CERES_X, has_dist_CERES_X_within_500kb) were recomputed for each TSG. Multivariable logistic models with the same covariates (gene length, gene density, distance to centromere and essential-gene proximity) were then refitted. The number and proximity of prostate-essential neighbours remained strong predictors of Epi2Hit versus homozygous loss across thresholds (**Supplementary Fig. 5c–d**, Supplementary Table 9), supporting a genuine constraint by essential neighbours' effect rather than structural artefacts or dependence on a particular essentiality definition.

Copy number loss frequency (ideogram-level).

For each ideogram interval (chromosome, start, end; hg19 autosomes), we calculated the proportion of tumour samples (n = 991) with overlapping homozygous loss (norm_total = –2) or hemizygous loss (norm_total = –1) in the segmentation data. Overlap was defined as segment_start < region_end and segment_end > region_start. Homozygous loss (hom %) and hemizygous-only loss (het %; excluding samples that also carried a homozygous loss in that region) were computed separately. Their sum (loss %) represented the total fraction of samples with any loss in the interval, without double-counting. Only intervals with loss % > 10% of samples were retained for ideogram plotting.

The chromosome ideogram was generated using the Python package *quyuan* (v1.1.3; https://github.com/tcztzy/quyuan).

Copy number loss frequency (chromosome-level).

For each autosomal chromosome, we determined the proportion of tumour samples (n = 991) with at least one segment meeting the loss criterion anywhere on that chromosome. Homozygous loss (hom %, norm_total = –2) and hemizygous loss (het %, norm_total = –1) were calculated separately, and the union of these sample sets (loss %) represented the total percentage of tumours with any loss on that chromosome, without double-counting those carrying both types of loss.

Exclusivity score of copy number alterations.

To quantify the tendency of driver genes to occur independently rather than co-occur with other driver genes across cancer samples, we applied the exclusivity score metric, as described by Gerhauser et al. (Cancer Cell, 2018)[14]. This score estimates the degree to which a given gene alteration is exclusive or co-occurs with other gene alterations

For each driver gene, the exclusivity score is calculated as the mean inverse of the number of co-altered driver genes in samples where the gene is present. Specifically, for each sample with an alteration of the target gene, the reciprocal sum of driver genes with the alteration is computed and the exclusivity score is calculated as the arithmetic mean of the reciprocal values across all relevant samples.

Formally, the exclusivity score is defined as:

$$(6)\ Exclusivity\ Score\ = \frac{1}{n}\sum_{i=1}^{n}\ \frac{1}{c_i}$$

Where:

n is the number of samples containing the target gene,

c_i is the number of driver genes altered in a sample

The exclusivity score ranges from 0 to 1. Higher values indicate greater exclusivity (occurring as the only driver alteration), while lower values suggest frequent co-occurrence with other driver genes.

Survival analysis

Lifelines package (lifelines.KaplanMeierFitter and lifelines.CoxPHFitter) (https://github.com/lifelines/lifelines) was used for survival analysis across subgroups.

Statistics & Reproducibility

All statistical tests were two- tailed, unless otherwise specified. For parametric data, we used tests assuming normal distribution. For non- parametric data, we used distribution- free tests. Significance thresholds and specific tests are detailed in the figure legends and Methods.

The Epi2Hit pipeline was implemented in Python and comprises modular steps for methylation processing, expression-methylation correlation, probe filtering and merging, gene annotation, chromatin state mapping, and integration with Hi-C, ATAC-seq, and long-read sequencing data. Default parameters and thresholds (CNV, KDE, regression covariates) are detailed in Supplementary Table 11.
The pipeline supports parallel processing through the joblib library (e.g., n_jobs=16) to accelerate steps such as correlation-based probe merging. All analyses were run on a shared Linux server with 64 CPU cores and 512 GB of RAM. Jobs were typically submitted with a memory request of up to 40 GB RAM. Runtime for the full pipeline applied to the PPCG cohort (~1,000 samples and ~450,000 probes) was approximately 3-4 hours, depending on data modalities and filtering settings. Due to its modular and parallelizable structure, the pipeline scales efficiently with increasing cohort size and is readily applicable to other tumour types and multi-omic datasets.

Epi2Hit is distributed as a Docker image available at https://hub.docker.com/r/al0ka/epi2hit. The container includes all necessary dependencies and project scripts and is available for both x86_64 (linux/amd64) and ARM64 (linux/arm64) architectures. Users can obtain the image by executing "docker pull al0ka/epi2hit:latest" and then run the workflow by following the included documentation. The image was tested using the included example data on an Ubuntu 24.04.3 LTS machine with 4GB of RAM and 4 CPU cores. The analysis consisted of three steps: the initial step (eCpG identification - run-epi2hit_py) took approximately 7 minutes, the second step (generating metadata.yaml) was nearly instantaneous, completing in about 1 second, and the final step (running biallelic_py) took approximately 1 minute.

All data analyses were performed using Python 3.8 (pandas v1.1.5, numpy v1.19.5, lifelines 0.27.7, scipy v1.5.4, and scikit-learn v0.23.2, statsmodels v0.13.2, joblib v1.2.0, tqdm v4.64.1, plotnine v0.10.1, pybedtools v0.10.0, pyBigWig v0.3.22, statannot v0.2.3) and and R 4.2.2 (MethylMix v2.41.0).
The plots and visualisations were generated using the seaborn v0.11.0, matplotlib v3.6.3, and additional figures were created using BioRender (BioRender.com) and quyuan (v1.1.3).

Data availability

PPCG dataset comprises whole-genome sequencing (WGS), RNA-seq, DNA methylation, clinical, and histopathological data from 2,021 prostate cancer donors. Due to the sensitive nature of human genomic/clinical data and participant-consent restrictions, PPCG data are provided under controlled access and are available only for approved research purposes.

Raw genome sequencing data have been deposited in the European Genome-Phenome Archive (EGA) under the study ID EGAS00001002876 (https://ega-

archive.org/studies/EGAS00001002876) and is described in the Reporting Summary and our companion manuscript [29]. In addition, PPCG working project data (e.g., variant calls, pipeline outputs and intermediate analyses) and harmonised RNA-seq/methylation data are made available to approved projects through secure transfer (Globus), and clinical/histopathological data are hosted in a GDPR-compliant secure environment (REDCap); access is limited to approved PPCG researchers.

Access to PPCG controlled data requires submission of a Project Concept Form, available at https://panprostate.org, and approval by the PPCG Steering Committee. Requests are submitted by emailing the completed form to PPCG@icr.ac.uk. We will respond to the data access request within 14 days. We will provide guidance on the application process; access, once granted, is provided for the duration of the approved project under the applicable data access agreement/terms.

To support reproducibility without redistribution of controlled PPCG data, we provide a compact, self-contained example dataset in the project repository that is sufficient to run the Epi2Hit workflow end-to-end and reproduce representative outputs. Specifically, the repository includes a TCGA-PRAD chromosome 8 example dataset (450K methylation β-values for chr8, a matched gene expression matrix, prostate ATAC-seq peaks, ChromHMM segmentation, and Hi-C loops), together with example mutation calls and copy-number segment inputs used for downstream biallelic analyses. These files are provided under the repository's data/ directory and are used by analysis/TCGA_run.ipynb (and the containerized demo) to reproduce the main workflow outputs on the example dataset.

The publicly available data used in this study are available in the NCBI Gene Expression Omnibus (GEO) database under accession code GSE164347 (prostate Hi-C loops): https://www.ncbi.nlm.nih.gov/geo/query/acc.cgi?acc=GSE164347 [37].

The publicly available data used in this study are available in the GEO database under accession code GSE188797 (tumour ATAC-seq peaks): https://www.ncbi.nlm.nih.gov/geo/query/acc.cgi?acc=GSE188797 [36].

The publicly available data used in this study are available in the GEO database under accession code GSE49402 (GSM1208743, ZFHX3 ChIP-seq): https://www.ncbi.nlm.nih.gov/geo/query/acc.cgi?acc=GSE49402 [72].

The publicly available data used in this study are available from the ENCODE Project database (epigenetic marks (H3K4me3, H3K27ac) and CTCF tracks derived for prostate cancer cells (PC-3, C4-2B)): https://www.encodeproject.org/ [110].

The remaining data are available within the Article, Supplementary Information or Source Data file.

Code availability

Code used to generate results and plots are available at https://github.com/panprostate/Epi2Hit. A static version of the code is available at doi:10.5281/ZENODO.18788787 [122]

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Competing interests

V.J.G. is honoraria from Janssen and JEB as a speaker. Member of external expert committee to Astra Zeneca UK. R.A.E. is Honoraria from GU-ASCO, Janssen, University of Chicago, Dana Farber Cancer Institute USA as a speaker. Educational honorarium from Bayer and Ipsen, member of external expert committee to Astra Zeneca UK and Member of Active Surveillance Movember Committee. Member of the SAB of Our Future Health. Undertakes private practice

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The remaining authors declare no competing interests.

Figures

Fig. 1: Prostate cancer is characterised by frequent hemizygous loss of putative TSGs.

a Chromosome ideogram representing frequently (>10%) deleted regions (hemizygous loss - light blue, homozygous loss - dark blue) in the cohort**. b** The distribution of the number of genes with hemizygous loss across samples. The plot shows a decrease in the number of genes with hemizygous loss as the percentage of samples with affected genes increases, revealing the genes that are consistently affected across most of the samples. **c** Venn diagram showing the overlap between genes with recurrent hemizygous loss and differential methylation. The diagram highlights 1187 genes that exhibit both events. **d** Box plot of absolute coefficients of gene expression regressed on proximal CpG sites in closed (*n*=12,317 CpGs) or open chromatin (*n*=4,548 CpGs) P-value (****$P = 1.09 \times 10^{-115}$): two-sided Mann-Whitney U test). Centre line, median; box, 25th–75th percentiles (IQR); whiskers, most extreme values within 1.5×IQR.**. e** Forest plot represents the linear regression coefficients of top tumour suppressor genes (*n*=13); dots indicate the estimated coefficient and horizontal lines show the 95% confidence interval. P values for each gene are shown in the plot.

Source data are provided as a Source Data file.

Fig. 2: Epi2Hit pipeline.

a Schematic overview of the Epi2Hit workflow**. b** Flowchart describes the steps of the pipeline for identification of eCpGs and Epi2Hit candidates. eCpGs are identified as CpG sites intersecting ATAC peaks (Accessible CpGs), annotated with the presence of promoter-enhancer loops (Regulatory CpGs). These CpGs are used for linear regression on gene expression to identify eCpGs. SCNA data is intersected with eCpGs to identify genes with biallelic inactivation involving epigenetic silencing. Created in BioRender. Weischenfeldt, J. (2026) https://BioRender.com/vfgm91z

Fig. 3: Epi2Hit workflow identifies TSGs susceptible to biallelic inactivation through the combination of hemizygous loss and hypermethylation.

a Bar plot indicates the number of patients harbouring different types of biallelic inactivation for the 2% most frequent TSGs. **b** Box plots showing the expression of TSGs for wt (white), hemizygous loss (grey), Epi2Hit (red) groups of samples. Number of samples is indicated for each group. Centre line, median; box, 25th–75th percentiles (IQR); whiskers, most extreme values within 1.5×IQR. P-value (***$P < 0.001$, **$P < 0.01$, *$P < 0.05$, - ns): two-sided Mann-Whitney U test for each comparing pair. **c** Somatic events leading to biallelic inactivation of the *APC* gene in two distinct cases. In case PPCG0857 *APC* is inactivated through a combined copy number loss and hypermethylation. In case PPCG0271 *APC* is inactivated by a copy number loss and an SNV. Y-axis displays the relative copy number across chromosome 5 and the *APC* locus. **d** IGV plot of the *APC* locus highlighting CpGs and eCpG sites (black). eCpG sites are located in a regulatory region. **e** Correlation matrix (Pearson) of four (cg23938220, cg02511809, cg24332422, cg15020645) *APC* CpG sites. Positive correlations are indicated in red. **f** Box plot shows *APC* expression levels between samples with *APC* High and *APC* Low eCpG methylation (two-sided Mann-Whitney U test, $P = 0.004$). Centre line, median; box, 25th–75th percentiles (IQR); whiskers, most extreme values within 1.5×IQR.. Number of samples is indicated for each group. **g** Box plots showing methylation (β-values) at different *APC* methylated CpGs (1-12) for high (above median, blue, *n*=168) and low (below median, red, *n*=168) expression groups. Each point represents one tumour sample. Centre line, median; box, 25th-75th percentiles (IQR); whiskers, most extreme values within 1.5×IQR of the lower and upper quartiles; P-value (*$P < 0.05$ (P=0.01), - ns): two-sided Mann-Whitney U test. **h** Scatter plot summarising sample-level frequencies of genetic and epigenetic inactivation. For each gene, the x-axis shows the percentage of tumours with hemizygous loss, and the y-axis shows the percentage of the same tumours with high eCpG methylation. Each point represents one gene, and bubble size reflects the percentage of tumours with biallelic hits (co-occurrence of hemizygous loss and hypermethylation in the same samples).

Source data are provided as a Source Data file.

Fig. 4: *ZFHX3* inactivation drives *MYC* upregulation.

a Oxford Nanopore-based phased methylation and somatic copy number, and chromatin context at the ZFHX3 locus. Top: three Epi2Hit prostate cancers show loss of Allele 1 (green dashed) and allele-2 hypermethylation at the eCpG cg16563255 (red arrow; β = 0.82–0.9), with reduced ZFHX3 expression. Bottom: three Epi2Hit WT tumours show balanced allelic copy number and no allele-specific methylation. Hi-C loops illustrate chromatin interactions within the region. Prostate-specific chromatin marks - H3K4me3 and H3K27ac and CTCF, and prostate ATAC-seq peaks denote an active, accessible regulatory region overlapping the eCpG region. **b** Box plot shows *MYC* expression levels between *ZFHX3* WT and *ZFHX3* biallelic inactivation samples, illustrating a significant upregulation of MYC in *ZFHX3* biallelic inactivation cases (two-sided Mann-Whitney U test, $P = 0.03$). Centre line, median; box, 25th–75th percentiles (IQR); whiskers, most extreme values within 1.5×IQR. Number of samples is indicated for each group. **c** ZFHX3 binding at the MYC promoter with conserved sites in colon and prostate. Chromatin marks (H3K4me3, H3K27ac) and ATAC-seq peaks confirm a prostate-specific active regulatory context. **d** Bar plot showing standardised mean expression differences (Cohen's *d*) for genes involved in prostate cancer progression, highlighting their differential expression in *ZFHX3* WT vs. biallelic inactivation cases. Positive values indicate higher expression in *ZFHX3* WT samples, whereas negative values reflect higher expression in *ZFHX3* biallelic inactivation cases. **e** Bar plot illustrating the distribution of *ZFHX3* wild-type (WT) and inactivation cases across high and low Gleason grade groups (High: $n = 324$ [WT = 241, inactivation = 83]; Low: $n = 493$ [WT = 417, inactivation = 76]; total $n = 817$). The plot shows a significant enrichment of *ZFHX3* inactivation in the high Gleason group compared to the low Gleason group (Chi-square test, $P = 0.0004$). **f** Kaplan–Meier survival curves illustrating metastasis-free survival (MFS) stratified by ZFHX3 status (WT, $n = 377$; inactivation, $n = 440$; among patients with available metastasis-free survival data, $n = 817$). Shaded bands indicate the confidence interval around the Kaplan-Meier estimate. Group differences were assessed using the log-rank test.
Source data are provided as a Source Data file.

Fig. 5: *Nearby essential genes surrounding never-homozygous deleted tumour suppressor genes.*

a Schematic representation of the relationship between tumour suppressor genes (TSGs) and nearby essential genes on chromosomes 13 and 16. The presence of essential genes (blue) adjacent to TSGs (pink) limits the likelihood of homozygous deletions in these regions, leading to an increased probability of hemizygous loss and hypermethylation as alternative mechanisms of inactivation**.** Created in BioRender. Weischenfeldt, J. (2026) https://BioRender.com/hj1igem. **b** Stacked bar plot illustrating the distribution of TSGs with homozygous loss and TSGs with methylation (Epi2Hit) based on the presence (red) or absence (grey) of essential genes (homozygous loss: $n = 76$ [presence = 5, absence = 71]; methylation DoubleHit: $n = 46$ [presence = 12, absence = 34]; total $n = 122$) (from the DepMap database, with a score <-1.2, indicating high essentiality for cell survival). A Chi-square test of independence was used to assess the statistical significance of the observed differences, with a resulting $P = 0.006$. **c** Box plot comparing the distance to the closest essential gene for TSGs with homozygous loss (blue, $n=113$) or Epi2Hit (red, $n=103$). Centre line, median; box, 25th–75th percentiles (IQR); whiskers, most extreme values within 1.5×IQR. ***$P < 0.001$ ($P = 0.00009$) (two-sided Mann–Whitney U test). **d** Empirical cumulative distribution function (ECDF) of the distance to the closest essential gene for TSGs affected in >2 patients by homozygous loss (blue) or Epi2Hit (red). *PTEN*, *KLF5* and *ZFHX3* are annotated. **e** Box plot comparing average gene expression ($\log_2$ (TPM+1)) of TSGs (pink, $n=104$) and essential genes (blue, $n=143$). Centre line, median; box, 25th–75th percentiles (IQR); whiskers, most extreme values within 1.5×IQR. *$P < 0.05$ ($P = 0.04$) (two-sided Mann–Whitney U test).
Source data are provided as a Source Data file.

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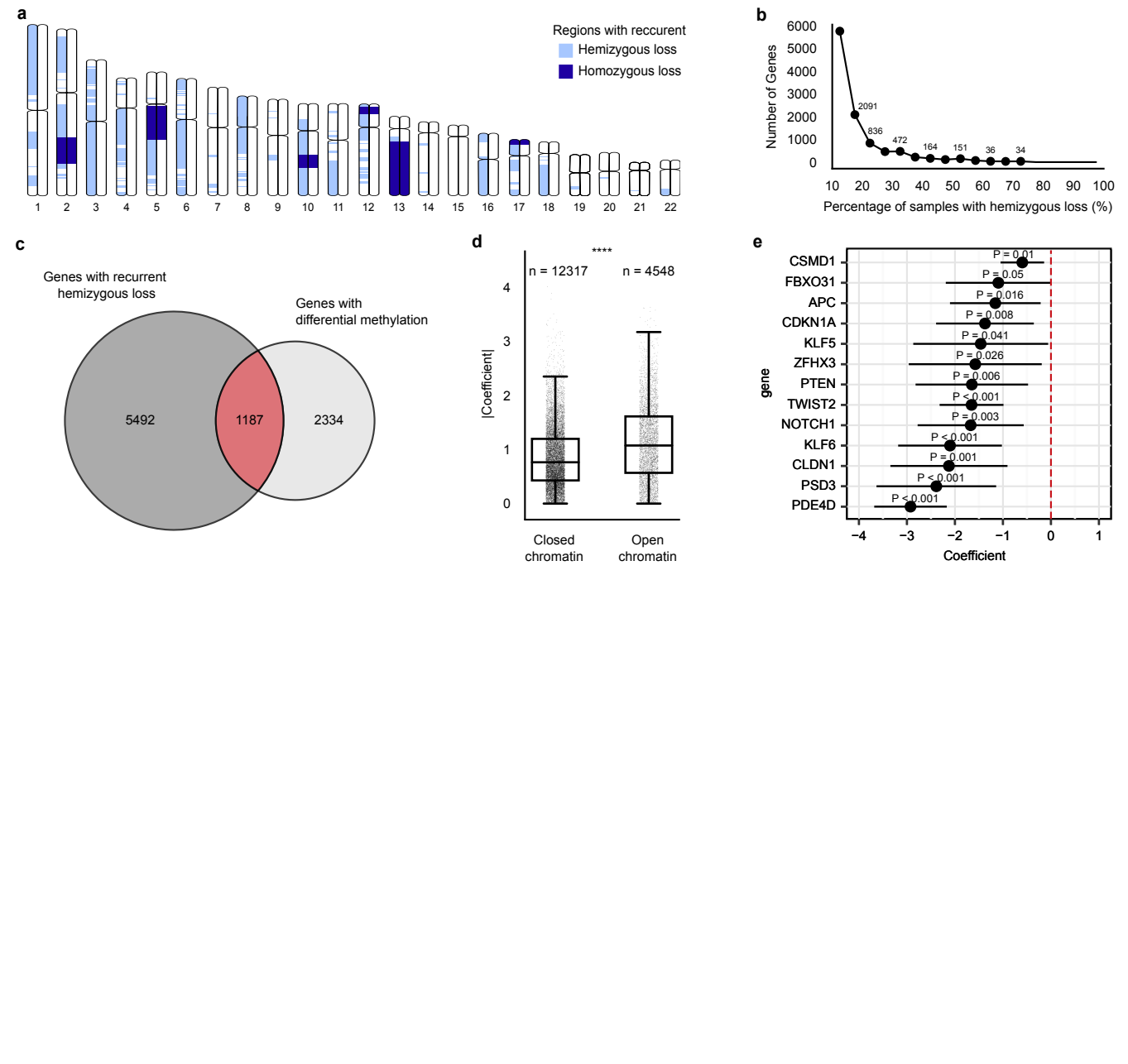
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Genes with recurrent hemizygous loss
Genes with differential methylation
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d
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n = 12317
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FBXO31
APC
CDKN1A
KLF5
ZFHX3
PTEN
TWIST2
NOTCH1
KLF6
CLDN1
PSD3
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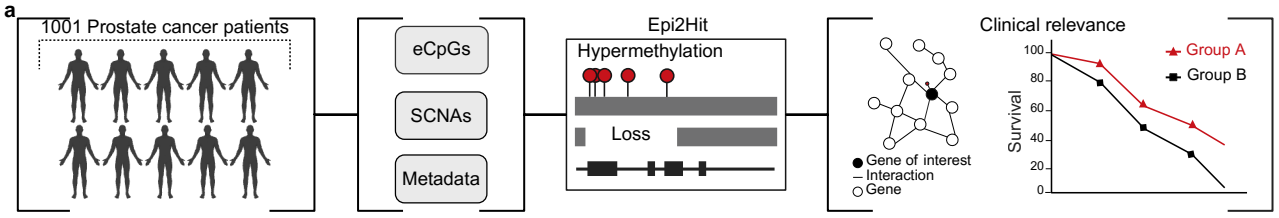
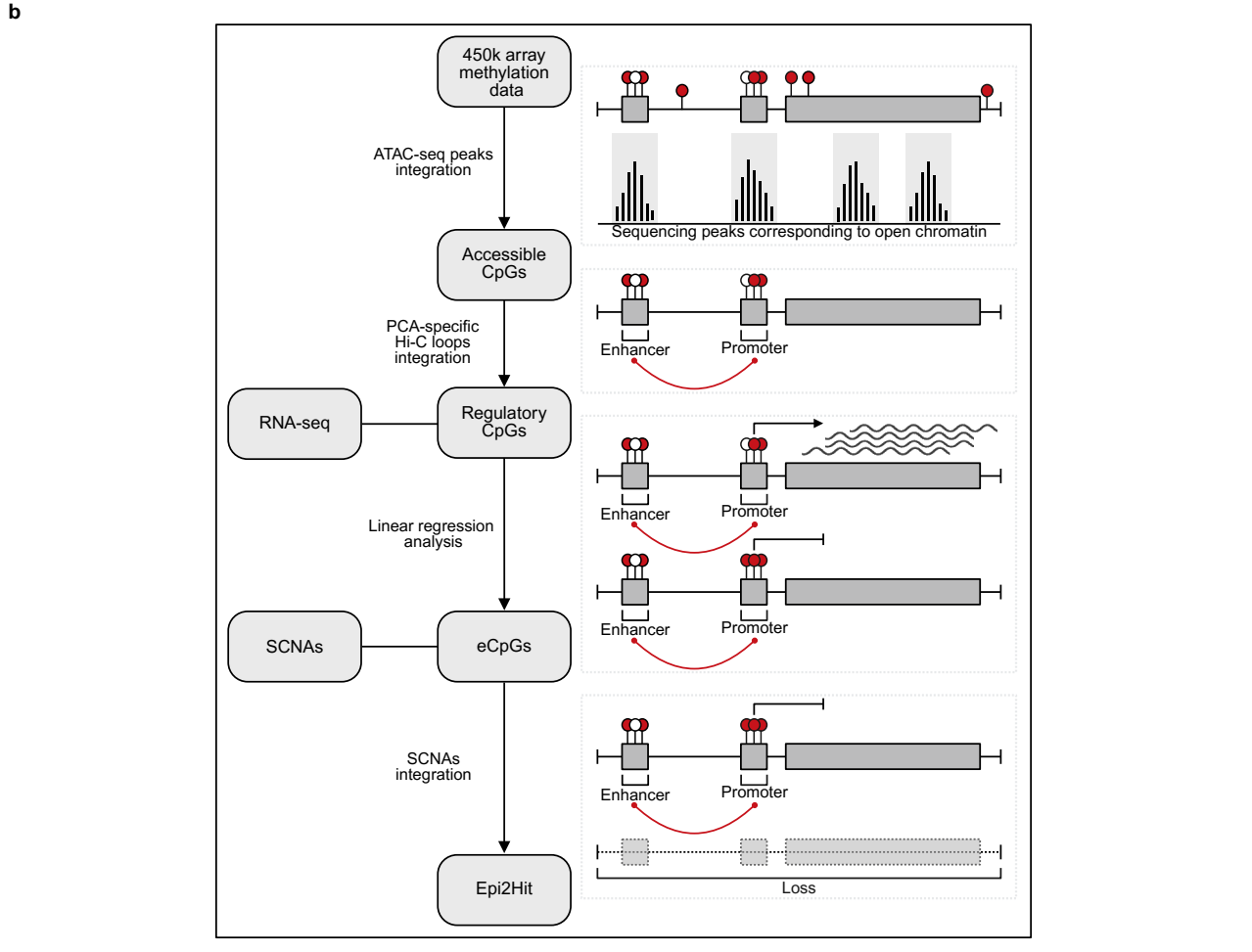
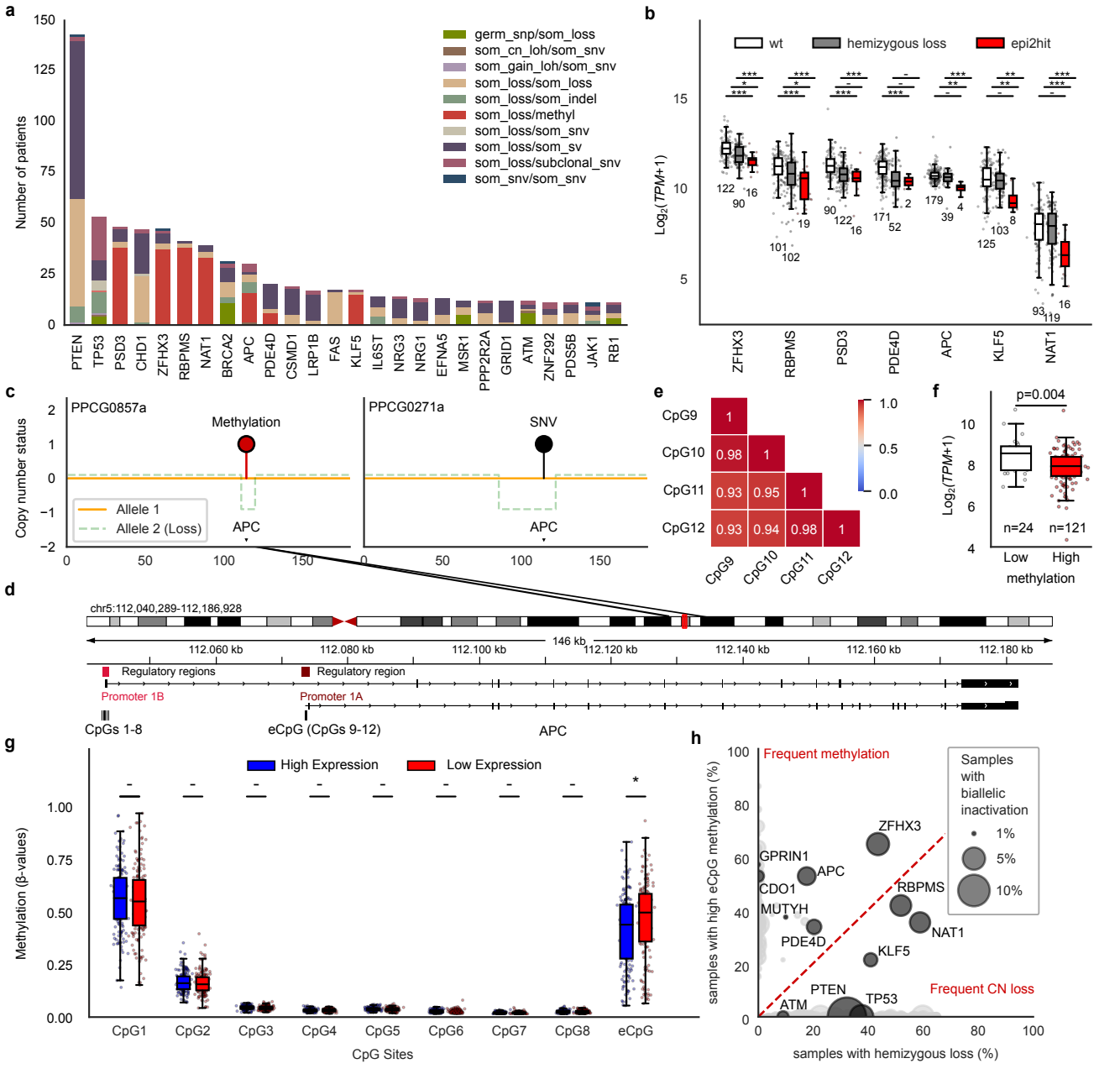
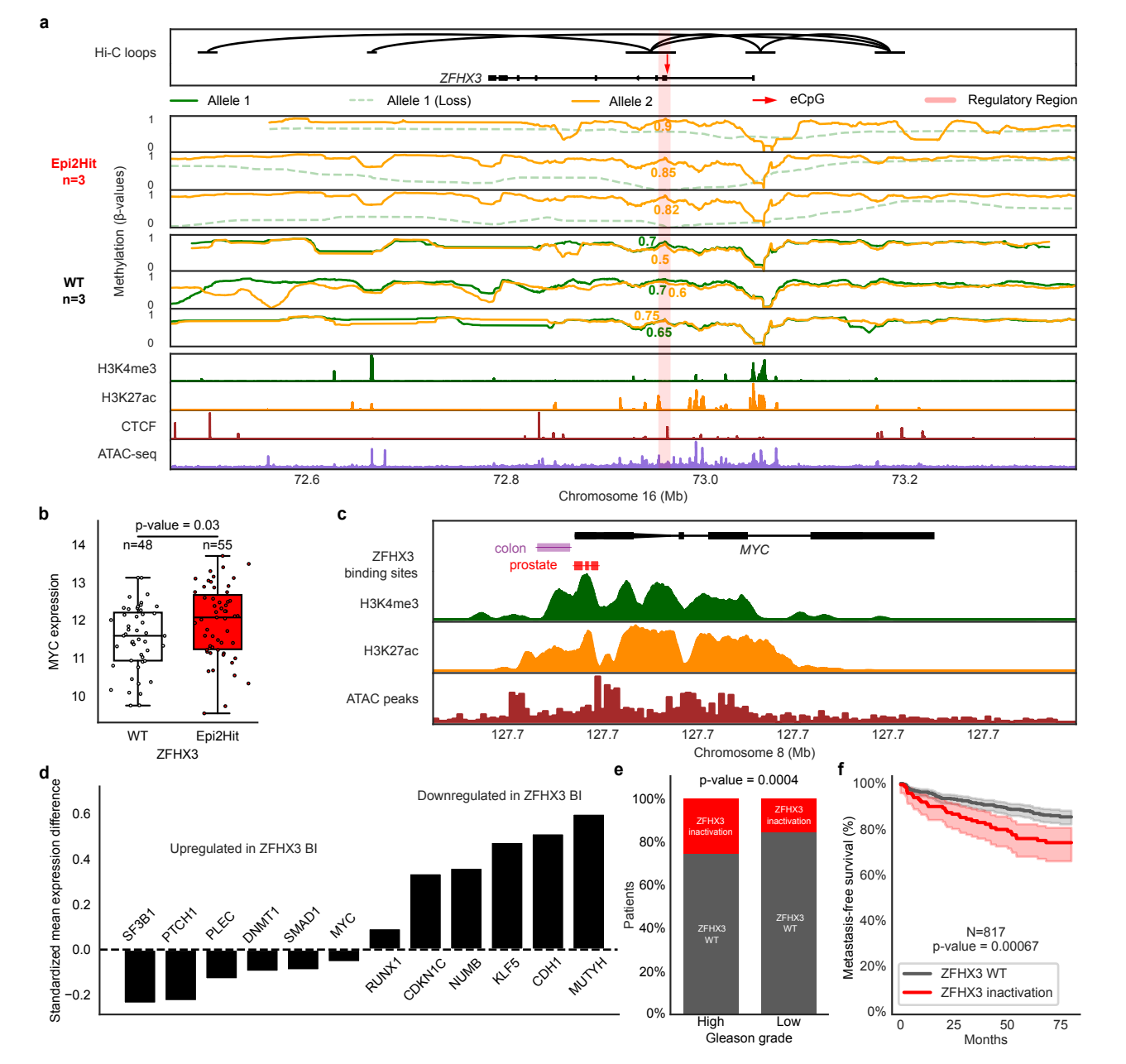
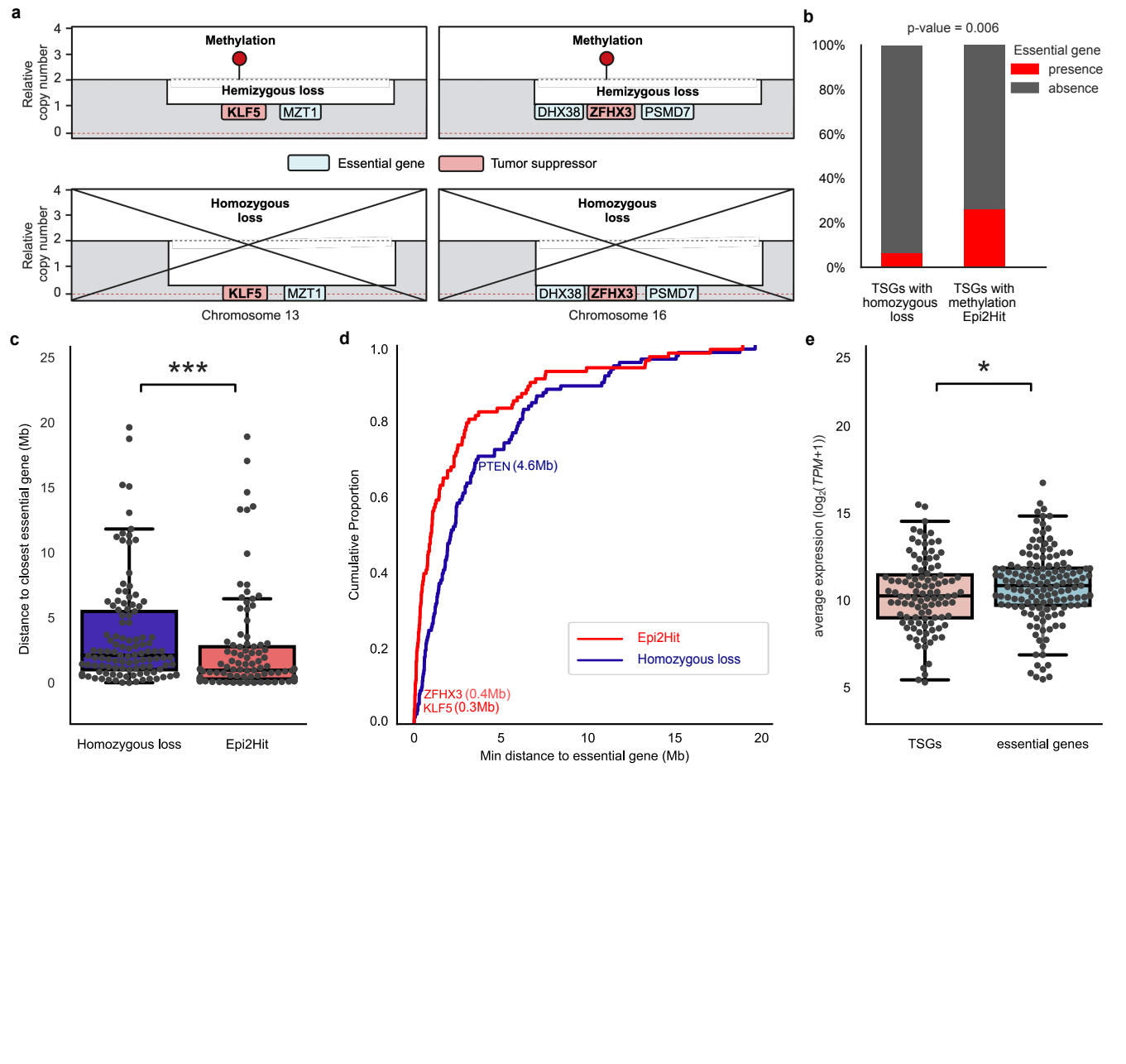
P = 0.003
P < 0.001
P = 0.001
P < 0.001
P < 0.001
−4
−3
−2
−1
0
1
Coefficient


a
1001 Prostate cancer patients
eCpGs
SCNAs
Metadata
Epi2Hit
Hypermethylation
Loss
Gene of interest
Interaction
Gene
Clinical relevance
Survival
100
80
60
40
20
0
Group A
Group B


b
450k array methylation data
ATAC-seq peaks integration
Sequencing peaks corresponding to open chromatin
Accessible CpGs
PCA-specific Hi-C loops integration
Enhancer
Promoter
RNA-seq
Regulatory CpGs
Linear regression analysis
SCNAs
eCpGs
SCNAs integration
Epi2Hit
Loss


a
Number of patients
germ_snp/som_loss
som_cn_loh/som_snv
som_gain_loh/som_snv
som_loss/som_loss
som_loss/som_indel
som_loss/methyl
som_loss/som_snv
som_loss/som_sv
som_loss/subclonal_snv
som_snv/som_snv
PTEN TP53 PSD3 CHD1 ZFHX3 RBPMS NAT1 BRCA2 APC PDE4D CSMD1 LRP1B FAS KLF5 IL6ST NRG3 NRG1 EFNA5 MSR1 PPP2R2A GRID1 ATM ZNF292 PDS5B JAK1 RB1
b
wt
hemizygous loss
epi2hit
Log2(TPM+1)
ZFHX3 RBPMS PSD3 PDE4D APC KLF5 NAT1
c
PPCG0857a
PPCG0271a
Methylation
SNV
Allele 1
Allele 2 (Loss)
APC
Copy number status
d
chr5:112,040,289-112,186,928
146 kb
Regulatory regions
Regulatory region
Promoter 1B
Promoter 1A
CpGs 1-8
eCpG (CpGs 9-12)
APC
e
CpG9 CpG10 CpG11 CpG12
1
0.98 1
0.93 0.95 1
0.93 0.94 0.98 1
f
p=0.004
n=24
n=121
Low
High
methylation
g
High Expression
Low Expression
Methylation (β-values)
CpG1 CpG2 CpG3 CpG4 CpG5 CpG6 CpG7 CpG8 eCpG
CpG Sites
h
Frequent methylation
Frequent CN loss
Samples with biallelic inactivation
1%
5%
10%
ZFHX3
GPRIN1
APC
CDO1
RBPMS
MUTYH
NAT1
PDE4D
KLF5
PTEN
TP53
ATM
samples with high eCpG methylation (%)
samples with hemizygous loss (%)


a
Hi-C loops
ZFHX3
Allele 1
Allele 1 (Loss)
Allele 2
eCpG
Regulatory Region
Epi2Hit
n=3
WT
n=3
Methylation (β-values)
0.9
0.85
0.82
0.7
0.5
0.7
0.6
0.75
0.65
H3K4me3
H3K27ac
CTCF
ATAC-seq
72.6
72.8
73.0
73.2
Chromosome 16 (Mb)
b
p-value = 0.03
n=48
n=55
MYC expression
WT
Epi2Hit
ZFHX3
c
ZFHX3
binding sites
colon
prostate
MYC
H3K4me3
H3K27ac
ATAC peaks
127.7
Chromosome 8 (Mb)
d
Standardized mean expression difference
Upregulated in ZFHX3 BI
Downregulated in ZFHX3 BI
SF3B1
PTCH1
PLEC
DNMT1
SMAD1
MYC
RUNX1
CDKN1C
NUMB
KLF5
CDH1
MUTYH
e
p-value = 0.0004
ZFHX3 inactivation
ZFHX3 WT
Patients
High
Low
Gleason grade
f
Metastasis-free survival (%)
N=817
p-value = 0.00067
ZFHX3 WT
ZFHX3 inactivation
Months


a
Methylation
Hemizygous loss
KLF5
MZT1
Methylation
Hemizygous loss
DHX38
ZFHX3
PSMD7
Relative copy number
Essential gene
Tumor suppressor
Homozygous loss
Homozygous loss
Chromosome 13
Chromosome 16
b
p-value = 0.006
Essential gene
presence
absence
TSGs with homozygous loss
TSGs with methylation Epi2Hit
c
***
Distance to closest essential gene (Mb)
Homozygous loss
Epi2Hit
d
Cumulative Proportion
PTEN (4.6Mb)
ZFHX3 (0.4Mb)
KLF5 (0.3Mb)
Epi2Hit
Homozygous loss
Min distance to essential gene (Mb)
e
*
average expression (log2(TPM+1))
TSGs
essential genes