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Blood methylation biomarkers are associated with diabetic kidney disease progression in type 1 diabetes

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Abstract

Background: DNA methylation differences are associated with kidney function and diabetic kidney disease (DKD), but prospective studies are scarce. Therefore, we aimed to study DNA methylation in a prospective setting in the Finnish Diabetic Nephropathy Study type 1 diabetes (T1D) cohort.

Methods: We analysed baseline blood sample-derived DNA methylation (Illumina's EPIC array) of 403 individuals with normal albumin excretion rate (early progression group) and 373 individuals with severe albuminuria (late progression group) and followed-up their DKD progression defined as decrease in eGFR to <60 mL/min/1.73m² (early DKD progression group; median follow-up 13.1 years) or end-stage kidney disease (ESKD) (late DKD progression group; median follow-up 8.4 years). We conducted two epigenome-wide association studies (EWASs) on DKD progression and sought methylation quantitative trait loci (meQTLs) for the lead CpGs to estimate genetic contribution.

Results: Altogether, 14 methylation sites were associated with DKD progression ($P < 9.4 \times 10^{-8}$). Methylation at cg01730944 near *CDKN1C* and at other CpGs associated with early DKD progression were not correlated with baseline eGFR, whereas late progression CpGs were strongly associated. Importantly, 13 of 14 CpGs could be linked to a gene showing differential expression in DKD or chronic kidney disease. Higher methylation at the lead CpG cg17944885, a frequent finding in eGFR EWASs, was associated with ESKD risk (HR [95% CI] = 2.15 [1.79, 2.58]). Additionally, we replicated meQTLs for cg17944885 and identified ten novel meQTL variants for other CpGs. Furthermore, survival models including the significant CpG sites showed increased predictive performance on top of clinical risk factors.

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Conclusions: Our EWAS on early DKD progression identified a podocyte-specific *CDKN1C* locus. EWAS on late progression proposed novel CpGs for ESKD risk and confirmed previously known sites for kidney function. Since DNA methylation signals could improve disease course prediction, a combination of blood-derived methylation sites could serve as a potential prognostic biomarker.

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1 BACKGROUND

2 Diabetic kidney disease (DKD) is a devastating complication of diabetes. One-third of 3 individuals with type 1 diabetes (T1D) and severe albuminuria develop end-stage kidney disease (ESKD).¹ Genetic variability affects the risk of DKD^{2,3} but recent studies highlight the 4 5 role of epigenetics as well.⁴ One common type of epigenetic modification is DNA methylation, 6 *i.e.*, the attachment of a methyl group at cytosine-guanine dinucleotide (CpG), which 7 contributes to the regulation of gene expression. Epigenome-wide association studies (EWASs) with blood-derived methylation data have identified methylation sites associated with DKD⁵⁻⁸ 8 9 and ESKD⁹ in T1D. Additionally, kidney function, assessed by estimated glomerular filtration rate (eGFR), is associated with DNA methylation, both in individuals with¹⁰⁻¹² and without¹³⁻ 10 ¹⁵ diabetes. Remarkably, some top findings, such as methylation site cg17944885 located in a 11 12 zinc finger gene cluster, have replicated across studies in diabetes cohorts, the general 13 population, and, importantly, multiple ethnic groups. Thus, DNA methylation studies may 14 provide both insights into causal disease pathways and robust prognostic biomarkers to identify 15 individuals at risk.

Epigenetic changes may be dynamic, and changes in DNA methylation can represent either the cause or consequence of DKD. Hyperglycemia can alter DNA methylation, and thereby contribute to metabolic memory — the prolonged effect of hyperglycemia on microvascular complications, even years after the improvement of hyperglycemia.^{16,17}

Additionally, genetic variation can regulate DNA methylation.^{18,19} Importantly, methylation quantitative trait loci (meQTLs) can be used to infer causality: We recently identified a methylation site in *REV1* as causally linked to DKD in T1D.⁷

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23 In diabetes, a cross-sectional study of 119 individuals showed differential blood DNA methylation at the early and late stage of DKD.²⁰ Furthermore, we have previously shown that 24 25 21 of 32 DKD-associated CpGs associated with progression to ESKD⁷, and recently, an EWAS on DKD progression to ESKD identified 17 associated CpGs.²¹ However, no EWAS has yet 26 27 explored CpGs associated with early progression of DKD in T1D. Here, we employed a 28 prospective study setting and analysed baseline DNA methylation as a predictive biomarker of 29 DKD progression both at the early and late stages of DKD in T1D. Additionally, we searched 30 for meQTLs and serum protein associations for our key methylation findings.

31 METHODS

32 Cohorts

33 The study participants were from the ongoing multicentre Finnish Diabetic Nephropathy 34 (FinnDiane) Study that is approved by the Ethics Committee of Helsinki University Central 35 Hospital (491/E5/2006, 238/13/03/00/2015, and HUS-3313-2018) and follows the Declaration 36 of Helsinki. At the study visit, after signing an informed consent, the participants complete 37 questionnaires with the attending nurse or physician, and basic anthropometric measurements 38 are taken.²² Blood samples are drawn for DNA extraction and, e.g., for serum creatinine 39 measurement. Albuminuria classification is based on two of three consecutive 24-hour or timed 40 overnight urine collections.

41 *DKD progression:* The early DKD progression sub-cohort comprised 403 individuals (**Figure** 42 1) with T1D duration \geq 10 years, normal albumin excretion rate (AER<30 mg/24h or <20 43 µg/min), and eGFR \geq 60 mL/min/1.73m². We collected serum creatinine data from baseline 44 visits and medical records until March 10, 2022, converted Jaffe-method measurements to 45 IDMS units (Creatinine_{IDMS}=0.953×Creatinine_{Jaffe}-7.261), and calculated eGFR using the 46 revised Chronic Kidney Disease - Epidemiology Collaboration formula (CKD-EPI).²³ Early medRxiv preprint doi: https://doi.org/10.1101/2024.11.28.24318055; this version posted November 29, 2024. The copyright holder for this preprint (which was not certified by peer review) is the author/funder, who has granted medRxiv a license to display the preprint in perpetuity. It is made available under a CC-BY-NC-ND 4.0 International license .

DKD progression was defined as eGFR<60 mL/min/1.73m². Thus, the follow-up time was
years between the baseline visit and the first date of eGFR<60 mL/min/1.73m² or the latest
available eGFR data point.

The 373 participants in the late DKD progression sub-cohort had T1D and severe albuminuria (AER>300 mg/24h or >200 μ g/min) and eGFR>15 mL/min/1.73m², at baseline. We collected data on ESKD, defined as requiring dialysis and/or a transplant, and data on mortality from the Finnish Care Register for Health Care, study visit questionnaires, and medical records. For individuals not yet treated for ESKD, an eGFR record <15 mL/min/1.73m² was considered an ESKD event. The participants were followed up until the event, death, or December 31, 2020.

56 Longitudinal samples: Altogether 52 individuals had DNA samples available at two time 57 points, 3.6–16.4 years apart. Of them, 45 had the second DNA sample analysed as part of the 58 DKD progression cohorts (Supplemental Figure 1), whereas seven individuals were new. 30 59 of 52 individuals had normal AER and eGFR>60 mL/min/1.73m² at both time points. The 60 remaining 22 individuals had normal AER (n=8) or moderate albuminuria (n=14; AER)61 between 30-300 mg/24h or 20-200 µg/min) at the first time point and progressed to severe 62 albuminuria during follow-up. Additionally, we calculated eGFR slopes between the time 63 points from \geq 3 eGFR values ranging over two years.

64 **DNA methylation assessment**

We analysed blood-derived genome-wide DNA methylation with Infinium HD MethylationEPIC v1.0 BeadChip (Illumina, San Diego, CA, USA) within the Northern Ireland Regional Genetics Centre in Belfast. Altogether 798 samples were from our previous crosssectional DKD EWAS⁷, while 100 were new. The quality control (QC) process details are in **Supplemental Methods**. In brief, from 898 samples and 866,895 methylation probes, one medRxiv preprint doi: https://doi.org/10.1101/2024.11.28.24318055; this version posted November 29, 2024. The copyright holder for this preprint (which was not certified by peer review) is the author/funder, who has granted medRxiv a license to display the preprint in perpetuity. It is made available under a CC-BY-NC-ND 4.0 International license .

sample and 105,357 probes were removed during QC. Thereafter, we extracted methylation Mvalues of the remaining 761,538 methylation probes from 897 samples using *'RnBeads'*.
Additionally, we calculated principal components (PC) from the non-negative control probe
intensities and mean methylation (mean M-value) of probes known to have invariable
methylation levels in blood-based DNA.²⁴ These variables were used in the subsequent EWASs
to correct for technical deviations.

76 Statistical analysis

DKD progression: We analysed associations between each methylation site and DKD progression separately for the early and late DKD progression cohorts using a Cox proportional-hazards model adjusted for sex, baseline age, six estimated white blood cell counts (WCCs), PCs 1–3, and intrapersonal mean M from invariable sites. The second model included baseline eGFR as an additional covariate. Significance threshold was $P < 9.4 \times 10^{-8}$, as recommended for the EPIC array.²⁵

83 *Longitudinal analyses:* Using longitudinal data, we compared methylation change 84 (Δ methylation) over time between DKD progressors and non-progressors using logistic 85 regression and residualised methylation values (**Supplemental Methods**). Additionally, we 86 tested the association between eGFR slope (dependent variable) and Δ methylation using linear 87 regression (**Supplemental Methods**).

Replication: We included several look-up replication cohorts: United Kingdom and Republic of Ireland (UK-ROI, n=372) T1D cohort with DKD EWAS data⁷, Joslin Kidney Study with prospective kidney failure EWAS data (n=277)²¹ as well as eGFR-EWAS summary statistics from the Chronic Renal Insufficiency cohort (CRIC)¹⁰, the Hong Kong diabetes register¹¹, and the general population.^{13–15} To assess whether diabetes contributed to the associations, we medRxiv preprint doi: https://doi.org/10.1101/2024.11.28.24318055; this version posted November 29, 2024. The copyright holder for this preprint (which was not certified by peer review) is the author/funder, who has granted medRxiv a license to display the preprint in perpetuity. It is made available under a CC-BY-NC-ND 4.0 International license .

compared ESKD-DKD (n=108) vs. ESKD due to other causes (n=71)⁹, DKD (n=252, UKROI) vs. individuals without diabetes nor kidney disease (n=340, from the Northern Ireland
Cohort for the Longitudinal Study of Ageing (NICOLA), and ESKD-DKD (n=108, UKROI/Renal Transplant Collection samples) vs. the 340 NICOLA participants.

Sensitivity analyses: We tested the association with baseline eGFR and carried out both 10 year-risk and competing risk analyses regarding late DKD progression. Additionally, we
 studied pleiotropy with correlation analysis of the methylation data and baseline characteristics

100 (Supplemental Methods).

101 Predictive power: We compared the concordance indices (C-index) of Cox models using 102 clinical risk factors, both with and without CpG methylation values. The chosen clinical 103 variables were associated with (early or late) DKD progression in a univariable ($P \le 0.25$) and 104 multivariable Cox regression models (P < 0.10). Additionally, we included age, sex, and 105 methylation assay QC-variables in all models, including the clinical model, to separate the 106 methylation effect from technical variability. We compared models: 1) clinical variables, 2) 107 clinical variables and baseline eGFR, and 3) clinical variables, eGFR, and CpG methylation. 108 Additionally, we created a model incorporating all significant CpGs with clinical variables and 109 eGFR to study the cumulative effect. An increase in the C-index (P < 0.05) was considered 110 significant.

111 Annotation of methylation sites

112 *CpG location:* We examined the overlap of CpG genomic locations with kidney open 113 chromatin peaks^{26–28} utilising the Susztaklab Kidney Biobank²⁹, with TF motifs^{30,31}, 114 quantitative trait methylation (eQTMs) datasets^{27,34-36,37}, and meQTLs^{32,33}. We performed a medRxiv preprint doi: https://doi.org/10.1101/2024.11.28.24318055; this version posted November 29, 2024. The copyright holder for this preprint (which was not certified by peer review) is the author/funder, who has granted medRxiv a license to display the preprint in perpetuity. It is made available under a CC-BY-NC-ND 4.0 International license .

meQTL analysis to identify local (*cis*, ± 1 Mb) and distal (*trans*) genetic effects for the CpGs

116 (Supplemental Methods).

117 Gene expression in the kidney: Differential gene expression in human diabetic kidneys, was 118 studied in datasets ^{38,39,40,41} collected into the Nephroseq database v5⁴² (Supplemental 119 Methods). Additionally, we studied two human DKD kidney tissue gene expression 120 datasets^{43,44}, preprocessed similarly to the previous study.⁴⁵ Kidney single-cell gene expression 121 data⁴⁶ were accessed through the Kidney Interactive Transcriptomics database.⁴⁷

122 Protein expression —Serum proteome data measured with OLINK[®] Ht assay at SciLifeLab in 123 Uppsala were available for 188 individuals with normal AER (main analysis group) and 127 124 individuals with severe albuminuria (replication group). We analysed the association between 125 methylation and proteins levels of *cis*-located genes (*i.e.*, *cis* protein quantitative trait 126 methylation (*cis*-pQTM), **Supplemental Methods**).

Enrichment analysis — We analysed the enrichment of Gene ontology (GO) terms and Kyoto
Encyclopedia of Genes and Genomes (KEGG) pathways with the R package *'missMethyl'*(v.1.22.0) *gometh*-function for early and late DKD progression separately. Additionally, we
assessed CpG trait enrichment using EWAS Toolkit.⁴⁸

131 **RESULTS**

132 CpGs associated with DKD progression

In the early DKD progression cohort of 403 individuals, 37% were women, and mean age was 42 years (**Table 1**). Over the 13.1-year (interquartile range: 8.4–16.9) follow-up, DKD progressed in 49 individuals. EWAS identified two methylation sites significantly associated $(P < 9.4 \times 10^{-8})$ with early DKD progression: cg25013571 between *PLPBP* and *ADGRA2* (HR

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137 [95%CI] = 3.35 [2.18, 5.13]) and cg05831784 in HAO1 (0.42 [0.30, 0.57]; Table 2, Figure 2, 138 Supplemental Figure 2). Cg25013571 (PLPBP/ADGRA2) remained significant in EWAS 139 adjusted for baseline eGFR, whereby the cg05831784 (HAO1) association was modestly 140 attenuated. Furthermore, in eGFR-adjusted EWAS, cg06334496 in TMEM70 and cg01730944 141 close to the transcription start site (TSS) of *CDKN1C*, alias $p57^{Kip2}$, were significantly 142 associated with early DKD progression. Cg01730944 was generally hypomethylated (beta-143 values<0.05) (Figure 3A, Supplemental Figure 3), and low methylation values were 144 associated with risk of DKD progression (Figure 3B).

- 145 The 373 individuals with severe albuminuria at baseline were followed-up for a median of 8.4
- 146 (interquartile range: 4.1–15.4) years. Altogether, 38% were women, and mean age 43 years.
- 147 Individuals (*n*=206, 55%) who developed ESKD had lower baseline eGFR compared to those

148 167 who did not progress to ESKD (43.5 *vs.* 84.9 mL/min/1.73m², **Table 1**).

EWAS on late DKD progression identified ten significant CpGs ($P < 9.4 \times 10^{-8}$) from nine genomic loci (**Table 2**). Higher methylation at the top site cg17944885 between *ZNF788P* and *ZNF625-ZNF20* (chr19p13.2) was associated with ESKD risk (HR [95%CI] = 2.15 [1.79, 2.58]). The nine additional CpGs exhibited lower methylation as risk for progression of DKD to ESKD (HRs<1.0), supporting the previously suggested trend of general hypomethylation in advanced DKD.⁸ In competing risk analysis (n=51 death events), eight CpGs remained significantly associated with ESKD risk (**Supplemental Table 1**).

156 The top ten CpGs were associated with baseline eGFR (Table 2), which likely attenuated their

- association with ESKD risk in the eGFR-adjusted EWAS (Supplemental Table 2), where no
- 158 epigenome-wide significant associations were seen (Supplemental Figure 4).

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Longitudinal dataset showed that methylation levels of the 14 DKD progression-associated CpGs seemed relatively stable over time: only at cg17944885 (chr19p13.2) progressors from normal AER to severe albuminuria had increase in methylation, *i.e.*, in the expected direction, when compared to non-progressors (P=0.049; non-significant after Bonferroni-correction; **Supplemental Figures 5** and **6**). No association between Δ methylation and eGFR slope was observed (**Supplemental Table 3**).

165 Replication

166 We studied several EWAS datasets to validate the lead findings. Notably, the CpGs associated 167 with early DKD progression were not associated with eGFR, implying that EWASs on eGFR 168 are unsuitable for replicating these signals, and no cohort with a comparable early progression 169 phenotype and EWAS data currently exists. Nevertheless, three of four early DKD progression-170 associated CpGs showed differential methylation in DKD (n=252) compared to healthy 171 individuals (n=340) without diabetes and kidney disease: cg25013571 (PLPBP/ADGRA2), cg05831784 (*HAO1*), and cg01730944 (*CDKN1C*), (*P*-values<1.4×10⁻⁶, Supplemental Table 172 173 4).

174 Eight of ten late DKD progression-associated CpGs were nominally (P < 0.05) or significantly $(P < 3.6 \times 10^{-3};$ Bonferroni correction) associated with eGFR in the replication datasets. 175 176 Remarkably, higher methylation at cg17944885 (chr19p13.2) was consistently associated with lower eGFR in five eGFR EWASs ($P < 1.4 \times 10^{-9}$), DKD in the UK-ROI cohort ($P = 9.5 \times 10^{-16}$), 177 178 and risk of ESKD in the JKS cohort ($P \le 6.2 \times 10^{-4}$). Additionally, cg00994936 and cg12272104 179 (DAZAP1) were robustly replicated; Cg12272104 is already a known eGFR-associated CpG.¹³ 180 Notably, the novel cg21871803 (AHCYL2) was significantly replicated in the eGFR slope EWAS $(P=1.3\times10^{-4})^{11}$ and nominally in EWAS on DKD progression to ESKD²¹. 181

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182 Association with clinical variables

Methylation sites associated with early DKD progression correlated only modestly with baseline clinical variables indicating that methylation at these sites is not strongly affected by these factors (**Supplemental Figure 7**). Nine of ten late DKD progression-associated CpGs correlated with baseline eGFR and only modestly with other clinical variables; for instance, only two sites correlated with HbA_{1c} (**Supplemental Figure 8**). Interestingly, methylation values of late DKD progression-associated CpGs correlated with one another (**Supplemental Figure 9**).

190 Prediction of kidney outcomes

191 When predicting early DKD progression, baseline eGFR did not improve the clinical model: 192 the C-index was 0.783 vs. 0.775 (Cox model with clinical variables). This implies that baseline 193 eGFR does not help distinguishing early DKD progressors. The top four CpG sites, separately, 194 did not improve the model (**Supplemental Figure 10**), whereas a model including all four 195 performed better compared with a model with clinical variables and eGFR (C-index 0.859 *vs.* 196 0.783, *P*=0.01, **Figure 4**).

197 As expected, adding baseline eGFR into the clinical model improved the Cox model for late 198 DKD progression (C-index 0.838 *vs.* 0.691, P<0.001). The significant CpGs, separately, did 199 not improve the model (**Supplemental Figure 11**) but a model including them all outperformed 200 the clinical model with eGFR (C-index 0.849 *vs.* 0.838, P=0.03).

201 *meQTLs*

202 We subsequently studied the impact of genetic variability on methylation levels at the top sites.

203 We identified nine independent cis-meQTLs associated with methylation at seven CpGs

204 (P<0.05 at FDR<0.05, Table 3, Supplemental Table 5). These included rs555097 for

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205 cg14999724 (*RP11-872D17.8*) without prior *cis*-meQTLs in the Genetics of DNA Methylation

- 206 Consortium (GoDMC) data (Supplemental Figure 12). Our lead cis-meQTL rs4804653 for
- 207 cg17944885 (chr19p13.2) was found also in the general population (GoDMC).

208 The 68 trans-meQTLs on chromosome 16 for cg17944885 were in linkage disequilibrium $(r^2>0.19, 1000$ Genomes Finnish population data; LDlink).⁴⁹ This locus affects (in *trans*) the 209 expression of zinc finger genes at chr19p13.2⁵⁰ and methylation at several loci¹⁹. The lead 210 211 trans-meQTL rs17611866, a missense variant p.Val325Ala in ZNF75A, associates with the 212 expression of nearby genes.⁵¹ Interestingly, three of the 45 CpGs regulated by rs17611866¹⁹ showed significant (cg17944885, chr19p13.2) or suggestive ($P < 10^{-4}$; cg18470038 [chr12] and 213 214 cg06158227 [chr15]) association with late DKD progression in our EWAS (Figure 5). 215 Furthermore, cg06158227 (chr15) was identified in an eGFR-EWAS.¹³

216 To investigate meQTL loci, we conducted phenome-wide association studies (PheWASs) in the Finnish biobank data FinnGen^{52,53} and T1D knowledge portal.⁵⁴ Although the robust *trans*-217 218 meQTL rs17611866 in ZNF75A showed no significant associations, rs1447267563 near 219 ZNF75A was the lead variant for "cystic kidney disease" and among the lead loci for 220 "Congenital malformations of the urinary system", supporting the link between this locus and 221 kidney health. Furthermore, rs555097 (meQTL for cg14999724/RP11-872D17.8) associated 222 with Cystatin C, rs12198601 (cg05831784/HAO1) with DKD, and rs34622118 223 (cg12272104/DAZAP1) with ESKD vs. macroalbuminuria analysis (Supplemental Table 6). 224 Altogether, these associations between kidney traits and meQTLs support the importance of 225 our top methylation sites in kidney disease.

226 *Gene and protein expression evidence*

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We investigated whether our top methylation sites were associated with gene expression. In blood cells, only cg17944885 was a significant *cis*-eQTM (**Table 4**). Remarkably, when examining data on other tissues including kidneys, 8 of 14 CpGs were significant eQTM for the closest gene (**Table 4**, **Supplemental Table 7**).

- 231 Our cis-pQTM analysis showed that cg14999724 methylation was associated with serum
- proteoglycan 3 levels, produced by the nearby *PRG3* gene (beta=-0.18, SE=0.04, *P*= 1.7×10^{-5} ,

233 Supplemental Figure 13, Supplemental Table 8). While *PRG3* shows limited expression in

234 kidneys, it is over-expressed in CKD tubules⁴¹ and collecting duct in diabetes^{46,47}

235 (Supplemental Figure 14).

236 We additionally studied whether the closest or eQTM-genes for the top CpGs show altered 237 expression in kidney disease. Notably, for 13 of 14 CpGs, the related gene was differentially 238 expressed in CKD/DKD ($P < 1.5 \times 10^{-3}$) or associated with eGFR in human kidneys 239 (Supplemental Table 9). For example, CDKN1C (near cg01730944) showed lower expression in DKD in glomeruli³⁸ (FC=-4.95, Figure 3E) and tubules⁴⁰ (FC=-1.55). Additionally, 240 241 AHCYL2 (near cg21871803) expression in glomeruli and tubules correlated with kidney 242 function (r=0.34).⁴⁰ For cg17944885 (chr19p13.2), four zinc finger eQTM-genes were nominally or significantly (ZNF136) upregulated in CKD tubules.⁴¹ 243

In whole kidney samples⁴⁴, 13 related genes were differentially expressed in advanced *vs.* early DKD, implying true biological differences related to the disease stage and justifying separate analyses like ours (**Supplemental Table 10**).

247 Open chromatin and TFs

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Early DKD progression-associated cg05831784 (*HAO1*), cg01730944 (*CDKN1C*, Figure 3C),

and cg06334496 (*TMEM70*) located at open chromatin peaks²⁷ in kidneys, thus, at potential

250 regulatory regions or actively transcribed DNA. The late DKD progression-associated loci

251 located outside of open chromatin.

Furthermore, CpGs associated with early DKD progression overlapped with several TF motifs³⁰ (**Supplemental Table 11**). For example, cg01730944 (*CDKN1C*) overlapped with EGR1 that is upregulated in hyperglycemia⁵⁵, exacerbates mesangial cell proliferation⁵⁵, and contributes to tubular fibrosis in diabetes⁵⁶. Taken together, snATAC-seq and TF analyses suggest that genomic regions at the novel early DKD progression -associated CpGs might have functional implications and, thus, potential relevance regarding disease progression.

258 Enrichment analysis

Genes related to CpGs with EWAS $P < 1 \times 10^{-4}$ were not enriched in GO terms or KEGG 259 260 pathways at FDR<0.05 (Supplemental Figures 15 and 16). In trait enrichment analysis, early 261 DKD progression-associated CpGs were enriched in "exposure on glucocorticoids" EWAS results⁵⁷ (OR=4.5, $P=1.3 \times 10^{-4}$). Notably, glucocorticoids are anti-inflammatory medications 262 263 used to improve kidney function in non-diabetic kidney disease. For late DKD progression, 264 "estimated glomerular filtration rate" and "kidney disease" were among the enriched traits, 265 demonstrating the consistency of our prospective EWAS with previous studies (Supplemental 266 Figure 17).

267 **DISCUSSION**

We and others have reported cross-sectional associations between DNA methylation and DKD or eGFR and have explored the potential of CpG methylation to predict ESKD.^{7,21} To our knowledge, this is the first EWAS on early progression of DKD in T1D, and the largest study

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to investigate CpGs associated with late progression of DKD to ESKD. We identified four
novel loci for early DKD progression, including the podocyte-specific *CDKN1C* locus. For late
DKD progression, we discovered nine loci — including two previously reported and four novel
sites with significant replication support from EWASs on eGFR, eGFR slope, or risk of ESKD.

275 Methylation levels at the CpGs associated with early DKD progression were not associated 276 with eGFR in our data, nor in other EWASs on eGFR. Furthermore, similar early DKD 277 progression EWAS datasets are lacking, complicating efforts to find supportive evidence. 278 Interestingly, CpGs at *CDKN1C*, the closest gene to cg01730944, were differentially 279 methylated in individuals with diabetes on hemodialysis, in a study of 27,000 methylation sites 280 in saliva samples.⁵⁸

281 CDKN1C is expressed almost exclusively in podocytes⁴⁶, the key cell type for glomerular 282 filtration. The Cancer Genome Atlas kidney expression data³⁷ suggest that lower methylation at 283 cg01730944 (risk of DKD progression) may be linked to higher CDKN1C expression; 284 however, human DKD kidney datasets consistently showed *lower CDKN1C* expression. Thus, 285 further eQTM evidence for cg01730944 is needed. Nevertheless, proximity to the TSS and 286 overlap with several putative TF motifs suggest that cg01730944 methylation might regulate 287 transcription. Notably, EGR1, a TF with a DNA-binding motif overlapping cg01730944, was 288 upregulated in podocytes in individuals with diabetic nephropathy and preserved eGFR.⁴⁶ 289 Further, JASPAR TF data show that podocyte-specific KLF15 binds at the cg01730944 290 location. Importantly, KLF15 overexpression in proteinuric mice was concomitant with 291 upregulation of *Cdkn1c* and improved kidney health.⁵⁹ Thus, previous research suggests that 292 cg01730944 locus is important for kidney health, although more direct evidence is still needed. 293 Notably, *CDKN1C* expression is regulated by the imprinting control region ICR2 such that

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294 *CDKN1C* is expressed mainly from the maternal allele, whereby loss of methylation at ICR2

295 decreases the expression.^{60,61}

296 The late DKD progression-associated cg17944885 (chr19p13.2) and cg00994936 (DAZAP1) 297 are known eGFR loci, first identified by Chu et al.¹³ Here, we identified seven novel CpGs for 298 ESKD risk in individuals with severe albuminuria. These sites were also associated with eGFR 299 in our study, and CpGs at AHCYL2, TAOK2, CDKN2AIPNL, and RP11-872D17.8 also in other eGFR EWASs.^{13–15} Importantly, the association between cg14999724 (RP11-872D17.8) and 300 301 ESKD risk was replicated in another prospective EWAS.²¹ We additionally identified a novel 302 *cis*-meQTL rs555097 for cg14999724 and showed that a decrease in cg14999724 methylation 303 (risk of ESKD) was associated with increase in serum PRG3 protein levels, in our data. 304 However, we only found a trend in PRG3 levels between the meQTL genotypes, thus, at this 305 site, no direct link can yet be drawn from the genetic variant, through methylation, to protein 306 levels. While proteoglycans are components of the endothelial cell glycocalyx, a protective barrier often disrupted in diabetes-related microvascular complications⁶², proteoglycan PRG3 307 308 is primarily expressed in the bone marrow. Nevertheless, *PRG3* is overexpressed in kidney 309 tubules in CKD. Thus, further research is needed to study its role in DKD.

The novel methylation site cg21871803 for ESKD risk, with supporting evidence from eGFR EWASs, is in *AHCYL2* (**Supplemental Figure 18**). AHCYL2 hydrolyzes S-adenosyl-Lhomocysteine into adenosine and L-homocysteine, a uremic toxin increased in CKD.⁶³ Kidney gene expression data suggests that lower cg21871803 methylation (risk of ESKD) correlates with *higher AHCYL2* expression. However, human kidney data are inconclusive: *AHCYL2* was upregulated in CKD⁴² but downregulated in advanced DKD.⁴⁴

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316 We noticed a strong genetic influence on some methylation sites: We identified ten novel 317 meOTLs and replicated *cis*- and *trans*-meOTLs for cg17944885. Interestingly, despite a high heritability of $h^2=0.4^{19}$ and robust meOTLs, *i.e.*, high genetic influence, cg17944885 318 319 methylation does not seem to be causal for DKD.⁷ Thus, kidney function decline might trigger 320 systemic perturbations that, possibly through meQTL loci, lead to cg17944885 321 hypermethylation. Indeed, trans-meQTL locus genes ZNF75A and ZNF200 were 322 downregulated in DKD (Nephroseq) and ZNF75A was under-expressed in individuals on 323 hemodialysis due to CKD.⁶⁴

324 The cg17944885 locus (chr19p13.2) zinc finger TFs participate in silencing of endogenous 325 retroviral sequences⁶⁵, transposable elements whose elevated levels exacerbate kidney disease 326 progression.⁶⁶ Notably, chr19p13.2 locus genes are mostly upregulated in CKD tubules 327 (Nephroseq), although cg17944885 hypermethylation (risk of ESRD) associate with lower 328 expression in blood cells. Moreover, cg17944885 methylation appears dynamic: our 329 longitudinal data showed a nominal increase in methylation in individuals with progressing 330 DKD during follow-up. Further, blood-derived hypermethylation at cg17944885 reversed to normal after kidney transplantation.⁶⁷ As the most replicated methylation site for kidney 331 332 function, blood-derived methylation at cg17944885 is a potential general biomarker that, along 333 with clinical factors and baseline eGFR, significantly improved the survival model for ESKD 334 when combined with other methylation sites. Indeed, methylation risk scores for disease 335 prediction are emerging.^{68,69}

Our prospective data are unique, but the study setting has its limitations. Individuals in the early DKD progression cohort had normal AER and good to moderate kidney function despite long-lasting diabetes. Notably, most individuals in this cohort were included in our crosssectional EWAS⁷, and unlikely included individuals with rapid DKD progression after diabetes

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onset. Moreover, we did not evaluate prospective albuminuria. Therefore, some individuals with persisting eGFR>60 mL/min/1.73m² may have developed albuminuria during follow-up potentially diluting our associations based on eGFR decline. Additionally, eGFR declines with aging, which we accounted for by adjusting the analysis for baseline age. Despite these limitations, we identified methylation sites near relevant genes, associated with future progression to DKD.

To conclude, our two prospective EWASs on the progression of DKD in T1D identified novel methylation sites for kidney disease progression and highlighted again cg17944885 as a lead locus in kidney disease. Our findings support the role of a podocyte marker *CDKN1C* for the initiation of DKD and provide further evidence that DNA methylation can be used as a dynamic marker to improve prediction of early and late progression of DKD.

351 Disclosures

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381 Author Contributions

A.S. designed the study, analysed the FinnDiane EWAS data, performed the downstream analyses, and drafted the manuscript. E.H.D. participated in the FinnDiane methylation data collection and QC and run meQTL analyses. L.J.S. generated the methylation EPIC data for the FinnDiane and UK-ROI cohorts, and quality-controlled and analysed the EWAS data of

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386	UK-ROI and NICOLA cohorts. C.H. analysed the human kidney expression data of Fan et al
387	and Levin et al. S.M. quality-controlled the OLINK® protein data for the FinnDiane. V.H. and
388	PH.G. acquired funding and phenotypic data for the FinnDiane study. Z.C. ran the EWAS in
389	the JKS cohort and provided the replication results. R.N. contributed the EWAS data of the
390	JKS. A.S.K. contributed to the JKS cohort data acquisition and analysis. A.P.M. contributed to
391	the interpretation of the data and UK-ROI cohort data. A.J.M. designed the study, acquired,
392	and analysed UK-ROI collection data and contributed to the interpretation of the results of the
393	study. N.S. designed the study, contributed to the FinnDiane data collection and interpretation
394	of the results of the study. Additionally, A.S., E.H.D., L.J.S., C.H., Y.G., V.H., Z.C., R.N.,
395	A.S.K., J.N.H., J.C.F., A.P.M., PH.G., A.J.M., and N.S. read and reviewed the manuscript
396	draft and all authors approved the final version.

397

398 Data Sharing Statement

399 The informed consent written by the participants does not allow the public sharing of the 400 FinnDiane data analysed during the current study. Readers can propose co-operative research 401 through the corresponding authors on reasonable request. Lookups on the supporting evidence, 402 meQTLs, eQTMs, kidney single-cell gene expression, and DKD kidney gene expression 403 datasets are based on published summary statistics downloadable or browsable online and 404 access to these data sets are described in Supplemental Methods. The GWAS summary 405 statistics of the Finnish biobank FinnGen study data freeze 10 was accessed at 406 (https://r10.finngen.fi).

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	Early DKD prog	gression cohort (<i>n</i> =403)	Late DKD progression cohort (<i>n</i> =373)		
	No eventEvent (eGFR decline <60) during follow-upNo event		Event (ESKD) during follow-up		
n	354	49	167	206	
Women, <i>n</i> (%)	131 (37)	20 (41)	53 (32)	89 (43)	
Age, years	42 ± 11	45 ± 14	43 ± 12	43 ± 10	
T1D duration, years	27 ± 9	28 ± 12	30 ± 9	30 ± 10	
Systolic blood pressure, mmHg	133 ± 18	135 ± 18	143 ± 17	149 ± 21	
Diastolic blood pressure, mmHg	78 ± 8.6	78 ± 9.7	82 ± 9.9	84 ± 11	
Pulse pressure, mmHg	55 ± 15	58 ± 19	61 ± 16	65 ± 19	
HbA _{1c} , mmol/mol (%)	66.2 ± 13.6	70.2 ± 15.8	71.7 ± 16.0	75.6 ± 18.0	
Central obesity, <i>n</i> (%)	163 (46.4)	31 (66.0)	119 (73.0)	135 (66.5)	
Triglycerides, mg/dL	82 (32, 113)	93 (75, 113)	113 (82, 165)	142 (105, 218)	
Granulocytes, %	63 (57, 70)	63 (57, 69)	67 (60, 73)	69 (64, 74)	
Monocytes, %	7 (5, 9)	8 (6, 9)	8 (6, 10)	8 (6, 9)	
CD4 ⁺ T-cells, %	11 (8, 14)	12 (8, 17)	10 (7, 13)	10 (6, 13)	
CD8 ⁺ T-cells, %	5 (2, 8)	3 (1, 8)	4 (2, 8)	4 (1, 7)	
B-cells, %	4 (2, 5)	3 (2, 5)	3 (2, 5)	2 (0.8, 4)	
NK-cells, %	4 (0.1, 7)	5 (1, 8)	0.9 (0.0, 4.6)	0.7 (0.0, 4.3)	
eGFR, mL/min/1.73 m ²	105 ± 14	100 ± 19	85 (71, 106)	44 (28, 67)	
Follow-up time, years	13.5 (8.9, 17.3)	9.7 (4.4, 14.4)	14.1 (7.5, 21.3)	6.1 (2.9, 10.2)	

Table 1. Baseline characteristics of the study participants

Data are expressed as mean \pm standard deviation or median (interquartile range)

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Ί	Table 2.	Epigenom	e-wide significant	t methylation	CpGs sites f	for the p	rogression	kidney
d	isease							

CpG probe	Chr	Closest gene(s)	Association wi	ith	Association with baseline eGFR in the sub-cohort ^b	Association with baseline eGFR in the total cohort				
			HR [95%CI]	Р	Р	Р				
Early DKD progression EWAS, <i>n</i> =403; <i>n</i> =49 eGFR decline <60 mL/min/1.73 m ² events										
cg25013571	8	PLPBP and ADGRA2	3.35 [2.18,5.13]	3.1×10 ⁻⁸	0.48	0.41				
cg05831784	20	HAO1	0.42 [0.30,0.57]	4.8×10 ⁻⁸	0.002	0.23				
Early DKD pr	rogressi	ion EWAS, eGFR a	djusted							
cg25013571	8	PLPBP and ADGRA2	3.53 [2.25,5.54]	4.1×10 ⁻⁸	0.48	0.41				
cg06334496	8	TMEM70	0.12 [0.06,0.26]	4.5×10 ⁻⁸	0.58	0.70				
cg01730944	11	CDKNIC	0.43 [0.31,0.58]	8.6×10 ⁻⁸	0.35	0.79				
Late DKD pro	ogressio	on EWAS, <i>n</i> =373; <i>n</i>	a=206 ESKD eve	nts)						
cg06536988	4	TMEM154	0.54 [0.43,0.67]	8.5×10 ⁻⁸	2.3×10 ⁻⁶	1.3×10 ⁻⁶				
cg03262246	5	CDKN2AIPNL	0.22 [0.13,0.38]	1.1×10 ⁻⁹	1.0×10 ⁻⁸	3.6×10 ⁻⁶				
cg11115840	6	TRMT11	0.41 [0.30,0.57]	7.6×10 ⁻⁸	1.5×10 ⁻⁹	1.6×10 ⁻¹⁰				
cg21871803	7	AHCYL2	0.37 [0.26,0.52]	1.5×10 ⁻⁸	6.9×10 ⁻⁹	6.8×10 ⁻¹⁰				
cg14999724	11	RP11-872D17.8 (PRG2 transcript variant 1)	0.29 [0.19,0.44]	2.4×10 ⁻¹⁰	7.8×10 ⁻¹¹	2.6×10 ⁻¹²				
cg10579797	15	SERF2	0.30 [0.20,0.46]	2.6×10 ⁻⁸	1.8×10 ⁻⁵	3.4×10 ⁻⁵				
cg04166335	16	TAOK2	0.282 [0.18,0.44]	4.4×10 ⁻⁹	4.0×10 ⁻⁶	1.1×10 ⁻⁵				
cg00994936	19	DAZAPI	0.23 [0.14,0.39]	1.4×10 ⁻⁸	6.9×10 ⁻¹⁰	6.9×10 ⁻¹¹				
cg12272104	19	DAZAPI	0.32 [0.23,0.44]	1.5×10 ⁻¹²	1.1×10^{-10}	2.7×10 ⁻¹²				
cg17944885	19	<i>ZNF788P</i> and <i>ZNF625-ZNF20</i>	2.15 [1.79,2.58]	2.9×10 ⁻¹⁶	2.5×10^{-20}	2.1×10 ⁻²⁶				

^a Cox proportional-hazards model results for DKD progression: same covariates were included in both early and late DKD EWASs: baseline age, sex, estimated six white blood cell proportions, technical PC1, PC2, PC3 and sample mean M from invariable sites.

^b Association with eGFR in the sub-cohort (early or late DKD progression). Association was calculated for log₂-transformed eGFR values with *limma* using the same covariates as in the Cox proportional-hazards model.

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^c Association with eGFR in the combined cohort including all individuals from the early and late DKD progression cohorts. Albuminuria status (normal AER / severe albuminuria) was added to the limma model containing the same covariates as in the sub-cohort analyses.

Table 3.	Significant	independent ^a	methylation	quantitative	loci	calculated	with	765	
participants from the FinnDiane study.									

CpG site				meQTL				meQTL association			
CpG probe	Chr	Closest gene	cis / trans	Chr	rs number	Distance to CpG	EA/ OA	beta	Р	FDR	
CpG associat	ed with	n early DKD progr	ression								
cg05831784	20	20 <i>HAO1</i>	cis	20	rs4815959	-949,339	A/G	0.183	1.6×10 ⁻⁴	0.02	
			trans	6	rs12198601	NA	G/T	0.373	3.0×10 ⁻⁹	3.4×10 ⁻¹⁸	
			trans	8	rs111233810	NA	A/AG	0.260	1.7×10 ⁻⁸	0.02	
CpG associate	ed with	n late DKD progre	ession			1		1			
cg06536988	4	TMEM154	cis	4	rs4569733	-457	C/T	0.092	4.0×10 ⁻⁴	0.04	
cg03262246	5	CDKN2AIPNL	cis	5	rs111929214	4,984	G/A	0.092	1.3×10 ⁻⁴	0.02	
cg11115840	6	TRMT11	cis	6	rs11154342	-2,071	T/A	0.262	2.6×10 ⁻³⁵	1.1×10 ⁻³¹	
cg14999724	11	1 RP11-872D17.8	cis	11	rs555097	-872	A/C	0.101	8.4×10 ⁻⁷	1.9×10 ⁻⁵	
			(P. var	(<i>PRG2</i> transcript variant 1)	cis	11	rs7107808	887,490	C/A	-0.072	6.8×10 ⁻⁴
cg17944885	19	ZNF788P and	cis	19	rs4804653	4,240	A/T	0.262	3.1×10 ⁻⁸	1.6×10 ⁻⁵	
		ZNF625-ZNF20	trans	16	rs17611866	NA	T/C	0.462	1.9×10 ⁻²⁵	3.4×10 ⁻¹⁸	
cg12272104	19	DAZAPI	cis	19	rs34622118	530,159	C/CA	0.116	7.8×10^{-5}	0.01	
			cis	19	rs2283578	-713,116	A/C	0.105	2.4×10 ⁻⁴	0.03	

^a Independent SNVs ($r^2 < 0.1$ with other SNVs) in 1000 genomes Finnish population data (assessed using LDmatrix tool at https://ldlink.nih.gov/). *Cis;* $<\pm 1$ Mb distance between the CpG probe and the meQTL variant. EA=effect allele, OA=other allele, FDR=false discovery rate

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Table 4. Significant *cis* expression quantitative trait methylation (*cis*-eQTM) loci in lookup analysis of 14 methylation sites for DKD progression in blood cell and kidney tissue datasets

CpG site		<i>cis</i> -eQTM (gene within 1M from the CpG)							
Methylation probe	Methylation risk for DKD progression	Gene	Tissue	Study- specific effect size	Р	Dataset	Ref.		
CpG associate	ed with early D	KD progressi	on						
cg01730944	lower	CDKNIC	kidney	<i>r</i> =–0.208	8.6×10 ⁻⁸	TCGA	37		
CpGs associat	ted with late D	KD progressio	n						
cg03262246	lower	C5orf15	kidney	beta=0.077	2.0×10 ⁻³	Susztaklab	27,29		
cg21871803	lower	AHCYL2	kidney	<i>r</i> =–0.261	1.4×10^{-11}	TCGA	37		
cg04166335	lower	NPIPB13	kidney	beta=-0.184	3.6×10 ⁻⁵	Susztaklab	27,29		
		DAZAPI	kidney	<i>r</i> =0.263	8.7×10 ⁻¹²	TCGA	37		
cg00994936	lower	EFNA2	kidney	beta=-0.243	3.6×10 ⁻⁴	Susztaklab	27,29		
		GAMT	kidney	beta=-0.109	1.1×10 ⁻³	Susztaklab	27,29		
12272104	lower	DAZAPI	kidney	<i>r</i> =0.219	1.6×10 ⁻⁸	TCGA	37		
cg122/2104		EFNA2	kidney	beta=-0.209	3.7×10 ⁻⁴	Susztaklab	27,29		
		ZNF788P	kidney	<i>r</i> =0.181	3.4×10 ⁻⁶	TCGA	37		
			monocytes	log ₂ FC=-0.045	2.5×10 ⁻⁸	MESA	34		
			whole blood	log ₂ FC=-0.081	5.9×10 ⁻⁸	HELIX	36		
			monocytes	beta=-0.026	6.0×10 ⁻⁶	MESA	34		
		ZNF09	whole blood	beta<0 ^a	1.9×10 ⁻⁵	Dutch Biobanks	35		
		7115420	monocytes	beta=-0.043	1.8×10 ⁻⁷	MESA	34		
cg17944885	higher	ZNF439	whole blood	log ₂ FC=-0.120	1.1×10 ⁻⁷	HELIX	36		
		7115044	whole blood	beta<0 ^a	3.6E×10 ⁻²⁶	Dutch Biobanks	35		
		ZNF844	whole blood	log ₂ FC=-0.275	3.2×10 ⁻¹⁶	HELIX	36		
		ZNF763	whole blood	log ₂ FC=-0.160	3.2×10 ⁻⁹	HELIX	36		
		ZNF44	whole blood	beta<0 ^a	2.5×10 ⁻⁹	Dutch Biobanks	35		
		ZNF136	whole blood	beta<0 ^a	5.9×10 ⁻⁵	Dutch Biobanks	35		
		ZNF433-AS1	whole blood	beta<0 ^a	3.8×10 ⁻⁶	Dutch Biobanks	35		

Look-up eQTM datasets: TCGA=The Cancer Genome Atlas datasets as represented in the EWAS Atlas; Susztaklab=Kidney expression data from Liu *et al.* browsed at SusztakLab Kidney BioBank²⁹; MESA=The Multi-Ethnic Study of Atherosclerosis; HELIX=Human Early-Life Exposome study that comprises six population-based birth cohorts; Dutch Biobanks=Four Dutch Biobank results meta-analysed.

^a Effect-size direction in individual Dutch Biobank studies; effect sizes available separately from four cohorts; meta-analysis effect estimates not available.

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Figures



Figure 1. Study setting. Abbreviations: AER=albumin excretion rate; *cis*-pQTM = *cis* protein quantitative trait methylation; DKD=diabetic kidney disease; EWAS=epigenome-wide association study; eGFR=estimated glomerular filtration rate; eQTMs=expression quantitative trait methylations; meQTL=methylation quantitative trait locus; snATAC-seq=single-nucleus transposase-accessible chromatin with sequencing. Created in BioRender. Syreeni, A. (2024) https://BioRender.com/.

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Figure 2 Manhattan plots show the results of EWASs on DKD progression. A) Results from the EWAS on early DKD progression, B) early DKD progression EWAS additionally adjusted for the baseline eGFR, and C) results from the EWAS on late DKD progression (to ESKD). X-axis shows the chromosomal position and y-axis shows the $-\log_{10}$ of the association *P*-value. Methylation sites reaching epigenome-wide significance ($P < 9.4 \times 10^{-8}$, green line) are annotated into the plot.

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Figure 3. Methylation site cg01730944 is located close to *CDKN1C*. A) Density plot of early DKD progression cohort (n=403) baseline methylation beta values of cg01730944 shows lower methylation in individuals with progressing DKD during follow-up [eGFR decline <60

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mL/min/1.73 m² (in orange)] compared to individuals who do not progress (light blue) **B**) Kaplan–Meier plot compares individuals in the lowest and highest tertile for cg01730944 methylation and shows the proportion of individuals progressing to eGFR<60 mL/min/1.73 m² during follow-up. **C**) Open chromatin peaks in kidney cell types; human kidney single-nucleus transposase-accessible chromatin data (Version 2) on 57,229 cells²⁷ accessed in Susztaklab Kidney Biobank.²⁹ Figure is adapted from https://susztaklab.com/Human_snATAC/, and cg01730944 position is incorporated. **D**) Kidney single-cell expression data of 23,980 nuclei⁴⁶ shows that *CDKN1C* is mainly expressed in podocytes. Adapted from Humphrey's Lab browser at http://humphreyslab.com⁴⁷ **E**) *In vivo* expression of *CDKN1C* in human glomerular cells³⁸ shows lower expression (fold-change=-4.95, *P*=4.9×10⁻⁵ in diabetic kidney disease (group 2, *n*=9) compared to individuals without DKD (group 1, *n*=13). Figure adapted from Nephroseq v.5 database⁴² at https://www.nephroseq.org/.

Abbreviations: PT-S1–PT-S3=proximal tubule segments 1–3; LOH=loop of Henle; DCT=distal convoluted tubule; PC=principal cells of collecting duct; IC=intercalated cells, Endo=endothelia; Podo=podocytes; Immune=immune cells; lymph=lymphocytes; MES=mesenchyme, PEC=parietal epithelial cell; PCT=proximal convoluted tubule; DCT/CT=distal convoluted tubule/connecting tubule; CD-PC=collecting duct - principal cell; CD-ICA=collecting duct - intercalated cells A; CD-ICB=collecting duct - intercalated cells B; Leuk=leukocytes

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Figure 4. Predictive power of the lead CpGs. The diamonds show the concordance (C-index) and its 95% confidence intervals of three Cox proportional-hazards models applied for the early (n=393 with non-missing variables) and late DKD progression (n=363 with non-missing variables) cohorts. *P*-values denote the significance of the increase in concordance index compared to the previous model; The significant *P*-values (P<0.05) are marked in the figure. The first model, "Clinical variables" (orange color), included baseline triglyceride concentration, central obesity, and current smoking status for the early DKD progression analysis, and triglyceride concentration, HbA_{1c}, and systolic blood pressure for the late DKD progression analysis. Additionally, the model included six white blood cell proportions, technical PCs 1–3, mean methylation M value from invariable sites, age, and sex. The second model (red color) included additionally baseline eGFR. The third model included methylation M values for four (early DKD progression-associated: cg25013571, cg05831784, cg06334496, and cg01730944) or nine (late DKD progression-associated: cg06536988, cg03262246, cg11115840, cg21871803, cg14999724, cg10579797, cg04166335, cg12272104, and cg17944885) methylation sites.

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Figure 5. Links between methylation and gene expression of trans-meQTL locus on chromosome 16. According to Huan *et al*¹⁹, SNV rs17611866 correlates (in *trans*) with methylation levels of 45 CpGs, of which eGFR-associated methylation sites cg17944885 (chr19p13.2 locus, in multiple EWASs) and cg06158227¹³ are shown in the figure. CpG cg17944885 has also a close SNV rs4804653 that is associated with its methylation levels in the general population (GoDMC) data. We replicated both the *cis*- and *trans*-methylation quantitative trait locus (SNV that affects gene expression); *cis*-meQTL=*cis* methylation quantitative trait locus; *trans*-meQTL=*trans* methylation quantitative trait locus; *trans*-meQTL=*trans* methylation quantitative trait locus (SNV that affects gene expression) quantitative trait locus (SNV that affects gene expression quantitative trait locus (SNV that affects gene expression quantitative trait locus (SNV that affects gene expression); *cis*-meQTL=*cis* methylation quantitative trait locus; *trans*-meQTL=*trans* methylation quantitative trait locus (SNV that affects gene expression quantitative trait locus (SNV that affects); *cis*-eQTM=*cis*-expression quantitative trait methylation (methylation site that associates with gene expression). Created in BioRender. Syreeni, A. (2024) https://BioRender.com/.

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Supplemental Material

The following supplemental material accompanies the current study:

Supplemental Methods

Supplemental Figure 1. Overlap of the individuals with longitudinal samples with the DKD progression cohorts.

- Supplemental Figure 2. QQ-plots of the four prospective EWASs.
- Supplemental Figure 3. Chromosome 11p15.5 region around cg01730944.
- *Supplemental Figure 4.* Manhattan plot of EWAS on late progression of DKD (to end-stage kidney disease), additionally adjusted for baseline eGFR.
- *Supplemental Figure 5.* Longitudinal change of cg17904885 methylation values (as residuals) in 52 individuals.
- Supplemental Figure 6. Longitudinal change of cg17904885 methylation beta values in 52 individuals.
- *Supplemental Figure 7.* Correlation of clinical characteristics and methylation CpGs of the early DKD progression cohort (*n*=403).
- *Supplemental Figure 8.* Correlation of clinical characteristics and methylation of top CpGs in the late DKD progression cohort (*n*=373).
- Supplemental Figure 9. Correlation (Spearman) of the top CpGs.
- Supplemental Figure 10. Predictive power of early DKD progression associated CpGs.
- Supplemental Figure 11. Predictive power of late DKD progression associated CpGs.
- Supplemental Figure 12. Chromosome 11p15.5 region around cg14999724.
- *Supplemental Figure 13.* CpG cg14999724 locus protein and SNV associations in 188 individuals with normal AER.
- Supplemental Figure 14. PRG3 expression in human kidney single cell data set.
- Supplemental Figure 15. Gene Ontology (GO) term enrichment results of the genes related to the early and late DKD progression –associated CpGs ($P < 10^{-4}$).
- *Supplemental Figure 16.* KEGG pathway enrichment results of the genes related to the early and late DKD progression –associated CpGs ($P < 10^{-4}$).
- *Supplemental Figure 17.* Enrichment of CpGs associated with early and late DKD progression in traits with EWAS results in EWAS Atlas.

Supplemental Figure 18. Chromosome 7 region around CpG cg21871803.

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Supplemental Figure 19. Physicians and nurses at the Finnish Diabetic Nephropathy (FinnDiane) study sites.

Supplemental Table 1. CpG sites associated with ESKD in the late DKD progression cohort: results from the competing risk and 10-year survival analyses.

Supplemental Table 2. EWAS associations with $P < 1.0 \times 10^{-4}$.

Supplemental Table 3. Association between eGFR slope and methylation change between two time points in the longitudinal cohort with eGFR slope data (n=51)

Supplemental Table 4. Replication evidence for the top methylation sites (*n*=14) from the DKD progression EWASs.

Supplemental Table 5. Top methylation quantitative locus (meQTL) results in the FinnDiane and general population meQTLs.

Supplemental Table 6. Phenome-wide associations of the 12 significant independent meQTL variants from the FinnDiane meQTL analysis.

Supplemental Table 7. Expression quantitative trait methylation (eQTM) dataset lookups for the top methylation sites from the DKD progression EWASs.

Supplemental Table 8. Cis protein quantitative trait methylation (*cis*-pQTM) associations in the FinnDiane.

Supplemental Table 9. Expression quantitative trait methylation (eQTM) dataset lookups.

Supplemental Table 10. Gene expression of the closest or the eQTM genes in kidney tissue in diabetic kidney disease.

Supplemental Table 11. Transcription factor binding motifs at the top CpG locations in the eFORGE-TF database.