Original Article Novel DNA methylation-based epigenetic signatures in colorectal cancer from peripheral blood leukocytes

Su Yon Jung $^\text{1,2,3}$, Herbert Yu $^\text{4}$, Xianglong Tan $^\text{5}$, Matteo Pellegrini $^\text{6}$

1Translational Sciences Section, School of Nursing, University of California, Los Angeles, CA 90095, USA; 2Department of Epidemiology, Fielding School of Public Health, University of California, Los Angeles, CA 90095, USA; 3Jonsson Comprehensive Cancer Center, University of California, Los Angeles, CA 90095, USA; 4Cancer Epidemiology Program, University of Hawaii Cancer Center, Honolulu, HI 96813, USA; 5Department of Biological Chemistry, University of California, Los Angeles, CA 90095, USA; 6Department of Molecular, Cell and Developmental Biology, Life Sciences Division, University of California, Los Angeles, CA 90095, USA

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Abstract: Colorectal cancer (CRC) is a multifactorial disease characterized by accumulation of multiple genetic and epigenetic alterations, transforming colonic epithelial cells into adenocarcinomas. Alteration of DNA methylation (DNAm) is a promising biomarker for predicting cancer risk and prognosis, but its role in CRC tumorigenesis is inconclusive. Notably, few DNAm studies have used pre-diagnostic peripheral blood (PB) DNA, causing difficulty in postulating the underlying biologic mechanism of CRC initiation. We conducted epigenome-wide association (EWA) scans in postmenopausal women from Women's Health Initiative (WHI) with their pre-diagnostic DNAm in PB leukocytes (PBLs) to prospectively evaluate CRC development. Our site-specific DNAm analyses across the genome adjusted for DNAm-age, leukocyte heterogeneities, as well as body mass index, diabetes, and insulin resistance. We validated 20 top EWA-CpGs in 2 independent CRC tissue datasets. Also, we detected differentially methylated regions (DMRs) associated with CRC, further mapped to transcriptomic profile, and finally conducted a Gene Set Enrichment Analysis. We detected multiple novel CpGs validated across WHI and tissue datasets. In particular, 2 CpGs (*B4GALNT4*cg10321339, *SV2B*cg18144285) had the strongest effect on CRC risk. Results from our DMR scans contained *MIR663*cg06007966, which was also validated in EWA analyses. Also, we detected 1 methylome region in *PEG10* of Chr7 shared across datasets. Our findings reflect both novel and well-established epigenomic and transcriptomic sites in CRC, warranting further functional validations. Our study contributes to better understanding of the complex interrelated mechanisms on the methylome underlying CRC tumorigenesis and suggests novel preventive DNAm-targets in PBLs for detecting at-risk individuals for CRC development.

Keywords: Colorectal cancer tumorigenesis, epigenetic signatures, pre-diagnostic DNA methylation, transcriptomics, postmenopausal women

Introduction

Colorectal cancer (CRC) is the third most frequently diagnosed malignancy and the second leading cause of cancer death in both sexes worldwide [1] and the third leading cause of cancer mortality in women in the U.S. [2]. CRC is a multifactorial disease characterized by environmental/behavioral factors and longterm genetic/epigenetic alterations and their interplay, transforming colonic epithelial cells into adenocarcinomas [3, 4]. Multiple behavioral factors have long been identified as CRC determinants [5-7], but the full extent of CRC's

genetic background remains incomplete, although it is equally critical for capturing the biologic mechanisms of CRC carcinogenesis. Identifying genetic variations has been challenging because CRC tumorigenesis is a complex process influenced by environmental/lifestyle factors that must be accounted for when exploring the genomic architecture of CRC development. Also, despite hundreds of mutations found in relation to CRC genomes, only a small set of functionally essential genes are proposed as driver mutations, which are insufficient in carcinogenesis [8, 9]. Epigenetic mechanisms may address these issues. In fact,

differential epigenetic patterns in CRC reflect interactions between environmental exposures and genetic influences, conferring cellular plasticity with specific cellular states, regulating gene expression, and consequently affecting cancer development [10-15]. Further, the epigenome influences accumulation of DNA mutations, controls important tumor cell phenotypes [16], and finally exerts a driving effect on CRC risk in the combined analyses of epigenetic alterations and genetic mutations [17], suggesting its crucial role during CRC development.

In particular, DNA methylation (DNAm) is a well-characterized major epigenetic modification that involves mitotically heritable and reversible attachment of methyl groups at the 5' carbon of cytosine in CpG dinucleotides (CpGs) [18, 19]. DNAm alteration has received growing attention as a promising biomarker for predicting CRC prognosis [20, 21], response to treatment [22], and early detection [23], since it presents high clinical sensitivity and dynamic changes by environmental cues [24] and occurs much in advance of the consequent changes in gene expression [25] and in clinical diagnoses of cancers, including CRC [26, 27]. Also, specific DNAm modification was detected in pre-cancerous "normal" colonic tissues that modify cancer risk [28-30], suggesting its occurrence at an earlier stage than carcinoma formation, thus playing a crucial role in CRC tumor initiation.

In general, global DNA hypomethylation is observed in CRC cells/tissues accompanied by local hypermethylation at regulatory regions such as promoters, leading to silencing of tumor-suppressor genes [31-33]. But the role of epigenetic mechanisms in CRC tumorigenesis is inconclusive, shown as a lack of consensus on DNAm markers in epigenetic studies; this is mainly owing to studies on heterogeneous populations in sex, age, and race/ethnicity, a lack of validation in independent samples, use of different biospecimens (e.g., tissues, blood, stool), and focus mainly on DNAm in promoter/CpG-island (i.e., CpG-rich) regions, although CpG-depleted regions, a large proportion of methylated positions, have potential effects on cancer [34-37]. In addition, few epigenome-wide studies [38-40] have examined non-invasive DNAm extracted from periph-

eral blood (PB) in CRC. Although DNAm is tissue specific, the correlations between PB and tissue are gene specific [26, 41, 42]. Given that obtaining intestinal tissues from healthy individuals is difficult, DNAm in PB is the most promising non-invasive risk marker for early identification of a population at high risk for CRC development [43]. Of note, most DNAm studies in PB for CRC have used post-diagnostic PB DNA, likely reflecting DNAm status as an early hematologic response to the presence of CRC cells, causing difficulty in postulating the underlying biologic mechanism of cancer initiation.

Our study addresses these critical gaps. We examined postmenopausal women, who are the most vulnerable to CRC (about 90% of CRC cases occur in individuals 50 years and older [2, 44]), focusing on white women. We conducted an epigenome-wide DNAm study by covering a majority of CpG-depleted regions or gene bodies in PB leukocytes (PBLs), reflecting the pre-diagnostic DNAm state (i.e., before CRC development). We validated our PBL-based findings in 2 independent CRC tissue cohorts by comparing the DNAm status between CRC tissues and normal colon tissues adjacent or obtained from non-tumor bearing patients. Finally, we mapped our findings to transcriptome profiles for investigating the cross-talk between DNAm and gene expression in CRC tissues. We hypothesized that the 2 CRC tissue cohorts are not exactly the same in DNAm status because the DNAm of normal tissues adjacent to CRC tissues differs from that of normal tissues derived from non-CRC patients [5, 45], but they are more similar to each other than DNAm from PBLs, reflecting somatic-specific epigenetic signatures. Ultimately, overlapping CpGs across the 3 cohorts may indicate longterm non-invasive surrogate markers in tissues, reflecting multiple CRC tumorigenic mechanisms in this population.

Materials and methods

Study population

For our epigenome-wide association (EWA) analysis in the discovery phase, we used data from the Women's Health Initiative (WHI) cohort, a large prospective study of postmenopausal women, ages 50-79 years at enrollment between 1993 and 1998 from 40 U.S. clinical

Figure 1. Diagram of EWA and CRC study populations from the WHI and GEO datasets. CpGs, CpG dinucleotides; CRC, colorectal cancer; EWA, epigenome-wide association; GEO, Gene Expression Omnibus; WHI, Women's Health Initiative. Note: *Data include 1 individual with missing data from covariates such as waist and hip circumferences, which was ultimately imputed on the basis of the na.roughfix method [111]. §Data include 64 CRC tissues from CRC patients and 41 normal colon tissues adjacent to CRC tissue from CRC patients. **Data include 36 CRC tissues from CRC patients and 34 normal colon tissues from non-CRC patients.

centers [46]. From the Database for Genotypes and Phenotypes (dbGaP) genetic repository, we included genome-wide DNAm data measured in PBLs available in a WHI ancillary study (AS), BAA23, by repurposing data that originally focused on the integrative genomics for heart disease and related phenotypes [47]. Because racial/ethnic variations exist in CRC-related DNAm [48, 49], we included in this study only self-reported non-Hispanic white women, a majority of the AS population: of 2,107 total, 998 whites, 600 African Americans, and 509 Asians/others. Among the 998 white women, 955 who had been followed for at least 1 year and not been diagnosed with any cancer at enrollment were included (Figure 1). They had been followed through March 6, 2021, with a 17-year mean follow-up, resulting in 29 who developed primary colorectal adenocarcinoma.

For our validation study, we used 2 independent methylation datasets from the National Center for Biotechnology Information Gene Expression Omnibus (GEO) databases, which included 64 CRC and 41 normal adjacent tissues (accession number GSE48684 [50]) and 36 CRC tissues from CRC patients and 34 normal colon tissues from non-CRC patients (GSE199057 [45]), after excluding 42 colorectal tubular adenoma (GSE48684) and 35 non-tumor tissues adjacent to CRC tissues (GSE199057) (Figure 1). The institutional review boards of each WHI clinical center and the University of California, Los Angeles, approved this study.

Data collection, laboratory method, and CRC outcome

For the WHI participants, self-administered questionnaires had been provided at enrollment to collect demographic information such as age and race and comorbidities, e.g., ever having been treated for diabetes (DM). Anthropometric measurements, including height and weight, had been assessed by trained staff at screening. Blood samples from WHI women after fasting 8 hours or longer had been collected at enrollment by phlebotomists and assayed for glucose and insulin concentrations, using the hexokinase method on a Hitachi 747 analyzer (Boehringer Mannheim Diagnostics, Indianapolis, IN) for glucose and via radioimmunoassay (Linco Research, Inc., St. Louis, MO) or automated ES300 method (Boehringer Mannheim Diagnostics) for insulin. The results from the 2 methods for insulin measurement were comparable at insulin concentrations < 60 µIU/ml, and the intra-class correlation coefficient with repeatedly measured insulin was 0.7 [51]. Homeostatic model assessment-insulin resistance (HOMA-IR), as a surrogate of IR, was estimated as glucose (unit: mg/dl) \times insulin (unit: μ IU/ml)/405 [52] and was included in the analysis as a covariate.

Primary CRC development among the WHI participants was initially ascertained from their self-report of a new cancer diagnosis, determined by a committee of physicians on the basis of a review of the patients' medical records and pathology/cytology reports, and

finally coded into the WHI database according to the National Cancer Institute's Surveillance, Epidemiology, and End-Results guidelines [53]. The time from enrollment until CRC development, censoring, or study end-point was measured as the number of days and then converted into years.

CRC tissue sample-based data from the GEO databases included patients' sex, race, and age. For this study purpose, data from Caucasians only were analyzed.

Epigenome-wide DNAm array

Genome-wide DNAm array of the WHI participants was conducted with their extracted PBL DNA, via Illumina 450 BeadChip. DNAm quality control procedures excluded poor-performing CpGs with $P > 0.01$ in $> 10\%$ of the samples. Data were beta-mixture quantile (BMIQ)-normalized [54] and batch-adjusted via random intercept for plate and chip and a fixed effect for row [47]. Leukocyte heterogeneities were estimated ([Table S1\)](#page-19-0) and adjusted for in the analysis using Houseman's method [55] (for CD4+ T cells, natural killer cells, monocytes, and granulocytes) and Horvath's method [56] (for plasma blasts, CD8+CD28- CD45RA- T cells, and naïve CD8 T cells).

In the GSE48684 cohort, a tissue-derived genome-wide DNAm assay was performed with the Illumina Infinium HM450K array, and unreliable probes were removed if *P* > 0.05. Using the R *minfi* package, data were normalized via Illumina background level corrections, color adjustment, and subset quantile within array normalization. CpGs were further filtered out if they contained single-nucleotide polymorphisms (SNPs) and were chromosome (Chr) X-associated. The ComBat algorithm was applied to correct for batch effects across all array runs [50]. In the GSE199057 cohort, Illumina EPIC array was performed, followed by data normalization via background correction based on normal-exponential out-of-band (Noob) [57] using *minfi*. SNP-associated and cross-reactive CpGs were excluded, and poorquality CpGs with missing \geq 20% of samples were also excluded. Batch effects were corrected using Bland Altman methods for replicate samples [45].

DNAm levels (β values) from Illumina 450K and EPIC array were calculated as the ratio of in-

tensities between the methylated and unmethylated probes, ranging from 0 (completely unmethylated) to 1 (completely methylated) [58]. Also, epigenetic ages (DNAm-predicted ages) were estimated using the Horvath clock [56] in the WHI and GSE199057 cohorts, where relevant data were available.

Statistical analysis

DNAm levels were standardized across samples in each cohort, resulting in 482,367 CpGs in the WHI, 485,577 CpGs in the GSE48684, and 866,091 CpGs in the GSE199057 included in our analysis; the effect size from the analysis reflected a 1 standard-deviation (SD) increase in DNAm on CRC risk.

For the DNAm site-specific analysis across the genome with CRC development in the WHI data, we conducted multiple Cox proportional hazards regression, with an assumption test met via a Schoenfeld residual plot and rho, adjusting for DNAm-predicted age, biologic age, and leukocyte heterogeneity, as well as body mass index (BMI), DM, and IR levels as key confounding factors [7, 14, 15, 59, 60] in associations between DNAm probes and CRC. With 20 top CpGs detected at the genome-wide level, we next performed logit regression for CRC outcomes in each GEO dataset by adjusting for sex and, in the GSE199057 only, DNAmpredicted and biologic ages. Two-sided *P* < 1E-007 (discovery) and < 2.5E-03 (= 0.05/20 top CpGs) (validation), after Bonferroni correction, were considered statistically significant.

Differences in DNAm levels of the modeled CpGs by CRC risk in each cohort and those of CpGs among the 3 cohorts of the CRC patients were tested using unpaired 2-sample t and 1-way ANOVA tests, respectively. If β values were skewed or had outliers, Mann-Whitney/ Wilcoxon's ranked-sum and Kruskal-Wallis tests were used as appropriate.

In addition to individual GpGs, we detected differentially methylated regions (DMRs) associated with CRC, using R *DMRcate* package on the basis of kernel smoothing of the differential methylation signal, with 1,000 lambda (Gaussian kernel bandwidth) and 2 C (scaling factor for bandwidth) as recommended, so that half a kilobase represents 1 SD of support [61, 62]. This method is superior to others (e.g., Bumphunter and Probe Lasso), removing the bias

from irregularly spaced methylation sites and filtering probes possibly confounded by SNPs and cross-hybridization [61, 62].

With the top genome-wide CpGs in the WHI discovery and those significant at the validation level in the GEO datasets, we finally conducted a Gene Set Enrichment Analysis (GSEA) using WebGestalt [63]. All statistical analyses were performed with R through UCLA's Hoffman2 high-performance computing cluster.

Transcriptomics analysis

Using R *TCGAbiolinks* package, we retrieved data from The Cancer Genome Atlas Colon Adenocarcinoma (TCGA-COAD) and TCGA-Rectum Adenocarcinoma (READ) projects, integrating 701 RNA-sequence (Seqs) samples comprising 1 metastatic, 2 recurrent, and 647 primary tumor tissues plus 51 normal adjacent tissues. Raw count normalization between the cancer and normal groups, followed by differential expression analysis, was conducted via *DESeq2* and *org.Hs.eg.db* package. Further, we calculated z-scores for each modeled gene and performed Uniform Manifold Approximation and Projection (UMAP) and heatmap analyses, producing graphic visualizations.

Results

Site-specific CpG analysis across genome for CRC outcomes

With 482,367 CpGs in the WHI discovery, our genome-wide DNAm scan detected the 20 top CpGs differentially methylated by CRC development (Table 1). The hazard ratios were consistent across the analyses accounted for age only; age plus BMI; and age plus BMI, DM, and IR levels. In the validations with 2 GEO datasets (Table 2), the effect sizes and directions of the top 20 CpGs were in general similar between datasets, reflecting somatic-specific DNAm profiles. Of the top 20 genome-wide CpGs, 11 were also significant at the validation level in either or both of the GEO cohorts. Six of the 11 CpGs presented similar risk magnitudes between the WHI and either/both GEO cohorts and in each dataset, the area under the receiver operating characteristic curve has been re-ported [\(Figure S1\)](#page-19-0): cg04958124, cg10321339, cg12704462, cg18144285, cg06007966, and cg17375901. In particular, 2 CpGs (*B4GAL-* *NT4*cg10321339 and *SV2B*cg18144285) had the strongest effect on CRC risk (32 and 22 times greater risk, respectively, each with a 1-SD increase in DNAm) in the GSE199057. Also, 2 other CpGs (*MIR663*cg06007966 and cg17375901) were validated in both GEO datasets; both are located in Chr20 with the same direction and similar risk magnitudes in the WHI discovery and both validation GEO datasets, but having more profound effects in the validations. Of interest, 1 CpG (cg05970116 in Chr10) had genome-wide significance in the discovery and both validation datasets, presenting different directions: a positive association of its 1-SD increase in DNAm with CRC development in the WHI, but an inverse association with CRC tissues in both GEO datasets.

We compared the DNAm levels of the top 20 CpGs by CRC status across Chr, CpG context, enhancer and/or promoter, and gene region within the WHI (Figure 2) and each GEO dataset [\(Figure S2](#page-20-0)). The mean levels of DNAm differed in Chr1, 6, 7, 10, and 15 in the WHI, where DNAm levels were higher in those with CRC development than in those without. Similarly, hypermethylation in CRC tissues was observed in Chr7 in GSE48684, but more substantial differences in Chr11 were found in the GEO datasets. Chr12 presented hypomethylation in CRC across all 3 cohorts, shown more profoundly in the WHI, and an apparent difference in DNAm mean level by CRC status was observed in GEO199057. Whereas CpG islands and S-Shores were hypermethylated in the WHI women with CRC, N-Shores were hypermethylated in both CRC GEO datasets. In the WHI, both enhancer and promoter were hypermethylated in CRC patients, but the opposite direction was observed in GSE199057, where promoter was hypomethylated in CRC tissues. In both the WHI and the GEO datasets, 5' untranslated regions (5'UTR) were hypermethylated in CRC patients and tissues.

Further, we compared DNAm levels of the top 20 CpGs within the CRC patients across the 3 cohorts in terms of Chr, CpGs, CpG context, and gene region [\(Figure S3\)](#page-22-0), showing consistent patterns in Figures 2 and [S2.](#page-20-0) We also compared among CRC patients the DNAm levels of 3 individual CpGs that were genome-wide significant at the validation level in both GEO datasets (Figure 3). Except for cg05970116, which

	CpG sites		Age adjusted		BMI & age adjusted		DM, IR, BMI & age adjusted		CpG		Gene
Chr		Position	HRT (95% CI)	P	HRT (95% CI)	P	HRT (95% CI)	P	context	Gene	region
chr1	cg14057946¥	713985	1.43 (1.25, 1.64)	$<$ 1E-007	1.43(1.25, 1.64)	$<$ 1E-007	1.42(1.23, 1.64)	2.00E-06	Island		Intergenic
chr1	cg04231937¥	714526	1.56 (1.33, 1.82)	$<$ 1E-007	1.56 (1.33, 1.82)	$<$ 1E-007	1.56(1.33, 1.83)	$<$ 1E-007	Island		Intergenic
chr1	cg04496485¥	714565	1.39(1.24, 1.57)	$<$ 1E-007	1.39(1.23, 1.56)	$<$ 1E-007	1.38(1.23, 1.56)	$<$ 1E-007	S Shore		Intergenic
chr1	cg02014020	1115461	0.67(0.57, 0.79)	1.00E-06	0.67(0.58, 0.79)	1.00E-06	0.67(0.57, 0.79)	2.00E-06	N Shore	TTLL10	Body
chr ₆	cg07572131*,¥	31430791	1.65 (1.37, 1.98)	$<$ 1E-007	1.64(1.35, 1.98)	$<$ 1E-007	1.58(1.29, 1.94)	9.00E-06	OpenSea	HCP ₅	TSS200
chr ₆	cg25410010	41554543	0.59(0.49, 0.72)	$<$ 1E-007	0.59(0.49, 0.72)	$<$ 1E-007	0.57(0.47, 0.70)	$<$ 1E-007	OpenSea	FOXP4	Body
chr ₆	cg06498809¥	111303174	1.45 (1.26, 1.68)	$<$ 1E-007	1.45(1.25, 1.67)	1.00E-06	1.45(1.25, 1.68)	1.00E-06	Island	RPF ₂	TSS200
chr6	cg00020352¥	111303252	1.50(1.27, 1.77)	2.00E-06	1.49(1.26, 1.77)	3.00E-06	1.47(1.24, 1.75)	1.30E-05	Island	RPF ₂	TSS200
chr ₆	cg10920427¥	111303363	1.33(1.19, 1.49)	1.00E-06	1.32 (1.18, 1.48)	1.00E-06	1.33(1.18, 1.48)	1.00E-06	Island	RPF ₂	Body
chr ₆	cg14498116¥	111303482	1.39 (1.22, 1.58)	$<$ 1E-007	1.38(1.22, 1.57)	1.00E-06	1.38(1.21, 1.57)	1.00E-06	Island	RPF ₂	Body
chr7	cg04958124¥	148823862	1.42 (1.25, 1.61)	$<$ 1E-007	1.43 (1.26, 1.62)	$<$ 1E-007	1.43(1.26, 1.63)	$<$ 1E-007	Island	ZNF398	5'UTR
chr10	cg18072629	8092036	1.30(1.17, 1.44)	1.00E-06	1.30(1.17, 1.44)	1.00E-06	1.30(1.17, 1.44)	2.00E-06	Island		Intergenic
chr10	cg05970116	75351076	1.48(1.28, 1.71)	$<$ 1E-007	1.50(1.29, 1.75)	$<$ 1E-007	1.51(1.29, 1.76)	$< 1E-007$	OpenSea		Intergenic
chr11	cg10321339	369810	1.54 (1.30, 1.83)	1.00E-06	1.55(1.30, 1.84)	1.00E-06	1.54 (1.29, 1.84)	1.00E-06	OpenSea	B4GALNT4	1st Exon
chr12	cg12704462	120151527	0.74(0.66, 0.83)	1.00E-06	0.74(0.66, 0.84)	1.00E-06	0.75(0.66, 0.84)	2.00E-06	OpenSea	MIR1178	Body
chr15	cg11823654¥	65117936	1.65 (1.35, 2.03)	1.00E-06	1.65(1.35, 2.02)	1.00E-06	1.68 (1.37, 2.06)	1.00E-06	S Shore	PIF1	TSS200
chr15	cg18144285	91643026	1.47 (1.26, 1.72)	1.00E-06	1.48(1.27, 1.72)	1.00E-06	1.46 (1.24, 1.72)	5.00E-06	Island	SV ₂ B	TSS200
chr16	cg04872027	29149757	0.73(0.64, 0.83)	1.00E-06	0.72(0.64, 0.82)	1.00E-06	0.73(0.64, 0.83)	3.00E-06	N Shelf		Intergenic
chr20	cg06007966	26188971	1.94(1.49, 2.52)	1.00E-06	1.94(1.49, 2.53)	1.00E-06	1.95(1.48, 2.56)	2.00E-06	Island	MIR663	TSS200
chr20	cg17375901	61754940	0.62(0.51, 0.74)	$<$ 1E-007	0.61(0.51, 0.74)	$<$ 1E-007	0.62(0.51, 0.75)	1.00E-06	Island		Intergenic

Table 1. WHIBAA23 dataset: differentially DNA-methylated top 20 CpGs genome-wide associated with CRC risk

BMI, body mass index; Chr, chromosome; CI, confidence interval; CpG, CpG dinucleotide; CRC, colorectal cancer; DM, ever having been treated for diabetes mellitus; HR, hazard ratio; IR, insulin resistance; TSS200, 0-200 bp upstream of transcription start site; UTR, untranslated region; WHI, Women's Health Initiative. CpGs in bold face are among those statistically significant, shared ones across WHIBAA23, GSE48684, and GSE199057. §Annotation used R v.0.6.0.IlluminaHumanMethylation450kanno.ilmn12.hg19: Annotation for Illumina's 450k methylation arrays. [HR adjusted by leukocyte heterogeneities (CD8+CD28·CD45RA· T cell, naïve CD8 T cell, plasma blast, CD4+ T cell, natural killer cell, monocyte, and granulocyte) plus DNA methylation-predicted age. ¥Promoter associated. *Enhancer associated.

Chr			GSE 48684	GSE199057	CpG		Gene		
	CpG site§	Position	OR¶ (95% CI)	P	OR£ (95% CI) P		context	Gene	region
chr1	cg14057946¥	713985	1.46 (0.89, 2.87)	0.211	0.97(0.59, 1.58)	0.907	Island		Intergenic
chr1	cg04231937¥	714526	1.06 (0.71, 1.68)	0.768	1.40(0.83, 3.03)	0.273	Island		Intergenic
chr1	cg04496485¥	714565	1.30(0.82, 2.48)	0.344	1.48 (0.88, 2.84)	0.167	S Shore		Intergenic
chr1	cg02014020	1115461	1.47 (0.98, 2.30)	0.076	3.55(1.88, 7.69)	3.52E-04	N Shore	TTLL 10	Body
chr ₆	cg07572131*,¥	31430791	0.66(0.42, 1.00)	0.057	1.04(0.62, 1.74)	0.875	OpenSea	HCP5	TSS200
chr ₆	cg25410010	41554543	1.06(0.69, 1.57)	0.793			OpenSea	FOXP4	Body
chr ₆	cg06498809¥	111303174	0.83(0.55, 1.24)	0.362	0.27(0.11, 0.55)	0.001	Island	RPF ₂	TSS200
chr ₆	cg00020352¥	111303252	0.61(0.39, 0.93)	0.025			Island	RPF ₂	TSS200
chr ₆	cg10920427¥	111303363	1.40 (0.92, 2.20)	0.126	1.55 (0.94, 2.66)	0.096	Island	RPF ₂	Body
chr ₆	cg14498116¥	111303482	0.32(0.15, 0.60)	0.001	0.61(0.33, 1.03)	0.085	Island	RPF ₂	Body
chr7	cg04958124¥	148823862	2.37(1.43, 4.37)	0.002	1.60(0.97, 2.85)	0.084	Island	ZNF398	5'UTR
chr10	cg18072629	8092036	3.00(1.42, 10.25)	0.025			Island		Intergenic
chr10	cg05970116	75351076	0.48(0.29, 0.75)	0.002	0.13(0.04, 0.31)	2.80E-05	OpenSea		Intergenic
chr11	cg10321339	369810	6.73 (2.29, 40.88)	0.008	32.38 (4.94, 568.21)	0.003	OpenSea	B4GALNT4	1st Exon
chr12	cg12704462	120151527	0.84(0.47, 1.28)	0.477	0.19(0.06, 0.46)	0.001	OpenSea	MIR1178	Body
chr15	cg11823654¥	65117936	0.39(0.23, 0.63)	2.45E-04	0.65(0.36, 1.08)	0.109	S Shore	PIF1	TSS200
chr15	cg18144285	91643026	199.31 (5.83, 59923.50)	0.023	22.60 (4.28, 246.53)	0.003	Island	SV ₂ B	TSS200
chr16	cg04872027	29149757	0.50(0.25, 0.86)	0.025	0.48(0.24, 0.83)	0.018	N Shelf		Intergenic
chr ₂₀	cg06007966	26188971	4.20(2.34, 8.59)	1.20E-05	8.05 (3.44, 25.24)	2.80E-05	Island	MIR663	TSS200
chr ₂₀	cg17375901	61754940	0.07(0.02, 0.22)	6.70E-05	0.03(0.003, 0.12)	1.23E-04	Island		Intergenic

Table 2. GSE datasets: differentially DNA-methylated top 20 CpGs identified from WHIBAA23 in association with CRC risk

Chr, chromosome; CI, confidence interval; CpG, CpG dinucleotide; CRC, colorectal cancer; OR, odds ratio; TSS200, 0-200 bp upstream of transcription start site; UTR, untranslated region; WHI, Women's Health Initiative. CpGs in bold face are among those statistically significant, shared ones across WHIBAA23, GSE48684, and GSE199057. §Annotation used R v.0.6.0.*IlluminaHumanMethylation450kanno.ilmn12.hg19: Annotation for Illumina's 450k methylation arrays. ^TOR adjusted by sex. £OR adjusted by sex plus age and DNA* methylation-predicted age. ¥Promoter associated. *Enhancer associated.

Figure 2. WHIBAA23: Bar plots for mean difference in DNAm levels of top 20 genome-wide CpGs stratified by CRC status. A. By chromosome. B. By CpG context. C. By enhancer and/or promoter. D. By gene region. CpG, CpG dinucleotide; CRC, colorectal cancer; DNAm, DNA methylation; TSS200, 0-200 bp upstream of transcription start site; UTR, untranslated region; WHI, Women's Health Initiative. Note: *Statistical significance after multiple comparison correction.

presented a different direction for CRC risk between the WHI and GEO datasets, 2 other CpGs (*MIR663*cg06007966 and cg17375901) had similar DNAm levels across the cohorts, suggesting DNAm parallelisms between PBLs and tissues in CRC patients.

DMR scans for CRC

Our DMR analyses showed distinct patterns between PBL- and tissue-based databases. In particular, both GEO datasets detected similar DMRs, showing that 4 of each top 5 DMRs $(Figure S4)$ $(Figure S4)$ and > 70 of each top 100 DMRs [\(Table S2](#page-25-0)) overlapped. Also, the combined results of our EWA and DMR analyses in each GEO contained multiple CpGs overlapping between the top 20 CpGs and the CpGs detected from DMR scans (Table 3). Of them, *PIF1*cg11823654, *RPF2*cg14498116, and *ZNF398*cg04958124 in the GSE48984, and *TTLL10*cg02014020, *SV2B*cg18144285, *B4- GALNT4*cg10321339, *RPF2*cg06498809, *MIR-1178*cg12704462, and cg05970116 in the

Figure 3. WHIBAA23, GSE48684, and GSE199057 in CRC patients (peripheral leukocytes for WHIBAA23 and CRC tissues for GSEs): Comparisons among the 3 studies for DNAm levels of 3 individual CpGs that are statistically significant and shared across the studies. A. Chr10, cg05970116. B. Chr20, cg17375901. C. Chr20, cg06007966, *MIR663*. Chr, chromosome; CpG, CpG dinucleotide; CRC, colorectal cancer; DNAm, DNA methylation; EWA, epigenome-wide association; WHI, Women's Health Initiative. Note: *Statistical significance after multiple comparison correction.

# of DMR	Segnames	Start	End	Width	Fisher	DMR: No. of CpGs	Overlapping CpGs¶	DMR: genes	Overlapping genes¥
<gse48684></gse48684>									
55	chr10	8088801	8103673	14873	4.18E-215	90	cg18072629	RP11-379F12.4, GATA3, GATA3-AS1, RP11-379F12.3	
2782	chr11	368351	369875	1525	2.56E-30	27	cg10321339	B4GALNT4	B4GALNT4
2910	chr15	91642470	91643742	1273	2.58E-29	15	cg18144285	SV ₂ B	SV ₂ B
2924	chr15	65115218	65119016	3799	3.34E-29	13	cg11823654§	PIF1	PIF1§
2931	chr20	26188639	26189240	602	3.72E-29	$\overline{7}$	cg06007966§.*	MIR663A	MIR663§.*
6682	chr1	1113501	1115920	2420	8.03E-13	16	cg02014020	TTLL10, TTLL10-AS1	TTLL10
8302	chr ₆	111302729	111303792	1064	9.06E-10	13	cg00020352. cg06498809. cg10920427. cg14498116§	RPF ₂	RPF ₂ §
17740	chr7	148822673	148823965	1293	0.013	13	cg04958124§	ZNF398, ZNF425, RN7SL521P	ZNF3988
20166	chr12	120151527	120152127	601	0.090	$\overline{7}$	cg12704462	CIT, MIR1178	MIR1178
<gse199057></gse199057>									
1979	chr20	26188639	26190354	1716	4.78E-56	10	cg06007966§.*	MIR663A	MIR663§.*
4442	chr1	1113624	1115920	2297	8.25E-36	17	cg02014020§	TTLL10, TTLL10-AS1	TTLL10§
4640	chr15	91641719	91643742	2024	4.98E-35	18	cg18144285§	SV ₂ B	SV ₂ B _S
5895	chr15	65116255	65119016	2762	1.46E-30	16	cg11823654	PIF1	PIF1
13206	chr11	368351	369875	1525	1.88E-16	25	cg10321339§	B4GALNT4	B4GALNT4§
14389	chr ₆	111301798	111303792	1995	4.06E-15	17	cg06498809§. cg10920427. cg14498116	RPF ₂	RPF2§
18934	chr12	120151527	120152127	601	5.19E-11	5	cg12704462§	CIT, MIR1178	MIR1178§
21755	chr10	75351076	75351888	813	5.84E-09	5	cg05970116§	USP54	
33351	chr7	148822673	148823862	1190	0.079	13	cg04958124	ZNF398, ZNF425, RN7SL521P	ZNF398

Table 3. Combined results from EWA and DMR analyses in GSE datasets

Among top 20 genome-wide CpGs, overlapping CpGs¶ and nearby genes¥. Chr, chromosome; CpG, CpG dinucleotide; DMR, differentially methylated region; EWA, epigenome-wide association. §CpGs and nearby genes that overlap between EWA and DMR analyses in each GSE, which are statistically significant at the validation level. *CpG and nearby gene that are statistically significant at the validation level and overlapping across the 2 GSE datasets.

UTR, untranslated region; WHI, Women's Health Initiative. Note: The score of 3 indicates that the 3 datasets have overlapping DMRs, and the 10 CpGs are not genome-wide site-specific CpGs. §Annotation used R v.0.6.0.*IlluminaHumanMethylation450kanno.ilmn12.hg19: Annotation for Illumina's 450k methylation arrays.* ¥All 10 CpGs are promoter associated.

GSE199057 were significant at the validation level. Of note, *MIR663*cg06007966, which was validated as positively associated with CRC in both PBL- and tissue-based databases, was also detected as an overlapped probe in the DMR scans of both GEO datasets.

A different pattern was observed in the DMR analysis for the WHI cohort, demonstrating no overlapping genome-wide CpGs in the DMRs. Moreover, the DMR shared across all 3 cohorts was only 1 region in *PEG10* of Chr7, and 10 CpGs detected in this DMR did not overlap with any genome-wide CpGs (Table 4). We further estimated the effect sizes of DNAm for these individual CpGs, displaying a consistently increased risk of CRC across the cohorts (Table [S3](#page-27-0)).

Transcriptomic profile and GSEA

Among 8 genome-wide genes from the EWA analysis plus 1 additional gene overlapped across the DMRs of the 3 cohorts, 7 passed the FDR $<$ 0.05 (Figure 4A, 4B). In particular, *B4GALNT4* and *PIF1*, whose related CpGs were hypermethylated (in both PBL- and tissuebased CRC) and hypomethylated (in CRC tissues), respectively, showed the strongest upregulation of mRNA-Seqs in CRC tissues (Figure 4C, 4D). In contrast, *SV2B* presented the strongest downregulation of mRNA-Seqs in CRC, where associated CpGs in our analyses of the WHI and GEOs showed hypermethylation in CRC (Figure 4E). Further, *FOXP4*, *RPF2*, and *TTLL10* were upregulated in CRC tissues with relevant-CpGs' hypomethylation in our CRC cohorts, whereas *ZNF398* displayed weak upregulation with hypermethylation of associated-CpGs in CRC [\(Figure S5](#page-28-0)).

Finally, with genome-wide CpGs from our EWA scan, we performed multiple analyses of GSEA gene ontology (GO) with biologic process, cellular component, and molecular functions, pathways with *KEGG* and *Reactome*, and diseases via *DisGeNET* and *GLAD4U* databases ([Table](#page-29-0) [S4](#page-29-0)). GO with biologic and molecular functions identified DNA/RNA biosynthetic processes, telomeres' organism/DNA binding, p53-mediated signal transduction, and catalytic/transferase activity on glycosyl groups. Gene-enrichment pathways were involved in extracellular matrix (ECM)-receptor interaction, which plays an important role in regulating cell behavior, communicating cell proliferation and migration, implicating a key role in CRC development [64, 65]. *Reactome* pathways and diseases were involved in neurotransmitter transport, infection, and neoplasms.

Discussion

To our knowledge, this study is the first genomewide scan in postmenopausal women, the population most vulnerable to CRC, with pre-diagnostic DNAm in PBLs to prospectively evaluate CRC development in both CpG site-specific and regionally differentiated methylation fashions. We further validated in CRC tissue-level datasets and finally, mapped to transcriptome profiles. As hypothesized, the DNAm levels and

Figure 4. mRNA-sequences mapping to genes in TCGA COAD and READ datasets. A. Volcano plot: Differentially expressed genes between CRC and normal adjacent tissues. B. Heat plot: Log, fold changes in modeled genes. C. UMAP plot: *B4GALNT4*. D. UMAP plot: *PIF1*. E. UMAP plot: *SV2B*. CRC, colorectal cancer; UMAP, Uniform Manifold Approximation and Projection.

risk magnitudes of detected CpGs as well as DMR patterns between 2 independent tissue datasets were similar, indicating somatic-level epigenetic signatures. Also, several genomewide CpGs in genes overlapped across PBLand tissue-based datasets, suggesting DNAm parallelisms between PBLs and tissues in a site-/gene-specific manner; these validated DNAm probes may have further implications as the best long-term surrogate markers in noninvasive tissues, reflecting multiple interconnected CRC tumorigenesis mechanisms.

In detail, DNAm of cg10321339 in the first exon of *B4GALNT4* was strongly associated with increased risk for CRC development in both PBL and tissue datasets, and also, the strongest upregulated expression of *B4GALNT4* was observed in CRC tissues. *B4GALNT4*, encoding an enzyme β-1,4-N-acetylgalactosaminyltransferase 4, is involved in LacdiNAc group synthesis, which is important in embryonic development and disease progression [66, 67]. It has been associated with progression of cancers, with decreased expression in breast carcinomas (BC) [68] and esophageal squamous cell carcinomas [69]. *B4GALNT3* has also been studied in CRC cells, demonstrating overexpression [70], similar to our transcriptomics finding. Our detected genome-wide CpG and overexpression of these *B4GALNT* gene groups in CRC tissues are novel findings, deserving further validation and functional studies.

The DNAm of cg18144285 in the CpG island within 200 bp upstream of the transcription start site (TSS200) of *SV2B* displayed the second strongest effect on increased risk for CRC, with strong down-regulation of *SV2B* in CRC tis-

sues. Synaptic vesicle glycoprotein 2B (SV2B) is essential to the synaptic machinery in neural and endocrine cells [71, 72] and is overexpressed in prostate small-cell neuroendocrine carcinoma [73] and glioblastoma [74]. Of note, our GSEA-GO analysis in CRC detected the ECM-receptor interaction pathways, which play an important role in modulating cancer-cell behaviors [64, 65], with *SV2B* as a key driver; this is consistent with previous findings in gastric cancer [75], which identified *SV2B* as a strong indicator of ECM-receptor interactions. However, the role of *SV2B* in tumors is still inconclusive.

Some other genes we detected at genomewide significance are also involved in cancer development and progression. For instance, *ZNF398*, encoding zinc finger protein 398, enables transcription of *TGF-β* downstream pluripotency/epithelial characters in human pluripotent stem cells [76] and, as an oncogene, was upregulated in tumor tissues [77, 78]. *PIF1*, conserving non-processive 5'-to-3' DNA helicase, has a functional role in tumor cell viability during replication stress and inhibits apoptosis, which is essential in the early stage of tumorigenesis [79, 80]; it is also overexpressed in lung cancer [81], BC [82], and neuroblastoma [83]. However, these genes' biologic function and detected DNAm probes' potential involvement in CRC tumorigenesis remain elusive, calling for functional/mechanical studies on the methylome of these genes in CRC.

Of noteworthy, cg06007966 in the CpG island at TSS200 of *MIR663* was validated genomewide across PBLs and 2 tissue datasets. MicroRNAs (miRNAs) are short non-coding RNAs that control gene expression by targeting mRNAs to promote either translation regression or RNA degradation [84, 85]. Aberrant miRNAs have been found in human cancers, correlated with tumorigenesis and progression. In particular, miR-663 has a strong binding affinity to *AATF* (an anti-apoptotic gene) mRNA, thus, promoting apoptosis in cancer cells, known as "apopto-miR" [86]. The miR-663 is regulated epigenetically; in particular, the CpG island promoter region of miR-663 is hypermethylated, showing decreased expression [85, 87-90], resulting in tumor cell growth, invasion, and metastasis in multiple cancer cells [85, 87-89, 91-95], including CRC [96, 97]. Our CpG in miR-663 was hypermethylated in CRC, presuming downregulation, consistent with those previous study findings. In contrast, miR-663 is also considered an "onco-miR" in several cancer cells with different target genes and downstream signaling involved in carcinogenesis and cancer growth [84, 90, 98-102]. Overall, the role of miR-663 and its abnormal expression regulated by the methylome is little known in CRC, warranting functional validation studies.

Finally, our DMR analyses detected 1 region shared across PBL and tissue cohorts in *PEG10* of Chr7 with 10 related CpGs, although these probes were not significant genome wide in our analysis. *PEG10* is considered an oncogene, a proliferation-positive, paternally expressed imprinted gene, overexpressed in cancer cells/ tissues [103-108]. CRC tissues also showed overexpression of *PEG10* through which a long non-coding RNA sponges miR-574 [109]. Interestingly, *PEG10* was the only gene differentially expressed in a study [110] comparing gene expression between early- and late-onset $(\geq$ age 65 years) CRC, in which its overexpression was found only in the early-onset group; this supports our finding of the 10 CpGs in *PEG10* that were hypermethylated in CRC (i.e., a negative effect on gene expression) in our postmenopausal women.

Our analysis of GSE48684 did not include DNAm-age prediction and tumor purity owing to a lack of data availability. Our transcriptome profile did not analyze miRNAs, as the data contained mRNA-Seqs only; this deserves future functional/mechanical laboratory studies of miRNAs for biologic implications in CRC. Also, data from the methylome for our EWA analyses and from the transcriptomics for gene expression were not paired; thus, our findings should be interpreted with caution. The two GEO tissue datasets have different tissue sources - tissues from CRC patients compared with their normal adjacent tissues and tissues from CRC patients compared with those from non-CRC patients - supporting that our validation studies reflect complex pathways underlying CRC. However, few DNAm probes from the GEO databases demonstrated an extreme risk magnitude, a replication study with a larger dataset is warranted. In addition, because we repurposed data from the WHI AS, samples

analyzed for our study may not fully reflect the source population, resulting in limited statistical power, and our study findings should not be generalized to populations other than white postmenopausal women.

In summary, we found multiple site-specific CpGs and differentially methylated regions across PBL- and tissue-level data at genomewide significance for CRC development which had been prospectively evaluated. Some are novel, but others are well-established in CRC, warranting epigenetic and functional validation. Our study contributes to elucidating the complex interrelated mechanisms on the methylome underlying CRC tumorigenesis and suggests novel preventive DNAm-targets in PBLs for capturing individuals at high risk for CRC development.

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Written informed consent was obtained from the participants at the source.

Disclosure of conflict of interest

None.

Address correspondence to: Dr. Su Yon Jung, Translational Sciences Section, School of Nursing, University of California, 700 Tiverton Avenue, 3-264 Factor Building, Los Angeles, CA 90095, USA. Tel: 310-825-2840; Fax: 310-267-0413; E-mail: [sjung@](mailto:sjung@sonnet.ucla.edu) [sonnet.ucla.edu](mailto:sjung@sonnet.ucla.edu)

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Figure S1. The area under the receiver operating characteristic curve (AUC) analysis with six CpGs (cg04958124, cg10321339, cg12704462, cg18144285, cg06007966, and cg17375901).

^c By enhancer and/or promoter ^D

By gene region

Island

 S Shore

<GSE48684>

<GSE199057>

${\bf C}$ By enhancer and/or promoter ^D

By gene region

Figure S2. GSE datasets: Bar plots for mean difference in DNAm levels of top 20 genome-wide CpGs across chromosome, CpG context, enhancer and/or promoter, and gene region, stratified by CRC status. CpG, CpG dinucleotide; CRC, colorectal cancer; DNAm, DNA methylation; TSS200, 0-200 bp upstream of transcription start site; UTR, untranslated region. Note: *Statistical significance after multiple comparison correction.

Figure S3. WHIBAA23, GSE48684, and GSE199057 in CRC patients (peripheral leukocytes for WHIBAA23 and CRC tissues for GSEs): Comparisons among the 3 studies for mean differences in DNAm levels of top 20 genome-wide CpGs across chromosome, CpG context, enhancer and/or promoter, and gene region. CpG, CpG dinucleotide; CRC, colorectal cancer; DNAm, DNA methylation; EWA, epigenome-wide association; TSS200, 0-200 bp upstream of transcription start site; UTR, untranslated region; WHI, Women's Health Initiative. Note: *Statistical significance after multiple comparison correction.

 $A1$ DMR1 (Chr6: 32036449-32059605: TNXB. RNA5SP206)

D1 DMR4 (chr2: 63273436-63287288; EHBP1, OTX1, AC009501.4)

B1 DMR2(Chr6: 33128825-33155135;

COL11A2)

開開電話

C1 DMR3 (Chr11:31817810-31841980; RCN1,

PAX6)

E1 DMR5 (chr7: 96641456-96657023; DLX6-AS1, DLX5)

- $A2$ DMR1 (chr6: 32036449-32059605: TNXB. RNA5SP206)
- Chromosome 6 **(Filippe Telephone Telephone** 32.03 mb 32.05 mb 32.01 mb 32.02 mb 32.04 mb 32.06 mb 32.08 mb 32.1 ml THE **T**hmson name is na i**n**diff \equiv $-$ con $-$ crc
- **B2** DMR2 (chr6: 33128903-33155135: COL11A2)

 $C₂$ DMR3 (chr7: 27178861-27198374; HOXA-AS3, RP1-170019.21, HOXA3, RP1-170019.22, HOXA5, HOXA6, RP1-170019.23, HOXA7)

- D₂ DMR4 (chr11: 31824327-31841980; RCN1,
- E₂ DMR5 (chr2: 63273436-63287686; EHBP1, OTX1, AC009501.4)

Figure S4. Top 5 differentially methylated regions (DMRs) in each GSE dataset. (A1-E1) for GSE48684 and (A2-E2) for GSE199057. A vertical bar on the chromosome schematic locates plotted region. The first track shows the CpG island context; the second track (yellow) shows the gene context i.e., the location of the DMR in the genome, the position of any genes that are nearby; the third track (light green) shows the base pair positions of the CpGs. Heatmap shows the methylation levels of the individual samples by colorectal cancer (CRC) status. The last smooth line graph shows the mean methylation levels for the samples grouped by CRC status.

Seqnames	Start	End	Width	Score
Chr1	25253237	25259034	5798	$\overline{2}$
Chr1	50879560	50893984	14425	2
Chr1	119526060	119532925	6866	$\overline{2}$
Chr1	217306700	217314284	7585	$\overline{2}$
Chr1	221057236	221070193	12958	$\overline{2}$
Chr ₂	45155201	45163188	7988	$\overline{2}$
Chr ₂	63273436	63287288	13853	2
Chr ₂	119602212	119613877	11666	$\overline{2}$
Chr ₂	223161771	223173061	11291	$\overline{2}$
Chr ₃	62353312	62365402	12091	2
Chr ₃	128203414	128212476	9063	$\overline{2}$
Chr ₃	137481938	137491164	9227	2
Chr ₃	147121892	147132559	10668	$\overline{2}$
Chr4	4854459	4864902	10444	$\overline{2}$
Chr4	96468962	96471143	2182	$\overline{2}$
Chr4	154709441	154714852	5412	$\mathbf 2$
Chr4	174447847	174453287	5441	2
Chr ₅	1882188	1888033	5846	$\overline{2}$
Chr ₅	37833969	37840839	6871	$\overline{2}$
Chr ₅	134361983	134367394	5412	$\overline{2}$
Chr ₅	170734312	170740937	6626	$\sqrt{2}$
Chr ₆	29520527	29521803	1277	2
Chr ₆	30078080	30080782	2703	$\overline{2}$
Chr ₆	32036449	32059605	23157	$\overline{2}$
Chr ₆	32060681	32066582	5902	\overline{c}
Chr ₆	32184296	32193235	8940	\overline{c}
Chr ₆	33128903	33155135	26233	2
Chr ₆	84417445	84419360	1916	$\overline{2}$
Chr ₆	108484512	108492769	8258	$\overline{2}$
Chr ₆	133561224	133564578	3355	\overline{c}
Chr ₆	152125861	152130332	4472	$\sqrt{2}$
Chr7	1265197	1281585	16389	2
Chr7	19155785	19158954	3170	$\overline{2}$
Chr7	27140797	27144854	4058	$\sqrt{2}$
Chr7	27180888	27185512	4625	$\overline{2}$
Chr7	49812836	49815938	3103	\overline{c}
Chr7	94284258	94287242	2985	$\overline{2}$
Chr7	96645989	96657023	11035	2
Chr7	130129946	130133110	3165	2
Chr ₈	25897201	25909599	12399	2
Chr ₈	69241923	69244553	2631	$\overline{2}$
Chr ₈	70980488	70984917	4430	\overline{c}
Chr ₈	72753268	72758701	5434	2
Chr ₈	97169621	97174382	4762	\overline{c}
Chr ₈	145103393	145107857	4465	$\overline{2}$
Chr10	7450112	7455714	5603	$\overline{2}$

Table S2. Among top 100 differentially methylated regions (DMRs) selected from each GSE dataset (GSE48684 and GSE199057), DMRs overlapping across the GSE datasets

The score of 2 indicates that the 2 datasets have overlapping DMRs. Chr, chromosome.

WHIBAA23: All HRs were adjusted by leukocyte heterogeneities plus DNA methylation-predicted age.										
CpG	age.HR*	age.SE	age.P	bmi.HR**	bmi.SE	bmi.P	DM.IR.HR¶	DM.IR.SE	DM.IR.P	
cg24885794	1.42	0.193	0.067	1.41	0.193	0.072	1.45	0.196	0.058	
cg26997085	1.44	0.152	0.017	1.42	0.154	0.023	1.45	0.158	0.019	
cg22331138	1.25	0.187	0.240	1.25	0.189	0.236	1.33	0.193	0.134	
cg16492735	1.07	0.202	0.731	1.07	0.202	0.738	1.07	0.210	0.750	
cg09512080	1.21	0.183	0.305	1.20	0.183	0.324	1.21	0.191	0.326	
cg00906934	1.50	0.187	0.031	1.49	0.187	0.032	1.45	0.197	0.060	
cg26503018	1.25	0.199	0.266	1.25	0.198	0.269	1.20	0.203	0.359	
cg27120649	1.26	0.208	0.274	1.27	0.208	0.251	1.29	0.216	0.241	
cg21771834	1.11	0.218	0.625	1.11	0.219	0.627	1.19	0.219	0.438	
cg27001184	1.17	0.188	0.402	1.17	0.188	0.412	1.18	0.195	0.405	
GSE48684: All ORs were adjusted by sex.										
CpG	ORS	SE	P	OR¥	SE	\boldsymbol{P}	OR£	SE	\boldsymbol{P}	
cg24885794	3.63	0.342	0.0002	3.63	0.342	0.0002	3.63	0.342	0.0002	
cg26997085	2.91	0.320	0.001	2.91	0.320	0.001	2.91	0.320	0.001	
cg22331138	1.97	0.260	0.009	1.97	0.260	0.009	1.97	0.260	0.009	
cg16492735	2.75	0.313	0.001	2.75	0.313	0.001	2.75	0.313	0.001	
cg09512080	2.43	0.294	0.002	2.43	0.294	0.002	2.43	0.294	0.002	
cg00906934	2.50	0.378	0.016	2.50	0.378	0.016	2.50	0.378	0.016	
cg26503018	1.63	0.233	0.036	1.63	0.233	0.036	1.63	0.233	0.036	
cg27120649	2.61	0.340	0.005	2.61	0.340	0.005	2.61	0.340	0.005	
cg21771834	1.29	0.218	0.244	1.29	0.218	0.244	1.29	0.218	0.244	
cg27001184	1.75	0.243	0.022	1.75	0.243	0.022	1.75	0.243	0.022	
GSE199057: All ORs were adjusted by sex plus age and DNA methylation-predicted age.										
CpG	ORS	SE	\boldsymbol{P}	OR¥	SE	P	0R£	SE	P	
cg24885794	2.99	0.445	0.014	5.73	0.538	0.001	5.08	0.455	0.0004	
cg26997085	3.79	0.511	0.009	3.39	0.515	0.018	3.56	0.410	0.002	
cg22331138	3.40	0.465	0.008	3.58	0.526	0.015	3.66	0.419	0.002	
cg16492735	4.83	0.532	0.003	6.18	0.555	0.001	4.19	0.426	0.001	
cg09512080	2.75	0.420	0.016	3.67	0.535	0.015	2.80	0.395	0.009	
cg00906934	2.14	0.347	0.028	4.54	0.530	0.004	3.20	0.406	0.004	
cg26503018	4.61	0.556	0.006	11.29	0.597	0.00005	5.40	0.463	0.0003	
cg27120649	6.69	0.598	0.001	7.27	0.543	0.0003	4.22	0.429	0.001	
cg21771834	5.65	0.620	0.005	4.47	0.529	0.005	5.72	0.484	0.0003	
cg27001184	1.91	0.319	0.043	2.03	0.492	0.151	2.38	0.377	0.022	

Table S3. Effect size of 10 CpGs in the differentially methylated region (Chr7) which overlaps across the WHIBAA23 and GSE datasets

BMI, body mass index; Chr, chromosome; CpG, CpG dinucleotide; DM, ever having been treated for diabetes; HR, hazard ratio; IR, insulin resistance; OR, odds ratio; SE, standard error; WHI, Women's Health Initiative. *Age adjusted; **BMI and age adjusted; ¶DM, IR, BMI and age adjusted; §CpG as continuous variable; ¥CpG as categorical variable (binary using a median); £CpG as categorical variable (ternary using 1st and 3rd quartiles).

Figure S5. UMAP plots of mRNA-sequences mapping to modeled genes in TCGA COAD and READ datasets. CRC, colorectal cancer; UMAP, Uniform Manifold Approximation and Projection.

N/A, not available. *BAA23 genes: 20 top CpGs at the genome-wide significance. TGSE48684 genes: among top 20 CpGs, only CpGs significant at the validation level. ¥GSE199057 genes: among top 20 CpGs, only CpGs significant a validation level. §GSE199057 of Pathway - Reactome: from Genome as Reference Gene Set.