Genetic-epigenetic interactions in paternal transgenerational inheritance of metabolic

disorders

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Running title: Paternal obesity alters sperm H3K4me3 and metabolic outcomes in descendants

Summary sentence: Paternal obesity impacts sperm H3K4me3 and is associated with placenta,

embryonic and metabolic outcomes in descendants.

Keywords: obesity, metabolism, chromatin, sperm, epigenetic inheritance

ABSTRACT

Parental environmental exposures can strongly influence descendant risks for adult disease.

Metabolic disorders arise from the intersection of environmental and genetic risk factors, with

epigenetic inheritance being at the center of the familial cycle of transgenerational disease. How

paternal high-fat diet changes the sperm chromatin leading to the acquisition of metabolic disease

in offspring remains controversial and ill-defined. Using a genetic model of epigenetic inheritance,

we investigated the role of histone H3 lysine 4 methylation (H3K4me3) in the paternal

transmission of metabolic dysfunction. We show that obesity-induced alterations in sperm

H3K4me3 associated with offspring phenotypes and corresponded to embryonic and placental

chromatin profiles and gene expression. Transgenerational susceptibility to metabolic disease was

only observed when grandsires had a pre-existing genetic predisposition to metabolic dysfunction

that was associated with enhanced alterations to sperm H3K4me3. This non-DNA based

knowledge of inheritance has the potential to improve our understanding of how environment

shapes heritability and may lead to novel routes for the prevention of disease.

INTRODUCTION

The prevalence of obesity and type II diabetes is growing globally at rates indicating that

environment rather than genes is the principal driver. Exposures to high-fat diet, toxicants or

micronutrient deficiency can impact our health and that of future generations (Gernand *et al.*, 2016;

Braun, Messerlian and Hauser, 2017; Donkin and Barrès, 2018; Eberle *et al.*, 2020). Only now are

we beginning to identify mechanisms linking these exposures to parental and offspring health. One

connection between environment and health is the epigenome. The epigenome refers to the

biochemical content associated with DNA that impacts gene expression, chromatin organization,

and is transmitted via the gametes to alter phenotypes across generations. Uncovering how

genomic information is organized and regulated through epigenetic processes to control gene

expression and cell functions in the next generation is still in a nascent stage. We and others have

shown that errors in epigenomic profiles in sperm can be induced by environmental exposure to

toxicants such as those in insecticides and plastics, obesity, and poor diet (Lambrot *et al.*, 2013;

Radford *et al.*, 2014; Donkin *et al.*, 2016; Wu *et al.*, 2017; Lismer, Dumeaux, *et al.*, 2021; Pilsner

et al., 2021). We recently demonstrated that these epigenome changes at the level of chromatin

can be transmitted via sperm to alter embryonic gene expression, development, and offspring

health (Lismer, Dumeaux, *et al.*, 2021). Parental health and fertility historically have focused

predominantly on the mother, although it is clear a father's health and lifestyle can also impact his

children's health. How epimutations in sperm functionally impact the embryo urgently require

elucidation to prevent transmission of disease from Father to offspring.

Metabolic disease including obesity and type II diabetes can in part be attributed to genetic factors

with a 5-10% increased risk (Voight *et al.*, 2010). The remaining risk is attributable to

environmental-epigenetic interactions including potentially those of our ancestors. This possibility

is supported by epidemiology and animal studies. For example, paternal diets high in fat and

associated with glucose intolerance and obesity, or low in folate, or protein, can alter phenotypes

in offspring, including metabolism (Carone *et al.*, 2010; Ng *et al.*, 2010; Lambrot *et al.*, 2013).

Transgenerational effects are suggested by epidemiological studies in humans that linked the food

supply of grandfathers to obesity and cardiovascular disease in their grandchildren (Kaati, Bygren

and Edvinsson, 2002; Pembrey *et al.*, 2006; Lumey and Poppel, 2013). Yet the ability for diet to

induce similar transgenerational effects in animal models remains controversial with some studies

indicating that multigenerational phenotypes are dependent on genetic-epigenetic interactions

(Siklenka *et al.*, 2015; Dalgaard *et al.*, 2016; Miska and Ferguson-smith, 2016). Prior studies have

shown that exposure of male mice to a high-fat diet altered the sperm epigenome at the level of

DNA methylation (Wei *et al.*, 2014), and the metabolic phenotype of the offspring (Ng *et al.*, 2010;

Wei *et al.*, 2014). In a similar study, offspring of males fed a low-protein diet (11% versus 20%)

had altered cholesterol and lipid synthesis (Carone *et al.*, 2010). Most studies on nutrition, obesity

and the sperm epigenome, have focused on the sperm DNA methylome and ncRNA as the potential

sperm-borne mediators of metabolic disease (Carone *et al.*, 2010; Radford *et al.*, 2014; Grandjean

et al., 2015; Chen *et al.*, 2016; Cropley *et al.*, 2016; de Castro Barbosa *et al.*, 2016; Sharma *et al.*,

2016). The role of sperm histone modifications in the transmission of metabolic phenotypes

remains unknown.

Diets high in fat alter epigenetic programming (Ng *et al.*, 2010), likely through the alteration of

cellular metabolism, which influences the availability of methyl donors and/or the activation or

inactivation of chromatin modifying enzymes . In overweight and obese individuals, homocysteine

is consistently elevated, and associated with reduced B12 and folate (Sánchez-Margalet *et al.*,

2002; Karatela and Sainani, 2009). In mammals, spermatogenesis is a highly rapid form of cell

division that proceeds from the least differentiated spermatogonia to mature spermatozoa. This

process is accompanied by dynamic changes to the sperm epigenome including histone

methylation which is susceptible to alterations induced by changes in methyl donor availability

(Lambrot *et al.*, 2013; Lismer, Dumeaux, *et al.*, 2021). Retained histones are conserved across

species from mice to men and are found at the gene regulatory regions implicated in

spermatogenesis, sperm function, embryo development, metabolism and routine cellular processes

(Hammoud *et al.*, 2009; Lambrot *et al.*, 2019).

We have shown in human and mouse sperm, histone H3 lysine 4 dimethylation (H3K4me2) and

trimethylation (H3K4me3) localize to genes involved in metabolism and development (Lambrot

et al., 2019; Lambrot, 2021; Lismer, Dumeaux, *et al.*, 2021). We and others have suggested that

histones in sperm may directly influence embryonic gene expression, development, and adult-

onset disease. In our prior studies, we aimed to determine whether sperm H3K4me served a

function in embryonic development and gene expression (Siklenka *et al.*, 2015; Lismer *et al.*,

2020). We generated transgenic mice that overexpressed the histone lysine demethylase KDM1A

in developing sperm only. Overexpression of KDM1A during spermatogenesis led to differential

enrichment of H3K4me1/2/3 at sperm promoters and enhancers. Offspring sired by KDM1A

transgenics had early postnatal death, and severe developmental abnormalities (Siklenka *et al.*,

2015). Differentially enriched H3K4me1/2/3 at promoters and enhancers in sperm was associated

with altered embryonic gene expression (Siklenka *et al.*, 2015; Lismer *et al.*, 2020).

The association of histone modifications in sperm with offspring phenotypes has since been

confirmed in other mouse models (Stringer *et al.*, 2018; Lesch *et al.*, 2019). The next challenge

for the field of epigenetic inheritance was to show that histones in the embryo are paternally

inherited and can be altered by exposures. We utilized a folate deficient diet (FD) that changes

methyl donor availability and in turn altered histone H3K4me3 in sperm at developmental genes

and putative enhancers. A subset of H3K4me3 alterations in sperm were retained in the pre-

implantation embryo and associated with deregulated embryonic gene expression. These findings

suggest that environmental exposure such as FD alters paternal H3K4me3 which is transmitted to

the embryo and influences gene expression and development (Lismer, Dumeaux, *et al.*, 2021).

In this study, we aimed to assess the non-genetic and genetic impact of high-fat diet (HFD) on the

paternal origins of adult-onset metabolic disorders across generations. We used wildtype (WT) or

KDM1A-overexpressing transgenic (TG) mice, in combination with a diet-induced obesity model

to investigate the following questions: 1) Are inherited metabolic phenotypes associated with

altered sperm histone H3K4me3 profiles?; 2) Do metabolic changes induced by an obese paternal

diet span generations, or is transgenerational inheritance dependent on genetic-epigenetic

interactions?; and 3) Do exposure-induced changes in sperm H3K4me3 enrichment associate with

embryonic, placenta and liver function in adult-onset of metabolic disease? We demonstrate that

a postnatal paternal high-fat diet induces F_0 obesity and metabolic dysfunction in the F_1.

Transgenerational phenotypes were observed only in the obese KDM1A TG F_2 descendants

indicating the involvement of genetic-epigenetic interactions in ancestral effects. Obesity-induced

alterations in sperm H3K4me3 were predominantly located within 1 kilobase from the TSS and in

intergenic regions. Gene ontology (GO) analysis revealed differentially enriched H3K4me3

(deH3K4me3) genes were involved in development, placenta formation, inflammatory processes,

glucose and lipid metabolic pathways. These enriched pathways are concordant with the metabolic

phenotypes observed in offspring. There was no clear relationship between sperm regions bearing

altered H3K4me3 and altered liver gene expression. However, embryonic and placenta gene

expression patterns overlapped with sperm H3K4me3 alterations suggesting developmental

origins of adult-onset metabolic dysfunction.

METHODS

Resource availability

Lead contact

Further information and requests for resources and reagents should be directed to and will be fulfilled by the Lead Contact, Sarah Kimmins (sarah.kimmins@mcgill.ca).

Materials availability

This study did not generate new unique reagents.

Data and code availability

The sperm H3K4me3 ChIP-Seq and liver RNA-Seq data generated during this study are available at the following GEO accession number: GSE178096.

Experimental model and subject details

Animals

All animal procedures were carried out in accordance with the guidelines of the Faculty Animal Care Committee of McGill University, Montreal. For the wild-type line (WT), C57BL/6NCrl 8-week old males and 6-week old females were purchased from Charles Rivers Laboratory and were allowed one week of acclimation before breeding. For the KDM1A transgenic line (TG), mice were generated as previously described (Siklenka et al., 2015), with the same genetic background as the wild-type line. Single males were housed with two females to generate the F_0 generation. All animals were given access to water and food *ad libitum* and were maintained on a controlled light/dark cycle.

Methods details

Diet experiments and animal breeding

The low-fat diet (LFD; D12450J) and high-fat diet (HFD; D12492) were obtained from Research

Diets, and selected based on the matched amounts of sucrose, vitamin mix and folate. Diets'

macronutrients composition are listed in Table S1. Males of the F_0 generation were generated from

at least 7 different sires per group. F_0 males were weaned at 3 weeks of age and randomly assigned

to either a LFD or HFD (WT LFD: n=17 animals, TG LFD: n=15 animals, WT HFD: n=24

animals, TG HFD: n=25 animals). Total body weights were monitored weekly. Cumulative caloric

intake was recorded weekly by weighting pellets from the food hopper and calculated as kilocalorie

per animal. The diet intervention spanned 10-12 weeks followed by 2 weeks of metabolic testing

(at 4 months of age), 1 week of rest and 1-2 weeks of breeding with 7-week old C57BL/6NCrl

females. In order to minimize maternal exposure to the intervention diets, females were housed

with males overnight and separated during the day, for a maximum of 3 nights per week for 2

weeks, or until a vaginal plug was detected. The same timeline was used to generate the F_1 and F_2

animals. All females used for breeding and all F_1 and F_2 were fed a regular chow diet (2020X

Teklad global soy protein-free extruded rodent diet, Envigo). All animals were sacrificed at 22

weeks (±2 weeks) by carbon dioxide asphyxiation under isoflurane anesthesia.

Metabolic testing

The number of animals per group, per sex and per generation, used for all metabolic

characterization tests can be found in Table S2. Assessment of metabolic parameters was

conducted at 4 months of age within 2 consecutive weeks according to the standard operating

procedures of the NIH mouse Metabolic Phenotyping Center (Ayala *et al.*, 2010). For the glucose

tolerance test, animals were fasted overnight for 15 hours (± 1 hour) starting at 6:00PM with free

access to water. Blood glucose was measured before and 15, 30, 60 and 120 minutes following an

intraperitoneal injection of 2 g/kg of a 20% glucose solution (D-glucose, G7021, Sigma Aldrich)

with one drop of blood from the tail-tip using a glucometer (Accu-Chek Aviva Nano). For the

insulin tolerance test, animals were fasted for 6 hours (1 hour), starting at 9:00AM with free access

to water. Blood glucose was measured before and 15, 30, 60 and 120 minutes following an

intraperitoneal injection of 1 IU/kg insulin (Insulin solution, I9278, Sigma Aldrich), with one drop

of blood from the tail-tip using a glucometer (Accu-Chek Aviva Nano). The area under the curves

(AUCs) for the tolerance tests were calculated using the trapezoidal rule (GraphPad Prism version

8). For the baseline blood glucose levels, blood glucose levels were measured after an overnight

fasting of 15 hours (± 1 hour) with one drop of blood from the tail-tip using a glucometer (Accu-

Chek Aviva Nano).

Tissue collection

At necropsy, mice were dissected to collect adipose tissue (gonadal and mesenteric white adipose

depots; gWAT and mWAT, respectively) and a liver lobe (left lateral lobe or *lobus hepatis sinister*

lateralis for RNA-sequencing). All tissues were weighed, transferred to a clean tube, snap frozen

in liquid nitrogen and stored at -80°C until subsequent downstream experiments. Cauda

epididymides were weighed and immediately used for sperm isolation.

Sperm isolation

Spermatozoa were isolated from paired caudal epididymides (Hisano *et al.*, 2013; Lismer,

Lambrot, *et al.*, 2021). Cauda epididymides were cut into 5 mL of freshly-prepared Donners

medium (25 mM NaHCO$_3$, 20 mg ml^{-1} BSA, 1 mM sodium pyruvate, 0.53% vol/vol sodium DL-

lactate in Donners stock) and gently agitated to allow to swim out for 1 hour at 37°C. The solution

was passed through a 40-μm cell strainer (Fisher Scientific, #22363547) and washed three times

with phosphate-buffered saline (PBS). The sperm pellet was cryopreserved in freezing medium

(Irvine Scientific, cat. #90128) and kept in a -80°C freezer until the chromatin
immunoprecipitation experiment.

RNA-Sequencing and library preparation

RNA extraction was performed using the RNeasy Mini Kit (Qiagen, cat. #74104) following the

manufacturer's protocol with slight modifications. In brief, 15-20 mg of liver lobes were cut on

dry ice using a sterile scalpel and Petri dish. Samples were lysed in 350 µL of a denaturing buffer

(*Buffer RLT* with beta-mercaptoethanol) and homogenized with homogenizer pestles. Lysates

were centrifuged at maximum speed for 3 minutes and the supernatants transferred to a clear tube.

Ethanol (50%) was added to lysates to promote selective binding of RNA molecules to the silica-

based membrane when applied to the spin columns. To avoid genomic DNA contamination, an

additional DNase digestion was performed. Finally, membranes of the spin columns were washed

twice with 500 µL of *Buffer RPE* and total RNA was eluted using 30 µL of RNase-free water.

Libraries were prepared and sequenced at the *Génome Québec Innovation Centre* with single-end

50 base-pair reads on the illumina HiSeq 4000 and paired-end 100 base-pair reads on the illumina

NovaSeq 6000 S2 sequencing platforms.

ChIP-Sequencing and library preparation

Chromatin immunoprecipitation was performed as we have previously described (Hisano *et al.*,

2013; Lismer, Lambrot, *et al.*, 2021). In brief, spermatozoa samples in freezing media were thawed

on ice and washed with 1 mL phosphate-buffered saline. For each sample, two aliquots of 10 µL

were used to count spermatozoa in a hemocytometer under microscope, and 10 million

spermatozoa were used per experiment. Sperm chromatin was decondensed in 1 M dithiothreitol

(DTT; Bio Shop, #3483-12-3) and the reaction quenched with N-ethylmaleimide (NEM). Samples

were lysed in lysis buffer (0.3M sucrose, 60mM KCl, 15mM Tris-HCl pH 7.5, 0.5mM DTT, 5mM

McGl2, 0.1mM EGTA, 1% deoxycholate and 0.5% NP40). An MNase enzyme (15 units; Roche,

#10107921001) was added to aliquots containing 2 million spermatozoa in an MNase buffer (0.3

M sucrose, 85 mM Tris-HCl pH 7.5, 3mM $MgCl_2$ and 2 mM $CaCl_2$), for exactly 5 minutes at 37°C.

The digestion was stopped with 5 mM EDTA. Samples were centrifuged at maximum speed for

10 minutes, and the supernatants of aliquots from each sample were pooled back together. Each

tube was supplemented with a protease inhibitor to obtain an 1X solution (complete Tablets

EASYpack, Roche, #04693116001). Magnetic beads (DynaBeads, Protein A, Thermo Fisher

Scientific, #10002D) were pre-blocked in a 0.5% Bovine Serum Albumin (BSA, Sigma Aldrich,

#BP1600-100) solution for 4 hours at 4°C and then used to pre-clear the chromatin for 1 hour at

4°C. Pulling down of the pre-cleared chromatin was performed with the use of magnetic beads

that were previously incubated with 5 µg of antibody (Histone H3 Lysine 4 trimethylation;

H3K4me3; Cell Signaling Technology, cat. #9751) for 8 hours at 4°C. Immunoprecipitation of the

chromatin with the beads-antibody suspension was performed overnight at 4°C. Beads bound to

the chromatin were subjected to a 3-step wash, one wash with Washing Buffer A (50 mM Tris-

HCl pH 7.5, 10 mM EDTA, 75 mM NaCl) and two washes with Washing Buffer B (50 mM Tris-

HCl pH 7.5, 10 mM EDTA, 125 mM NaC). The chromatin was eluted in 250 µL of Elution Buffer

(0.1 M HaHCO3, 0.2% SDS, 5 mM DTT) by incubating the beads twice (2 x 125 µL) shaking at

400 rpm for 10 minutes at 65°C, vortexing vigorously and transferring the chromatin elute in a

clean tube. The eluted chromatin was finally treated with 5 µL of RNase A (Sigma Aldrich,

#10109169001) by shaking in a thermomixer at 400 rpm for 1 hour at 37°C, and then with 5 µL

of Proteinase K (Sigma Aldrich, #P2308) overnight at 55°C. DNA was extracted and purified using

the *ChIP DNA Clean and Concentrator kit* (Zymo Research, #D5201) using the manufacturer's

protocol, eluted with 25 µL of the provided elution buffer. Size selection of the mononucleosomes

(147 bp) was performed with the use of Agencourt AMPure XP beads (Beckman Coulter,

#A63880). Libraries were prepared in-house using the Ultra-low Input Library kit (Qiagen;

#180495). Libraries were sequenced with single-end 50 base-pair reads on the illumina HiSeq

4000 sequencing platform (n=5 samples per experimental group).

Pre-processing

Liver RNA-Sequencing data

All samples were processed with the same parameters with the exception of those sequenced on

the NovaSeq platform to adapt for paired-end sequencing and sequencing read length. Reads were

trimmed using *Trim Galore* (version 0.5.0, parameters for HiSeq: --phred33 --length 36 -q 5 --

stringency 1 -e 0.1; parameters for NovaSeq: --paired --retain_unpaired --phred33 --length 36 -q 5

--stringency 1 -e 0.1) (Krueger, 2015). Trimmed reads were aligned to the *Ensembl* Genome

Reference Consortium mouse reference 38 (GRCm38) primary assembly using *hisat2* (version

2.1.0, parameters: -p 8 --dta) (Kim, Langmead and Salzberg, 2015). Aligned files with SAM

format were converted to binary SAM format (BAM) and sorted by genomic position using

SAMtools (version 1.9) (Li *et al.*, 2009). Transcripts were assembled and gene abundances

calculated using *Stringtie* (version 2.1.2, parameters: -p 8 -e -B -A) (Pertea *et al.*, 2015).

Sperm ChIP-Sequencing data

Sequencing reads were trimmed using *Trimmomatic* on single-end mode to remove adapters and

filter out low-quality reads (version 0.36, parameters: 2:30:15 LEADING:30 TRAILING:30)

(Bolger, Lohse and Usadel, 2014). Trimmed reads were aligned to the *Mus Musculus* mm10

genome assembly using *Bowtie2* (version 2.3.4) (Salzberg, 2013). Unmapped reads were removed

using *SAMtools* (version 1.9) (Li *et al.*, 2009), and those with 3 mismatches or more were filtered

out using *Perlcode*. BAM coverage files (BigWig) were generated using *deeptools2 bamCoverage*

function (version 3.2.1, parameters: -of bigwig -bs 25 -p 20 --normalizeUsing RPKM -e 160 --

ignoreForNormalization chrX) (Ramírez *et al.*, 2016).

Other publicly available ATAC-Sequencing or ChIP-Sequencing datasets

Raw files for 2-cell H3K4me3 and H3K27me3 ChIP-Seq (Liu *et al.*, 2016) (GEO: GSE73952),

MII oocyte H3K4me3 ChIP-Seq (Zhang *et al.*, 2016) (GEO: GSE71434), sperm ATAC-Seq (Jung

et al., 2017) (GEO: GSE79230), 4-cell and morula ATAC-Seq (Liu *et al.*, 2019) (NCBI SRA:

SRP163205),TE H3K4me3 ChIP-Seq (Liu *et al.*, 2016) (GEO: GSE73952), and placenta

H3K4me3 ChIP-Seq (Shen *et al.*, 2012) (GEO: GSE29184) were downloaded from the National

Centre for Biotechnology Information (NCBI) using the Sequencing Read Archive (SRA) Toolkit.

Files were pre-processed as described above for the sperm H3K4me3 ChIP-Sequencing with slight

modifications to adapt for datasets with paired-end reads and for different sequencing read lengths.

Other publicly available RNA-Sequencing data

Raw files for 4-cell and morula (Liu *et al.*, 2019) (NCBI SRA: SRP163205), TE (Liu *et al.*, 2016)

(GEO: GSE73952), and placenta (Chu *et al.*, 2019) (NCBI SRA: SRP137723) RNA-Seq were

downloaded from the National Centre for Biotechnology Information (NCBI) using the

Sequencing Read Archive (SRA) Toolkit. Files were pre-processed as described above for the

sperm H3K4me3 ChIP-Sequencing with slight modifications to adapt for datasets with paired-end

reads and for different sequencing read lengths.

Paternal allele 2-cell embryo ChIP-Sequencing data

Raw files for 2-cell H3K4me3 ChIP-Seq (Zhang *et al.*, 2016) (GEO: GSE71434) were downloaded

from the National Centre for Biotechnology Information (NCBI) using the Sequencing Read

Archive (SRA) Toolkit. *SNPsplit* (version 0.3.2) was used to build a reference genome with

PWK_PhJ SNPs masked (Krueger and Andrews, 2016). Reads were aligned to the generated

PWK_PhJ SNPs N-masked reference genome using *Bowtie2* (parameters: -p 10 -t -q -N 1 -L 25 -

X 2000 --no-mixed --no-discordant). Aligned files with SAM format were converted to binary

SAM format (BAM) and sorted by genomic position using *SAMtools (*version 1.9) (Li *et al.*, 2009).

SNPsplit (version 0.3.2) was used to assign reads to either the paternal (PWK_PhJ) or the maternal

(C57BL/6) genome based on SNPs origin. BAM coverage files (BigWig) were generated using

deeptools2 bamCoverage function (parameters: -of bigwig -bs 25 -p 20 --normalizeUsing RPKM

-e 160 --ignoreForNormalization chrX).

Quantification and statistical analysis

Visualization and statistical analyses for metabolic characterization

Visualization of the metabolic characterization data was performed using Jupyter Notebook

(version 6.0.1) with Python (version 3.7.4), with the use of the following packages: *seaborn*

(version 0.9.0) (Waskom, 2021), *numpy* (version 1.17.2) (Harris *et al.*, 2020), and *panda* (version

0.25.2) (Mckinney, 2010). The *pyplot* and *patches* modules were loaded from the *matplotlib* library

(version 3.4.2) (Hunter, 2007). Statistical analyses were conducted using GraphPad Prism 8. For

all tests, a p-value less than 0.05 was considered significant. Significance for individual time points

on the blood glucose curves for the glucose and insulin tolerance tests, for cumulative energy

intake and for growth trajectories during the diet intervention, was tested using multiple t-test with

a Holm-Sidak correction. Significance for total body weight, mesenteric and gonadal white

adipose tissue weight, baseline blood glucose and the area under the curve for the glucose and

insulin tolerance tests, was tested using two-way ANOVA followed by Fisher's LSD.

Bioinformatics analysis

All bioinformatics analyses were conducted using R version 4.0.2 (R Core Team, 2018).

Liver RNA-Sequencing data

Transcripts with a mean count below 10 were filtered out, conferring a total of 27,907 and 45,992 detected expressed transcripts in samples sequenced on the illumina HiSeq and NovaSeq platforms, respectively. Differential expression analysis was conducted using *DESeq2* (version 1.28.1) (Love, Huber and Anders, 2014), by including sample's RIN value and group in the design formula. Independent hypothesis weighting (IHW, version 1.16.0) was used to correct for multiple testing and prioritization of hypothesis testing based on covariate (i.e. the means of normalized counts) (Ignatiadis *et al.*, 2016). IHW calculates weight for each individual p-value and then applies the Benjamini-Hochberg (BH) procedure to adjust weighted p-values (Benjamini and Hochberg, 1995). Finally, we used the Lancaster method to perform a gene-level analysis at single transcript resolution (*aggregation* package, version 1.0.1) (Yi *et al.*, 2018). Lancaster applies aggregation of individual transcripts p-values to obtain differentially expressed genes while capturing changes at the transcript level. Genes with a Lancaster p-value below 0.05 were considered significant.

For data visualization, transcript counts were normalized using variance stabilizing transformation without the use of blind dispersion estimation (i.e. with parameter *blind=FALSE*) (Love, Huber and Anders, 2014). This transformation approach translates data on a $\log_2$ scale, allows correction for library size and removes the dependence of the variance on the mean (heteroscedasticity). Variance-stabilized transcript counts were corrected for RIN values using *limma's removeBatchEffect* function (version 3.44.3) (Ritchie *et al.*, 2015). Pearson correlation heatmaps were generated using the *corrplot* package (version 0.88) (Taiyun, Wei, Simko, 2021), with samples ordered by hierarchical clustering. Principal component analysis was performed using *DEseq's plotPCA* function, with RIN values and sexes labeled. Heatmaps of differentially

expressed genes were generated with the *Pheatmap* package (version 1.0.12) (Kolde, 2019), with

transcripts ordered by k-means clustering (n kmeans=2) and samples ordered by hierarchical

clustering using complete-linkage clustering based on Euclidean distance. Alluvial plots were

generated with *ggplot2* (version 3.3.3) (Wickham, 2016), and overlap of differentially expressed

genes across genotypes, generations and sexes were determined by the *GeneOverlap* package

(version 1.24.0) (Shen, 2014), which uses a Fisher's exact test to compute p-values.

Visualization, Semantic similarity, and Enrichment Analysis of Gene Ontology (ViSEAGO)

Gene ontology (GO) analysis was performed using the *ViSEAGO* package (version 1.2.0)

(Brionne, Juanchich and Hennequet-Antier, 2019). Gene symbols and *EntrezGene* IDs from the

org.Mm.eg.db database were retrieved using the *AnnotationDbi* package. GO annotations were

retrieved from *EntrezGene* for the *Mus Musculus* species (ID="10090") using the *ViSEAGO*

EntrezGene2GO followed by *annotate* functions. ViSEAGO uses topGO to perform GO terms

enrichment tests on the sets of genes of interest (differentially expressed genes). We used the

Biological Process (BP) ontology category with Fisher's exact test (classic algorithm), and a p-

value below 0.01 was considered significant. Results of enrichment tests for each set of genes of

interest were then merged and hierarchical clustering was performed based on Wang's semantic

similarity distance and *ward.D2* aggregation criterion. Results are visualized on a heatmap where

GO terms are ordered by hierarchical clustering based on their functional similarity and GO terms

enrichment significance is shown as a color gradient (-$\log_{10}$ p-value) in each set of differentially

expressed genes of interest.

Sperm ChIP-Sequencing data

To detect genomic regions enriched with H3K4me3 in sperm, we used *csaw* (version 1.22.1) (Lun

and Smyth, 2016) to scan the genome into windows of 150-bp. Windows with a fold-change

enrichment of 4 over bins of 2,000 bp (background) were considered enriched. Enriched regions

less than 100 bp apart were merged for a maximum width of 5,000 bp, conferring a total of 30,745

merged enriched regions. Counts in enriched regions were normalized using TMM normalization

followed by *ComBat's* correction for batch effects (*sva* package, version 3.36.0) (Leek *et al.*, 2012;

Zhang, Parmigiani and Johnson, 2020). Spearman correlation heatmaps and MA-plots were

generated using raw and normalized counts at enriched regions using *corrplot* (version 0.88)

(Taiyun, Wei, Simko, 2021), and *graphics* packages, respectively.

Principal component analysis was conducted on normalized counts in enriched regions, by

comparing WT HFD vs WT LFD (effect of diet in WT), TG HFD vs TG LFD (effect of diet in

TG), and WT LFD vs TG HFD (effects of genotype and HFD). Based on visual assessment of the

separation of samples according to dietary or genotype groups along Principal Component 1 (PC1;

x axis) or 2 (PC2; y axis), the top 5% regions contributing the PC of interest were selected.

Permutational multivariate analysis of variance (PERMANOVA) was conducted to determine

whether variation is attributed to dietary/genotype group, using the *adonis* function (*vegan*

package, version 2.5-7) (Oksanen *et al.*, 2007). Euclidean distances were used as a metric, 999

permutations were performed, and a $p < 0.05$ was considered significant. The directionality change

in enrichment was identified based on the positive (up-regulated regions) and negative (down-

regulated regions) $\log_2$ fold change values of the median of normalized counts using *gtools'*

foldchange2logratio function. Regions with increased and decreased enrichment for each

comparison of interest were visualized using *Pheatmap* (version 1.0.12) (Kolde, 2019). Regions

distance relative to transcription start site (TSS) were annotated and visualized using the package

chipenrich (version 2.12.0) (Welch *et al.*, 2014). Gene ontology analysis was performed using

topGO (version 2.40.0) for genes with increased or decreased H3K4me3 enrichment at the

promoter region for each comparison of interest. We used the Biological Process (BP) ontology

category with Fisher's exact test *weight01Fisher* algorithm (Alexa, Rahnenführer and Lengauer,

2006), and a p-value less than 0.05 was considered significant. Genomic regions with deH3K4me3

were annotated using *annotatr* (version 1.14.0) (Cavalcante and Sartor, 2017) including CpG

annotations and basic genes genomic features. Upset plots were generated using *UpsetR* (version

1.4.0) (Conway, Lex and Gehlenborg, 2017)*,* by ordering each set by frequency and displaying 12

sets. Z-scores were calculated using *regioneR's overlapPermTest* (version 1.20.1) which performs

a permutation test (n=1,000 permutations) to assess whether a set of regions is significantly

enriched to a specific genomic feature compared to genomic regions from the whole genome (Gel

et al., 2016). Genome browser snapshots were generated using *trackplot* (Pohl and Beato, 2014).

To assess linear trends associated with the cumulative exposure of KDM1A overexpression and

high-fat feeding in sperm, we ran *DESeq2* (version 1.28.1) on the top 5% regions contributing to

Principal Component 2 (PC2; n=1,538 regions) associated with sample separation when

comparing WT LFD and TG HFD normalized counts. In the design formula, we included sample's

batch information, and assigned a numerical value for each sample based on their group category

(WT LFD=1, WT HFD=2, TG LFD=2, TG HFD=3). Independent hypothesis weighting (IHW)

was used to correct for multiple testing and prioritization of hypothesis testing based on covariate

(i.e. the means of normalized counts) (Ignatiadis *et al.*, 2016). Median of normalized counts were

used to depict the increased and decreased trend of significant regions (adjusted p-value less than

0.2) across groups recoded on a numerical scale as defined above.

RESULTS

Paternal obesity induces transgenerational metabolic phenotypes in a sex-specific manner

that are enhanced in KDM1A transgenic descendants

Impact of paternal obesity on offspring bodyweight and fat accruement

Beginning at weaning until 20 weeks, inbred C57BL/6NCrl control mice (WT), or KDM1A

heterozygous transgenics (TG) were fed either a calorie-dense high-fat diet (HFD; 60% kcal fat),

or a sucrose- and vitamin-matched low-fat diet (LFD; 10% kcal fat) (Fig. 1A-C and Table S1).

Table S2 provides the animal numbers by sex, generation, and genotype for each metabolic

analysis. In the 2 weeks post-weaning, F_0 males on the HFD consumed more calories and gained

significantly more weight than LFD males irrespective of genotype (Fig. S1A-B). These effects

persisted throughout the diet intervention (Fig. S1A-C), with TG HFD males weighing the most at

4 months (Fig. S1C_i). This trend continued in the TG male F_1 and F_2 descendants (fed regular

chow), with weights being significantly more than the F_1 and F_2 of TG LFD and WT HFD (Fig.

S1C_{ii-iii}). Indicating sex-specific responses to paternal obesity, in female descendants the changes

in body weight and fat deposition differed from the males (Fig. S1C-E). For example, female F_1

HFD descendants showed no changes in body weight, while F_2 TG HFD females weighed more in

comparison to F_2 WT HFD females (Fig. S1C_{iv-v}, respectively). Unexpectedly, F_2 WT HFD

females weighed less than F_2 WT LFD. To assess fat accruement, we measured visceral mesenteric

(mWAT) and gonadal white adipose tissue (gWAT). All male (F_0) on the HFD accumulated more

mWAT compared to LFD males, with no genotype effect (Fig. S1D_i). Male and female F_1

offspring sired by WT HFD or TG HFD had increased mWAT fat mass compared to WT LFD and

TG LFD (Fig. S1D_{ii} and S1D_{iv}, respectively). Strikingly, mWAT stores were greater in TG HFD

F_1 and F_2 males and females compared to WT HFD descendants (Fig. S1D_{ii-v}). Gonadal fat depots

in F_0 males were not impacted by the HFD (gWAT; Fig. S1E$_i$), while male WT HFD F_1 showed

increased gWAT, and TG HFD F_1 did not (gWAT; Fig. S1E$_{ii}$). In the male F_2, TG HFD descendants

had increased gWAT, but not WT HFD (Fig. S1E$_{iii}$). Consistent with the unusual decrease in body

weight in female F_2 WT HFD vs F_2 WT LFD, mWAT and gWAT were also reduced in female F_2

WT HFD (Fig. S1D$_v$ and S1E$_v$, respectively). Perhaps indicative of a sex-specific over-correction

in female F_2 to grand-sire obesity. Like for body weight and mWAT, female F_2 TG HFD had

increased gWAT in comparison to WT HFD (Fig. S1E$_v$). Overall analysis of body weight and fat

accruement revealed sex-specific responses in descendants with transgenerational effects of

paternal obesity being enhanced in the TG HFD descendants of both males and females. In female

descendants of obese sires, intergenerational effects were more subtle in the F_1.

Impact of paternal obesity on glucose homeostasis

Next, we assessed glucose metabolism and insulin sensitivity by glucose tolerance (GTT), and

insulin tolerance tests (ITT). These were conducted following the standard operating procedures

of the NIH mouse Metabolic Phenotyping Center (Ayala *et al.*, 2010). First, we assessed the effects

of the HFD on baseline fasting blood glucose. Consumption of a HFD resulted in elevated baseline

glucose in male (F_0) WT HFD and TG HFD in comparison to WT LFD and TG LFD, respectively

(Fig. S2A$_i$). Male TG HFD descendants (F_1 and F_2), but not WT HFD descendants had

significantly elevated fasting blood glucose (Fig. S2A$_{ii-iii}$). In contrast, the glycemic status of all

descendant females (F_1 and F_2) did not differ (Fig. S2A$_{iv-v}$). The same animals used to assess

baseline glucose were then given an intraperitoneal glucose challenge and the rate of glucose

disposal measured. Analysis of GTT data showed that F_0 WT HFD and TG HFD were glucose

intolerant following glucose injection in comparison to F_0 LFD males as shown by their elevated

blood glucose curves that persisted across the time course of 15-120 min (Fig. 1D$_i$). Note that at

T0, before the glucose challenge, F$_0$ WT HFD males had significantly elevated blood glucose in

comparison to F$_0$ WT LFD which is in line with the baseline glucose measures (Fig. 1D$_i$ and Fig.

S2A$_i$). In contrast, the T0 blood glucose levels did not differ between male F$_0$ TG LFD and F$_0$ TG

HFD even though baseline measures after fasting were significantly different (Fig. 1D$_i$ and Fig.

S2A$_i$). These non-congruent findings are attributable to multiple testing correction to adjust for the

high number of simultaneous tests conducted in the analysis of GTT curves. Intergenerational

effects of the paternal HFD were apparent as male (F$_1$) sired by WT HFD and TG HFD were also

glucose intolerant (Fig. 1D$_{ii}$). Indicating that there was enhanced metabolic disruption in the male

F$_1$ TG HFD, elevated glucose levels persisted across the GTT time-course for the F$_1$ TG HFD but

not the F$_1$ WT HFD. Interestingly, glycemic response impairments persisted in the F$_2$ generation

of male descendants of TG HFD only (Fig. 1D$_{iii}$). Although fat measures were impacted in female

F$_1$ and F$_2$ HFD, they did not exhibit glucose impairment (Fig. 1D$_{iv-v}$). Analysis of the area under

the curve (AUC) for the GTT was consistent with the male and female glycemic responses shown

in the glucose curves (Fig. S2B$_{i-v}$). In line with the observed glycemic responses, the insulin

tolerance test and the corresponding AUC demonstrated that male F$_0$ WT HFD and TG HFD were

insulin insensitive (Fig. 1E$_i$ and S2C$_i$). Analysis of the AUC indicated that F$_1$ WT HFD and F$_1$ TG

HFD were insulin insensitive (Fig. S2C$_{ii}$). Like the glucose tolerance test, there were more

pronounced impairments revealed by the ITT for the F$_1$ TG HFD in comparison to the F$_1$ WT HFD

and only the F$_2$ TG HFD showed impaired whole body insulin action (Fig. 1E$_{iii}$ and Fig. S2C$_{ii-iii}$).

Like the GTT, there was no indication of insulin impairment in female HFD F$_1$ nor F$_2$ (Fig. 1E$_{iv-v}$,

S2C$_{iv-v}$).

To summarize, the effects of paternal high-fat diet on glucose homeostasis were sex-

specific; male descendants had impaired glucose homeostasis, whereas females did not. Many

factors can influence the outcomes of GTT and ITT measures such as the length of fasting, age

and strain of mice (Ayala *et al.*, 2010; Bowe *et al.*, 2012). It is worth considering that even though

female descendants of HFD (F_{1-2}) showed alterations in fat accretion but not in glucose

homeostasis, there remains the possibility that findings may have been different had measurements

been taken after a reduced fasting period, or beyond 4 months of age. Taken together, the

assessments of weight and metabolic testing indicate that the TG descendants had enhanced

responses to paternal obesity in comparison to WT descendants.

Paternal obesity was associated with altered liver gene expression in the F_0-F_1 with unique

genes being differentially expressed in KDM1A descendants (F_1-F_2)

Obesity and metabolic syndrome contribute to steatosis of the liver which is a central organ for

glucose and lipid metabolism. To determine whether the altered metabolic status of HFD sires and

their descendants (F_1-F_2) was associated with differential gene expression in the liver, we

performed RNA-sequencing on the left lateral lobe (*lobus hepatis sinister lateralis*) of adult mice

(F_0-F_2). Sequencing quality was high with most RNA profiles having a Pearson correlation

coefficient > 0.8 (Fig. S3A). The initial quality assessment of the data revealed that samples tended

to cluster by RNA Integrity Number (RIN), which was corrected for in the differential analysis

(Fig. S3B). Interestingly, principal component analysis of sequencing data revealed distinct

hepatic transcriptomic profiles between males and females that was independent of experimental

group and genotype (Fig. S3C). We compared hepatic transcriptome profiles by diet, sex, genotype

and generation using a gene-level analysis at single-transcript resolution (Yi *et al.*, 2018). As

expected, obesity was associated with differential liver gene expression. Liver from obese F_0 WT

males showed differential expression of 2,136 genes in comparison to non-obese F_0 WT males

(Fig. 2A, Lancaster p<0.05). Similarly, when comparing obese F_0 TG to non-obese F_0 TG, 1,476

genes were differentially expressed (Fig. 2B, Lancaster p<0.05). Of these differentially expressed

genes (DEGs), 448 were commonly altered by obesity in both the F_0 WT and F_0 TG (p<0.0001;

Fig. 2_i). To identify which genes were altered due to genotype, we compared WT obese to TG

obese and identified 524 DEGs, suggesting that obesity had a unique effect in TG mice due to an

interaction between diet and genotype (Fig. 2C, Lancaster p<0.05).

To determine if the effects of paternal obesity on liver function were intergenerational, we

compared the liver transcriptome of male and female F_1. In comparison to F_1 WT LFD and TG

LFD males, livers of F_1 WT HFD and TG HFD, showed differential expression of 1,015 and 794

genes (Fig. 2D and 2E, respectively, Lancaster p<0.05). A total of 165 DEGs overlapped between

F_1 WT and TG (p<0.0001; Fig. 2_{ii}). Of the DEGs between the WT LFD and HFD in the F_1, 139

were the same deregulated genes as identified in the F_0 WT LFD vs HFD males (p=0.76; Fig 2_{iv}).

Similarly, there were 103 shared transcripts identified as differentially expressed between the F_1

TG LFD vs HFD, that were also altered in the F_0 TG LFD vs HFD (p=0.003; Fig 2_v). This suggests

that a common set of genes maintain dysfunction as a consequence of direct exposures to obesity

and these changes are maintained in the non-obese F_1. When comparing genes altered by genotype

in the F_1 (WT HFD vs TG HFD), 961 were significantly altered (Fig 2F, Lancaster p<0.05), with

78 overlapping DEGs between the F_0 and the F_1 (p<0.0001; Fig 2_{vi}). The overlap in deregulated

genes between the F_0 and F_1 indicates that the metabolic phenotypes generated by the paternal

HFD persist intergenerationally despite the F_1 being fed a regular chow diet. There were also

novel genes in the F_1 that were deregulated, suggesting secondary intergenerational effects of the

paternal HFD. As expected, there was a reduction in the number of deregulated genes in the F_1

WT and TG males compared to the F_0 which is consistent with the milder metabolic phenotypes

observed in the F_1 in comparison to the directly HFD-exposed F_0. Likely reflecting the enhanced

genotype influence of the F_0 TG HFD sires that resulted in more severe weight changes and higher

baseline glucose in their descendants compared to the WT HFD descendants, there were more

DEG in the male F_0 compared to the male F_1 TG HFD (524 in F_0 versus 961 in F_1; Fig. 2_{vi}).

The last comparisons in liver transcriptomes were between the F_1 male and female. Despite

the female F_1 having no metabolic phenotype detected by our measures, there was significantly

altered gene expression in the livers of F_1 female offspring of WT HFD vs WT LFD sires (830;

Fig 2G, Lancaster $p<0.05$) Of these, 153 were in common with the F_1 male WT HFD sired

offspring ($p<0.0001$; Fig 2_{vii}). Likewise, the F_1 female sired by TG HFD had 1,125 DEGs in

comparison to females sired by TG LFD (Fig. 2H, Lancaster $p<0.05$) with 148 in common with F_1

male TG HFD sired offspring ($p<0.0001$; Fig. 2_{viii}). Of these altered transcripts, 160 were in

common between F_1 female descendants of WT HFD and TG HFD ($p<0.0001$; Fig. 2_{iii}). Like the

F_1 male TG HFD offspring, there were unique transcripts altered in F_1 female TG HFD offspring

(1,370; Fig. 2I, Lancaster $p<0.05$), with 181 differentially expressed in both F_1 males and females

($p=<0.0001$; Fig. 2_{ix}). These may reflect genes impacted by genotype regardless of sex. An

interesting finding from the F_2 phenotyping was those transgenerational metabolic effects of the

HFD were only detected in the male descendants of TG. Therefore, we only profiled F_2 male livers

by RNA-seq. This analysis revealed differential expression of 2,141 genes between the F_2 WT

HFD and TG HFD (Fig. 2J, Lancaster $p<0.05$) with 129 overlapping with the F_1 WT HFD vs TG

HFD males ($p=0.06$; Fig 2_x). The number of differentially expressed genes increased every

generation in comparisons between the WT HFD and the TG HFD ($F_0=524$, $F_1=961$, $F_2 = 2,141$).

This sustained deregulated gene expression in the livers of TG HFD F_2, matches the enhanced

metabolic phenotypes observed in only F_2 TG HFD males but not in the F_1 WT HFD. It also

indicates a dilution in phenotype by reprogramming in the WT HFD descendants.

Paternal diet-induced obesity disrupts gene expression in functional processes that differ

between genotypes, sex and generations

To gain insight into the physiological implications of obesity-induced altered hepatic

transcriptomes, we used a gene ontology (GO) approach combined with functional similarity

clustering to compare processes in the liver impacted by diet across genotype and sex, and those

impacted by genotype across generation (Fig. 3A-C, Supplemental files 1-3 and Table S3-5)

(Brionne, Juanchich and Hennequet-Antier, 2019). Interactive heatmaps that facilitate in-depth

probing of the gene frequency and the $-\log_{10}$ p-value of enriched GO terms within each cluster are

found in Supplemental files 1-3. The non-interactive heatmaps are shown in Fig. 3. Overall, there

were similar processes altered by obesity in F_0 WT and TG livers, including lipid, amino acid, and

small molecule metabolism (Fig. 3A, Supplemental file 1 and Table S3; clusters 1-5), homeostasis

and environmental responses (clusters 8-10), and cellular differentiation and signalling (clusters

11-13). However, the gene frequency (# of genes annotated to that process) within processes

differed by genotype. For example, genes involved in lipid metabolic processes (cluster 2),

specifically the carboxylic acid metabolic process was more enriched at 19.03% gene frequency

in the F_0 WT HFD ($-\log_{10}$ p-value 6.18), than in the F_0 TG HFD at 14.7% gene frequency ($-\log_{10}$

p-value 4.37). In contrast, genes involved in environmental responses (cluster 8) such as to alcohol,

were similarly enriched in both the F_0 WT HFD with a gene frequency of 19.19% ($-\log_{10}$ p-value

1.3) and of 19.19% in the F_0 TG HFD ($-\log_{10}$ p-value 2.29). Interestingly, deregulated genes

involved in insulin, protein and metal ion transport were only enriched in F_0 TG HFD livers

(clusters 6-7).

When the altered functional pathways were compared between F_1 WT LFD vs WT HFD

males and females, there were clear impacts of obesity on the liver functional pathways of

offspring, and these differed by sex (Fig. 3B, Supplemental file 2 and Table S4). Reflecting sex

differences, a greater number of GO terms related to inflammation (cluster 4), and cell cycle,

differentiation and signalling regulation (clusters 10-11) were significantly enriched in males

compared to females. Of note, genes involved in the regulation of proinflammatory cytokines were

particularly enriched in males but not females (clusters 4 and 6). This concurs with the more severe

phenotypes observed in the males. Conversely, genes involved in DNA/RNA biosynthesis,

transcription factors and telomere activity (clusters 1-3), and macromolecule and nitrogen

metabolism (cluster 5) were more enriched in females. Interestingly, pathways associated with

chromatin and cellular organization and protein metabolism (clusters 8-9) were differentially

enriched by paternal obesity in both sexes.

Next, we compared the intergenerational and transgenerational effect of the interaction

between the KDM1A transgene with obesity in terms of differences in process enrichment across

generations when comparing F_{0-2} WT HFD with F_{0-2} TG HFD (Fig. 3C, Supplemental file 3 and

Table S5). Reflecting the increasing generational changes in liver gene expression in the TG HFD

descendants, there was an increase in the number of significantly enriched GO terms when

comparing WT HFD vs TG HFD across generations (F_0 male=79; F_1 male=118; F_1 female=159;

F_2 male=206; Supplemental file 4). This finding is concordant with the metabolic phenotypes

detected in the TG HFD male F_2 descendants, but not in the F_2 male WT HFD (Fig. 1, Fig. S1, Fig.

S2; Fig. 3C and Supplemental file 3). An interesting finding that supports a unique genotype

response in the male F_1 TG HFD in comparison to the male F_1 WT HFD, is the over-representation

of genes implicated in chromatin remodelling and transcription (clusters 17-19). This may reflect

the activation of genetic response to reprogram the KDM1A-diet-induced sperm epimutations. In

addition, there was an enrichment in the differential expression of genes with functions related to

inflammation and environmental response (clusters 3-5), and metabolic processes (clusters 11-14).

Genes involved in lipid catabolic processes (cluster 13) were increasingly enriched across

generations, with 3.54% (F_0), 6.69% (F_1 male), 8.66% (F_1 female) and 20.87% (F_2) gene

frequency. Like the males, female F_1 WT HFD vs F_1 TG HFD showed differences in enrichment

pathways that reflect the interaction between obesity and the KDM1A transgene in the F_0 and the

sex differences observed in the phenotypes (Fig. 3C)

Obesity in combination with expression of the KDM1A transgene increases differential

enrichment of sperm H3K4me3 at genes involved in metabolism and development

Previously we associated paternal folate deficient diets with altered H3K4me3 in sperm

and showed that these alterations are transmitted to the embryo and in line with offspring

phenotypes (Lismer et al., 2021). We hypothesized that the sperm epigenome at the level of

H3K4me3 would be altered by obesity and that this effect would be enhanced in KDM1A TG

males with pre-existing alterations in sperm H3K4me3. To test these hypotheses, we performed

native chromatin immunoprecipitation followed by deep sequencing (ChIP-seq) targeting histone

H3K4me3, using sperm from individual WT or TG males fed either a LFD or HFD (N=5 per

experimental group, on average 33.3 million reads per sample with an alignment rate of 97%,

Table S6). H3K4me3 localized to 30,745 genomic regions, with a Spearman correlation coefficient

of 0.98 between samples (Fig. 4A and S4). Principal component analysis of H3K4me3 profiles

revealed a clear separation of samples according to dietary treatment within genotype groups (Fig.

4 B-C). WT samples separated along Principal Component 1 (PC1) with 37.41% of variance

attributed to diet (Fig. 4B; PERMANOVA, permutation-based p=0.01). TG samples separated on

PC1 with 32.68% of the variability, with diet as the second source of variance (PC2), at 25.56%

(Fig. 4C; PERMANOVA, permutation-based p = 0.009).

To focus our analysis on the regions most impacted by diet we selected the top 5%

differentially enriched H3K4me3 regions (deH3K4me3, n=1,538) in each genotype (PC1 in WT,

PC2 in TG) (Fig. 4Di-iv). The genome distribution analysis for specific annotations showed that

diet-sensitive H3K4me3 regions were predominantly located in CpG islands, promoters, exons,

and intergenic regions (Fig. S5). To a lesser extent, deH3K4me3 also occurred at transposable

elements (LINE, SINE and LTR), where epigenetic de-repression is associated with the use of

alternative promoters and long- and short-range enhancers that are implicated in embryo

development and pluripotency (Gerdes *et al.*, 2016) (Fig. S5). Representative genome browser

tracks (Fig. S5) showing enrichment gains and losses for H3K4me3 at gene promoters are shown

for *Pde1c* (phosphodiesterase 1C; affects the olfactory system), *Bcdin3d* (RNA methyltransferase;

highly expressed in embryonic development), *Sh2d4a* (Sh2 domain containing protein 4A;

expressed during development and associated with endocrine and liver function), and *Col15a1*

(collagen alpha-1; cell differentiation and development, endocrine, cardiovascular system and

more) (*Mouse Genome Informatics*, no date).

Next, we compared the regions of H3K4me3 that were altered by obesity, their genomic

location, directionality change and functions between diets and genotype (Fig. 4). As a response

to obesity, H3K4me3 enrichment gains were more predominant than losses for both F_0 WT HFD

and TG HFD (Fig. 4D). In the WT HFD 1,323 regions gained and 215 lost H3K4m3 in comparison

to the WT LFD (Fig. 4D$_{i-ii}$). Similarly, in the F$_0$ TG HFD sperm, 1,067 regions gained and 471

lost H3K4me3 in comparison to the F$_0$ TG LFD (Fig 4Diii-iv). Regions with deH3K4me3 in WT

HFD had an 15.6% overlap (240/1,538 regions) with those of TG HFD (Fig. 4E). Of those

common 240 regions, 162 had the same directionality change in both WT and TG HFD, with 159

regions with a gain and 3 regions with a reduction in H3K4me3 enrichment (Fig. 4 F and G,

respectively). The non-overlapping regions of deH3K4me3 in WT HFD and TG HFD sperm could

be a consequence of genetic-epigenetic interactions where the TG mice respond uniquely to

obesity as was observed in the phenotypic characterization. The proximity to the TSS of the

deH3K4me3 regions in sperm altered by obesity in the F$_0$ WT HFD and TG HFD were similar

(Fig. 4H).

Next, we performed a gene ontology (GO) enrichment analysis on promoters to gain

functional insight into the genes disturbed by obesity and how they may relate to offspring

phenotypes. This analysis revealed that changes in H3K4me3 occurred at promoters of genes that

function in reproduction and development which is expected as these processes are known to be

enriched for H3K4me3 in sperm (Fig. 4I and Tables S7-10). Supporting the idea that deH3K4me

is specifically impacted by obesity and may be implicated in the transmission of metabolic disease

to offspring is the finding that enriched genes were identified in processes related to metabolism

and the impact of obesity. These included inflammatory processes, glucose and lipid metabolic

pathways, and one-carbon cycle metabolism (Fig. 4I$_{i-iv}$; Tables S7-10). Notably, some of the

significantly enriched pathways are concordant with disturbed metabolic phenotypes of the F$_0$-F$_2$

including, for example, carbohydrate metabolic processes, glycolysis, growth hormone signaling

and insulin signaling (Fig 4I, Tables S7-10).

The metabolic phenotypes of WT HFD and TG HFD descendants were similar, although

the F_{1-2} TG HFD showed enhanced abnormalities. We hypothesized that these differences in

offspring metabolic disturbances may relate to the degree of H3K4me3 alteration in F_0 sperm, the

directionality of the change (gain versus loss), and the functionality of genes bearing alterations.

Interestingly, when comparing WT LFD with TG HFD sperm, samples separated along PC2, with

26.69% of variance associated with genotype and diet (Fig. 5A; PERMANOVA, permutation-

based p=0.006). Of the top 5% impacted regions selected (n=1,538), a greater proportion showed

a gain of enrichment for H3K4me3 in TG HFD sperm in comparison to WT LFD (Fig. 5B, n=1,071

regions with gains; Fig. 5C. n=467 regions with losses). We analyzed the detected regions

impacted by genotype and diet (n=1,538) for differential enrichment to determine whether obesity

in combination with KDM1A overexpression led to greater changes in H3K4me3 enrichment. This

analysis identified 264 regions with a significant linear trend, where TG HFD sperm showed a

greater degree of change in enrichment, and TG LFD and WT HFD showed intermediate changes

in comparison to WT LFD (Fig. 5D-E, adjusted p<0.2). There were only 9 significant regions

with further increase in H3K4me3 in the TG HFD (Fig. 5 D), whereas 255 regions showed a

greater loss of H3K4me3 enrichment in the TG HFD (Fig. 5E). Consistent with the stronger

metabolic phenotypes observed in the TG HFD F_{1-2}, the functional analysis of the promoters

showing significant linear trends (n=104) for H3K4me3 across experimental groups occurred at

genes implicated in metabolic and cardiovascular disease progression (Fig. 5F, Table S11).

Paternal obesity impacts sperm H3K4me3 at regions that coincide with open chromatin and

gene expression in pre-implantation embryos

We recently demonstrated that sperm H3K4me3 is transmitted to the embryo and associated with

gene expression (Lismer, Dumeaux, *et al.*, 2021). We hypothesized that obesity-altered sperm

H3K4me3 is transmitted and associated with chromatin accessibility in the early embryo, which

in turn could influence gene expression and offspring phenotypes. To assess this possibility, we

investigated the relationship between deH3K4me3 in sperm in relation to H3K4me3 in the embryo,

the oocyte and open chromatin (Zhang *et al.*, 2016; Jung *et al.*, 2017; Liu *et al.*, 2019). We used

existing datasets from mouse 2-cell embryos (Zhang *et al.*, 2016), generated by crossing males and

females of different strains, permitting the assignment of reads to the paternal-specific allele. In

line with a preferential paternal contribution of H3K4me3 to the 2-cell embryo, regions enriched

for H3K4me3 in sperm, including those altered by obesity are not enriched in the oocyte (Fig 6A).

Next, we examined the relationship between sperm H3K4me3, chromatin accessibility and

embryonic gene expression at the 4-cell and morula stages (Fig. 6 and Fig. S6A). We focused on

the 4-cell and morula stages as this is when large-scale embryonic transcription directs

development (Jukam, Shariati and Skotheim, 2017). There is an association between sperm

H3K4me3 and embryonic gene expression (Lismer *et al.*, 2020; Lismer, Dumeaux, *et al.*, 2021)

(Fig. S6 A_i). Strikingly, sperm H3K4me3 including obesity-sensitive regions are associated with

ATAC-seq signal in pre-implantation embryos (Fig. 6A and 6B). To determine the functional

relationship between the H3K4me3 obesity-altered regions and embryonic gene expression, we

compared these with 4-cell and morula expressed genes and performed a gene ontology analysis.

Of the sperm deH3K4me3 regions overlapping promoters (n=738), 51.8% (n=382) are expressed

in the 4-cell embryos, 44.3% (n=327) are expressed in the morula embryos, and 39.7% (292)

overlap in both (Fig. S6A_{ii}). To gain insight into what obesity-altered H3K4me3 associated genes

in sperm relate to embryonic gene expression, we performed a GO analysis on the regions that are

deH3K4me3 in sperm and the corresponding genes expressed in 4-cell and morula embryos (Fig.

6C$_{i-ii}$). Again, supporting a role for sperm H3K4me3 in paternal transmission of metabolic disease,

with both the 4-cell and the morula gene processes significantly enriched specific to metabolism

(Fig. 6C$_{i-ii}$ and Tables S12-13).

Unlike our previous studies on the function of H3K4me3 sperm where we found strong

associations between deH3K4me3 and birth defects (Lismer *et al.*, 2020; Lismer, Dumeaux, *et al.*,

2021), in this study the defects in descendants appear to be limited to metabolic dysfunction and

not development. To further probe the bias of obesity altered H3K4me3 for genes that function in

metabolism and not post-implantation development, we examined the relationship between

deH3K4me3 and H3K4me3/H3K27me3 bivalency. Genes that are bivalent for

H3K4me3/H3K27me3 in sperm and embryos are termed as poised genes and are expressed later

in embryo development (Hammoud *et al.*, 2009; Brykczynska *et al.*, 2010). Some promoters with

high H3K4me3 enrichment in sperm are associated with bivalency in the 2-cell embryos (Fig.

S6B$_i$). The obesity-altered H3K4me3 regions are predominantly not associated with

H3K4me3/H3K27me3 bivalent genes in the embryo (Fig. S6C$_{ii}$). Taken together these findings

suggest a preferential contribution of H3K4me3 on the paternal chromatin in the early embryo that

includes obesity-sensitive regions that may be instructive of metabolic-associated gene expression

and a direct route for epigenetic inheritance.

HFD alters the sperm epigenome at regions instructive for placenta development

The placenta is a key extra-embryonic organ that represents the uterine-fetal interface and

plays a central role in energy allocation, nutrient exchange, and developmental progression.

Placental abnormalities have been linked to late onset cardiometabolic diseases, highlighting the

importance of the *in utero* environment for adulthood metabolic health (Perez-Garcia *et al.*, 2018).

Our gene ontology analysis on diet-induced deH3K4me3 regions in sperm revealed significant

enrichment of genes involved in placenta development (Fig. 4I and Tables S7-10). Given the sperm

epigenome influences placental gene expression (Wang *et al.*, 2013), we were interested in the

prospect that diet-induced epimutations in sperm affect placenta gene expression that could

influence metabolic phenotypes across generations. To investigate this possibility, we used

existing H3K4me3 and transcriptomic datasets from mouse trophectoderm – the embryonic

precursor of placenta lineage – and placenta (Shen *et al.*, 2012; Wu *et al.*, 2016; Chu *et al.*, 2019).

We compared the enrichment profiles of H3K4me3 in sperm, trophectoderm and placenta, at all

H3K4me3-enriched regions in sperm (n=30,745) and at those sensitive to diet (n=2,836). Most

regions showed presence of H3K4me3 in both the trophectoderm and the placenta (Fig. 7A). Of

the 738 deH3K4me3 regions localizing to promoters in sperm, 56.8% (n=418) were expressed in

the trophectoderm, 76.8% (n=567) were expressed in the placenta, and 54.6% (n=403) were

expressed in both (Fig. S6Cii). Gene ontology analysis of the shared H3K4me3 in sperm with TE

and placenta revealed that there was an association with placenta function including at

deH3K4me3 regions (Fig. 7Bi and iii, Tables S14 and S16). The GO analysis of the H3K4me3

regions that were not common with TE and placenta were involved in spermatogenesis,

fertilization and sperm function (Fig. 7Bii and iv, Tables S15 and S17).

Next, we compared gene enrichment of sperm H3K4me3 with low- and high-expressed

genes in the TE and placenta. Suggesting an influential role of sperm H3K4me3, the highly

expressed genes and to a lesser extent the lowly expressed genes in placenta were positively

correlated with sperm H3K4me3 (Fig. 7Ci-iv). Notably when the same comparisons were made

with the deH3K4me3 there was a significant relationship with both lowly- and highly-expressed

placenta genes (p=1.2e-11 and p=0.008, respectively; Fig. 7Cv-viii). In addition, the GO analysis

of TE- and placenta-expressed genes that overlap with deH3K4me3 promoters are in line with the

metabolic phenotypes in offspring (Fig. 7D i-ii, Tables S18-19). Taken together this analysis raises

the possibility that obesity-induced alterations in sperm may influence embryonic and placenta

gene expression to alter metabolic function of offspring.

Obesity-induced sperm epigenomic and hepatic transcriptomic alterations are unrelated

In a recent study, paternal low-protein diet was associated with reduced H3K9me2 at genes in

sperm and were suggested to modulate gene expression profiles in the liver (Yoshida *et al.*, 2020).

We aimed to assess whether a similar association between obesity-induced deH3K4me3 in sperm

would relate to differential expression in the livers of the next generation. We focused on the

obesity-associated sperm deH3K4me3 at promoters in F_0 sires and their relationship to

differentially expressed genes in the liver (DEGs) of F_1 males. This analysis revealed that genes

with differential expression in livers (n=1,644) were by in large unrelated to genes bearing

deH3K4me3 in sperm. Only 9.1% (n=67) of promoters with deH3K4me3 in sperm were

differentially expressed in the liver of F_1 males sired by HFD-fed sires (Fig. S7 A-B). We then

asked if deH3K4me3 promoters in sperm and liver DEGs had related biological functions.

Strikingly, sperm- and liver-altered genes showed few functional similarities (Fig. S7C,

Supplemental file 5 and Table S20). Functional pathways specifically enriched in deH3K4me3

promoters involved development and differentiation processes (clusters 12-15). As expected in a

paternal obesity model, gene processes altered in offspring livers included: regulation of

transcription and RNA splicing (clusters 1-3), protein and histone post-translational modifications

(clusters 4-5), and metabolism of lipid, nitrogen and glucose (clusters 6-8). Pathways enriched in

both the deH3K4me3 promoters in sperm and the DEGs in liver were involved in cell cycle,

transport and signaling (clusters 16-19), and response to stress and inflammation (clusters 20-22).

These commonly enriched pathways might reflect obesity-associated systemic inflammation

which could affect multiple organs in a similar manner. These findings indicate that paternal

obesity alters the sperm epigenome at distinct genes and functional pathways than those

differentially expressed in offspring livers and fits with a developmental origin of adult metabolic

dysfunction that could be related to alterations in gene expression in the embryo and placenta.

DISCUSSION

Epidemiological studies and animal models point to the world-wide increases in childhood obesity

and diabetes being in part attributed to environment-epigenetic interactions in the gametes

(Huypens *et al.*, 2016; Isganaitis, Suehiro and Cardona, 2017; Sales, Ferguson-Smith and Patti,

2017). With the prevalence of childhood obesity predicted to reach 70 million by 2025 (Brown *et*

al., 2015), it is urgent to gain a better understanding of the underlying heritable mechanisms.

Studies of obesity in mice and men have focussed on the role of sperm DNA methylation and non-

coding RNA as mediators of paternal non-genetic inheritance of metabolic dysfunction (Carone *et*

al., 2010; Fullston *et al.*, 2013; Lambrot *et al.*, 2013; Martínez *et al.*, 2014; Chen *et al.*, 2016;

Soubry *et al.*, 2016; Youngson *et al.*, 2016; Zhang *et al.*, 2018; Salas-Huetos *et al.*, 2021). At the

mechanistic level, how sperm altered DNA methylation and non-coding RNA lead to metabolic

phenotypes in offspring remains unresolved. In contrast to the voluminous studies on the response

of sperm DNA methylation to paternal obesity/diets, there have been only a handful of studies on

the role of chromatin. The few chromatin studies have been limited by either the state of the

available technology, methodology used, or gene targeting approaches (Carone *et al.*, 2011;

Palmer *et al.*, 2011; Martínez *et al.*, 2014; Donkin *et al.*, 2016).

Here we focused on sperm chromatin, specifically histone H3K4me3, as we have shown

previously that it is impacted by the environment, is transmitted to the embryo, and functions in

transgenerational inheritance (Lismer *et al.*, 2020; Lismer, Dumeaux, *et al.*, 2021). Our findings

implicate obesity-induced alterations in H3K4me3, in the transmission of metabolic disease. The

effects of obesity on the paternal epigenome were specific and linked with the metabolic

dysfunction in the descendants; deH3K4me3 occurred at the promoters of genes involved in

fertility, metabolism, and placenta processes. Indicative of paternal transmission of sperm altered

H3K4me3 as a mechanism of metabolic dysfunction was the strong relationship between

deH3K4me3, an open chromatin state and gene expression in embryos and placenta.

In this study we modeled how genetic-epigenetic interactions in the paternal germline can

synergize in response to obesity to worsen metabolic dysfunction in descendants. The enhanced

phenotypes observed in the descendants of obese F_0 TG revealed an increased susceptibility to the

HFD in the TG line. An explanation for this response is that the F_0 TG were descendants from a

lineage with pre-existing alterations in the sperm epigenome due to the genetic modification

causing KDM1A overexpression. This genetic stress in combination with the environmental

challenge of the HFD resulted in a uniquely altered sperm epigenome in comparison to the WT,

and worsened offspring phenotypes. Notably, paternal obesity-induced transgenerational

metabolic disturbances in offspring were only observed in descendants of obese TG males. This

transgenerational effect may be attributed to TG KDM1A obese sires having a pre-existing altered

sperm epigenome at regions that escape reprogramming (Lismer *et al.*, 2020). In support of this

rationale that a subset of H3K4me3 regions in sperm are conserved across generations, is the

observed continuity in liver gene expression alterations from the F_0-F_2.

In the context of this study, our findings suggest that transgenerational inheritance via the

paternal germline is exceptional. Indeed, the phenomena of transgenerational inheritance has been

most documented in genetic mouse models of epigenetic inheritance and studied in relation to

DNA methylation patterns. These include the Avy agouti model (Morgan *et al.*, 1999; Dolinoy *et*

al., 2006; Cropley *et al.*, 2016), the kinky tail model (Axin[Fu] allele) (Rakyan *et al.*, 2003), and in

mice bearing a mutation in the *Mtrr* gene, a folate metabolism enzyme (Padmanabhan *et al.*, 2013).

In the context of environmental challenges, paternal transgenerational inheritance has been

associated with altered sperm DNA methylation when there has been gestational exposure to

toxicants and undernutrition (Anway *et al.*, 2005; Martínez *et al.*, 2014), and in a non-genetic

pharmacologically-induced prediabetes model begun at weaning (Wei *et al.*, 2014). Taken

together, this growing body of evidence indicates that transgenerational inheritance occurs under

genetic influence, or when exposures coincide with developmental programming. The male F_0

mice in this study were exposed to the paternal HFD from weaning and not *in utero*, which may

account for why transgenerational effects were not observed in WT HFD descendants. Another

possibility is that transgenerational responses in the WT may have become detectable in older

mice.

Our analysis indicates that the inherited metabolic disturbances observed in adult

descendants originated early in development. In rodent models, paternal obesity and *in utero*

undernutrition has been linked to altered gene expression in offspring livers and pancreatic islets

with some minor links to concordant DNA methylation changes (Carone *et al.*, 2011; Martínez *et*

al., 2014; Wei *et al.*, 2014). It has been suggested that diet-associated alterations in DNA

methylation in sperm are retained through embryogenesis and maintained in adult tissues

mediating paternally-induced phenotypes (Martínez *et al.*, 2014; Wei *et al.*, 2014). Consistent with

these studies, altered hepatic gene expression occurred in F_{1-2} offspring of obese sires. In contrast,

we observed minimal overlap of genes and functional pathways between altered H3K4me3

enrichment in sperm, with those differentially expressed in F_1 livers. Instead, we demonstrate a

significant overlap of obese sperm H3K4me3 profiles with the expression of metabolic-related

genes in the embryo and placenta. Based on these findings, we suggest that the metabolic

phenotypes we observe originate in early embryogenesis and through changes in placental gene

expression.

There is a bounty of research linking maternal obesity to adverse metabolic consequences

for the offspring that coincide with altered placental gene expression and function (Kerr *et al.*,

2018; Franzago *et al.*, 2019). On the other hand, it is an emerging concept that the paternal

environment including factors such as diet and age can influence placental development and

function. It is known that paternally expressed genes contribute to placental growth, trophoblast

invasion and insulin resistance and adiposity (Moore, 2001; Binder, Hannan and Gardner, 2012;

Wang *et al.*, 2013; Rosenfeld, 2015; Naruse *et al.*, 2019; Michelle M Denomme *et al.*, 2020;

Michelle M. Denomme *et al.*, 2020). In humans, errors in epigenomic programming have been

associated with gestational trophoblast disease and pre-eclampsia, but the role of the obese father

in these conditions has been entirely unexplored (Gabory, Attig and Junien, 2011; Nelissen *et al.*,

2011). Previous studies support a connection between paternal diets, obesity, and placental

dysfunction as a developmental route to metabolic disease in children. For example, we have

shown that a folate deficient paternal diet and altered sperm DNA methylation coincided with

deregulated placenta gene expression of *Cav1* and *Txndc16* (Lambrot *et al.*, 2013). Moreover,

paternal obesity in mice has been attributed to defective placental development (Binder, Hannan

and Gardner, 2012; Binder *et al.*, 2015). In women, altered DNA methylation in the regulation of

some genes in preeclampsia has been established. However, many genes with deregulated

expression were not associated with DNA methylation raising the possibility of altered chromatin

signatures leading to abnormal gene expression in this placental disorder (Leavey *et al.*, 2018).

Indeed, upregulated expression of LncRNA by increased H3K4me3 has been observed in

preeclampsia placentas (Sun *et al.*, 2020), and the levels of H3K4me3 as detected by

immunocytochemistry are decreased (Meister *et al.*, 2021). Until now the connection between

sperm chromatin and placenta function has been unexplored. Our analyses revealed that most of

the obesity-altered H3K4me3 at promoters occurred at loci involved in placental development and

inflammatory processes (56.6% and 76.8% of deH3K4me3 occurred at promoters expressed in the

trophectoderm and placenta, respectively). Remarkably, deregulated expression of genes

implicated in inflammation have been implicated in hypertensive disorders in pregnancy including

pre-eclampsia. This raises the possibility that the paternal sperm epigenome may influence

maternal health during pregnancy in addition to that of the developing fetus. Hypertensive

disorders in pregnancy have been associated with increased risk for developing cardiovascular

disease (Naruse *et al.*, 2019).

As in previous studies we found that paternal obesity resulted in sex-specific differences

in metabolism and fat accruement with males being more impacted. The underlying mechanisms

that lead to the greater susceptibility of males may be related to sexually dimorphic placental gene

expression (Eriksson *et al.*, 2010). In support of this possibility, paternal environment (diet)

influenced placental function in a sex-specific manner (Binder *et al.*, 2015). Alternatively,

different metabolic responses in male and female offspring may be due to hormonal responses

where estrogen has been shown to protect against altered glucose homeostasis (Gupte, Pownall

and Hamilton, 2015; Lainez *et al.*, 2018).

In summary, we provide evidence that paternal obesity induced altered H3K4me3

signatures in sperm that may in part contribute to the transgenerational inheritance of metabolic

disease. The finding that genetic-epigenetic interactions may function in disease susceptibility via

sperm H3K4me3 brings to light that paternal metabolic disease transmission may be heightened

in situations where several environmental stressors converge on the sperm epigenome. Our

findings indicate further studies on the relationship between sperm chromatin, the placental

chromatin and gene expression are warranted and could lead to a better understanding of paternal

sperm epigenome transmission of metabolic disease. The translational validation of these findings

will be important in developing intervention strategies focused on paternal health that could impact

the health of future generations (Barratt *et al.*, 2021).

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1212

1213 **AUTHOR CONTRIBUTIONS**

1214 SK conceived, designed, funded and guided the study. ASP developed the model and conducted

1215 the animal studies with assistance from CL and RL with associated laboratory analysis. ASP

1216 conducted the bioinformatic analysis with assistance and oversight from VD. ASP and SK

1217 assembled and wrote the manuscript which was edited by VD.

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1219 **COMPETING INTEREST**

1220 The authors declare no competing interests.

Figure 1

A

C57BL/6NCrl WT   C57BL/6NCrl KDM1A+/- TG

F0   ♀   ♂ ← LFD / HFD   ♀   ♂ ← LFD / HFD

F1   ♀   ♂   ♀   ♀   ♂   ♀

F2   ♀   ♂   ♀   ♂

B

3 weeks → 15 weeks → 17 weeks → 20 weeks

Weaning / Metabolic testing / Breeding / Necropsy

Adiposity (mWAT, gWAT)

RNA-seq

ChIP-seq

C

WT LFD   WT HFD

—●— WT LFD   ····●···· WT HFD   —●— TG LFD   ····●···· TG HFD

F0♂   F1♂   F2♂   F1♀   F2♀

D Glucose tolerance test

(i) (ii) (iii) (iv) (v)

Blood glucose (mM)

Time after glucose injection (min)

E Insulin tolerance test

(i) (ii) (iii) (iv) (v)

Blood glucose (mM)

Time after insulin injection (min)

Figure 1: Paternal obesity induces transgenerational metabolic phenotypes in a sex-specific

manner that are enhanced in KDM1A descendants A) Experimental mouse model depicting

breeding scheme and generations studied. Male C57BL6NCrl (WT) and KDM1A$^{+/-}$ transgenics

(TG, C57BL6NCrl) were fed either a low-fat diet (LFD) or high-fat diet (HFD) from weaning for

10-12 weeks, then mated to 8-week-old C57BL6NCrl females fed a regular chow diet (CD).

Animals studied per experimental group: F_0 (n=15-25 males), F_1 (n=28-49 per sex) and F_2 (n=8-

21 per sex) B) Experimental timeline for metabolic testing and downstream experiments

performed for each generation (F_{0-2}). Metabolic profiles were measured after the diet intervention

at 15 weeks of age and included: baseline blood glucose, and intraperitoneal glucose and insulin

tolerance tests (ipGTT and ipITT, respectively). Visceral adipose depots were weighed (mWAT:

mesenteric white adipose tissue and gWAT: gonadal white adipose tissue) and the left lateral lobe

of the liver used for RNA-sequencing (RNA-seq). Sperm from cauda epididymides were used for

chromatin immunoprecipitation followed by sequencing (ChIP-seq), targeting histone H3 lysine 4

tri-methylation (H3K4me3). C) Age-matched male mice fed either a low-fat diet (left) or a high-

fat diet (right) for 12 weeks. D) Glucose tolerance test. Blood glucose levels before and after

(shaded in grey) an intraperitoneal glucose injection, after overnight fasting (15 ±1 hour) at 4

months of age in F_0 males (i), F_1 males (ii), F_2 males (iii), F_1 females (iv) and F_2 females (v). E)

Insulin tolerance test. Blood glucose levels before and after (shaded in grey) an intraperitoneal

insulin injection, after a 6-hour (±1 hour) fasting at 4 months of age in F_0 males (i), F_1 males (ii),

F_2 males (iii), F_1 females (iv) and F_2 females (v). Results are shown as mean ± SEM. Statistical

analyses were performed using multiple t-test with Holm-Sidak correction. *P<0.05, **P<0.01,

***P<0.001, ****P<0.0001 (in blue; WT LFD vs WT HFD, in green; TG LFD vs TG HFD) and

#P<0.05, ##P<0.01 (WT HFD vs TG HFD).

Figure 2

Figure 2: Paternal obesity is associated with altered gene expression in the livers of the F_0-F_2

A-J) Heatmaps of normalized expression values scaled by row (z-score) for transcripts that code

for differentially expressed hepatic genes (Lancaster p-value<0.05) for each comparison assessed

across sex and generation. Individual transcripts (rows) are ordered by k-means clustering and

samples (columns) are arranged by hierarchical clustering, using complete-linkage clustering

based on Euclidean distance. F_0 WT LFD vs WT HFD males (A), F_0 TG LFD vs TG HFD males

(B), F_0 WT HFD vs TG HFD males (C), F_1 WT LFD vs WT HFD males (D), F_1 TG LFD vs TG

HFD males (E), F_1 WT HFD vs TG HFD males (F), F_1 WT LFD vs WT HFD females (G), F_1 TG

LFD vs TG HFD females (H), F_1 WT HFD vs TG HFD females (I), and F_2 WT HFD vs TG HFD

males (J). i-x) Alluvial plots depicting frequency distributions of significant (colored boxes) and

non-significant (grey boxes) genes for each comparison and their overlap across genotype (i-iii),

across F_0 and F_1 males (iv-vi), across F_1 males and females (vii-ix) and across F_1 and F_2 males (x).

Significance of overlap between differentially expressed genes lists was calculated by Fisher's

exact test. P-values are included for each comparison above the respective alluvial plot.

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Figure 3

Figure 3: Obesity-induced hepatic transcriptome disturbances show functional similarities

across genotype, sex and generation A-C) Heatmaps of significant gene ontology (GO) terms

clustered by functional similarity, comparing enriched biological functions for each comparison

of interest across genotype (A), sex (B) and generation (C). Columns represent enriched GO terms

which are ordered by hierarchical clustering based on Wang's semantic similarity distance and

ward.D2 aggregation criterion. Each row represents a comparison of interest for which enriched

GO terms were annotated based on the list of significant genes. The color gradient depicts the GO

term enrichment significance (-$\log_{10}$ p-value). Interactive versions of these figures can be found in

Supplemental files 1-3 and the complete lists of significantly enriched GO terms can be found in

Tables S3-5.

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Figure 4

Figure 4: Genomic location, directionality change and functions of regions with altered

H3K4me3 enrichment by obesity A) Histogram showing frequency distributions of read

abundances in 150 bp windows throughout the genome. Windows with an abundance below

$\log_2(4)$ fold over background bins of 2,000 bp were filtered out as indicated by the vertical red

line. Enriched regions less than 100 bp apart were merged for a maximum width of 5,000 bp,

conferring a total of 30,745 merged enriched regions. Reads were counted in merged enriched

regions and normalized counts were used for downstream analyses. (see Material and Methods)

B-C) Principal component analysis on normalized counts at merged enriched regions comparing

WT LFD vs WT HFD (B) and TG LFD vs TG HFD (C). The top 5% regions contributing to

separation of samples along Principal Component 1 (in B; PC1; x axis) or PC2 (in C; y axis) were

selected. The PERMANOVA p-values indicating significance associated with dietary treatment

are included under each PCA plot. D) Heatmaps of log2 normalized counts of deH3K4me3 regions

in sperm with increased enrichment in WT HFD (i; n=1,323), decreased enrichment in WT HFD

(ii; n=215), increased enrichment in TG HFD (iii; n=1,067) and decreased enrichment in TG HFD

(iv; n=471) in each group. Samples (columns) and regions (rows) are arranged by hierarchical

clustering using complete-linkage clustering based on Euclidean distance. Colored boxes indicate

sample groups (light blue=WT LFD, dark blue=WT HFD, light green=TG LFD, dark green=TG

HFD). E-G). Venn diagrams showing the overlap of deH3K4me3 in sperm of WT HFD (blue) and

in TG HFD (green), for all detected regions (E), those gaining H3K4me3 (F) and those losing

H3K4me3 (G). H) Barplots showing the distribution of altered regions based on the distance from

the TSS of the nearest gene, for regions with increased enrichment in WT HFD (i; n=1,323),

decreased enrichment in WT HFD (ii; n=215), increased enrichment in TG HFD (iii; n=1,067),

and decreased enrichment in TG HFD (iv; n=471). The color gradient represents the distance of

the regions to TSS in kilobase. I) Gene ontology analysis of diet-induced deH3K4me3 regions at

promoters with increased enrichment in WT HFD (i; n=381), decreased enrichment in WT HFD

(ii; n=34), increased enrichment in TG HFD (iii; n=230) and decreased enrichment in TG HFD

(iv; n=150). Barplots show 8 selected significant GO terms with their respective $-\log_2$(p-value).

Tables S7-10 include the complete lists of significantly enriched GO terms.

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Figure 5

Figure 5: Additive effects of KDM1A overexpression and diet-induced obesity in the sperm

epigenome at the level of H3K4me3

A) Principal component analysis on normalized counts at merged enriched regions comparing WT

LFD vs TG HFD. The top 5% regions contributing to separation of samples along Principal

Component 2 (PC2; y axis) were selected. The PERMANOVA p-value under the plot indicates

significance. B-C) Profile plots of RPKM H3K4me3 counts +/- 1 kilobase around the center of

regions with increased H3K4me3 (B) and +/- 2.5 kilobase around the center of regions with

decreased H3K4me3 enrichment in TG HFD (C). D-E) Line plots showing the median of

normalized sperm H3K4me3 counts for each experimental group at regions showing a significant

trend (n=264, adjusted p-value<0.2) with a linear increase in H3K4me3 enrichment (D; n=9) or a

linear decrease in H3K4me3 enrichment (E; n=255) from WT LFD, WT HFD, TG LFD to TG

HFD groups. F) Gene ontology analysis on the regions associated with a significant linear trend at

promoters (n=104). Barplots show 8 selected significant GO terms with their respective $-\log_2$(p-

value). Table S11 includes the complete list of significantly enriched GO terms.

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Figure 6

Figure 6: Sperm H3K4me3 regions sensitive to obesity occur at genes with an open

chromatin state and expressed in the pre-implantation embryo A) Heatmaps of RPKM counts

signal +/- 10 kilobase around the center of regions enriched with H3K4me3 in sperm (i; n=30,745)

and regions with obesity-induced deH3K4me3 in sperm (ii; n=2,836) for H3K4me3 enrichment

levels in sperm (this study), 2-cell embryo (Liu *et al.*, 2016), 2-cell embryo on the paternal allele

and MII oocyte (Zhang *et al.*, 2016), and for chromatin accessibility signal in sperm (Jung *et al.*,

2017), 4-cell embryo and morula embryo (Liu *et al.*, 2019). B) Scatterplots showing H3K4me3

enrichment in sperm (x axis; log2 counts + 10), chromatin accessibility signal (y axis; log2 counts

+ 10; (Jung *et al.*, 2017)) and gene expression levels (color gradient; log2 FPKM + 10; (Liu *et al.*,

2019)) in 4-cell (i,ii,v,vi) or in morula (iii,iv,vii,viii) embryos, at either all genes with promoters

enriched with H3K4me3 in sperm (i-iv) or at diet-sensitive genes (v-viii). The top row of

scatterplots includes lowly-expressed genes (bottom 50%) in 4-cell (i and v) or morula (iii or vii)

embryos. The bottom row of scatterplots includes highly-expressed genes (top 50%) in 4-cell (ii

and iv) or morula (vi and viii) embryos. Pearson's correlation coefficients and their associated p-

values are indicated above each scatterplot, comparing H3K4me3 enrichment in sperm versus

H3K4me3 enrichment in 4-cell or morula embryos. C) Gene ontology analysis of genes expressed

in the 4-cell (i) or the morula (ii) embryos, overlapping with diet-sensitive promoters in sperm.

Barplots show 8 selected significant GO terms with their respective -log$_2$(p-value). Tables S12-13

include the complete lists of significantly enriched GO terms.

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Figure 7

Figure 7: Obesity-induced deH3K4me3 regions overlap with genes marked by H3K4me3 and

expressed in the trophectoderm and placenta A) Heatmaps of RPKM counts signal +/- 5

kilobase around the center of regions enriched with H3K4me3 in sperm (i; n=30,745) and at

regions with diet-induced deH3K4me3 in sperm (n=2,836) for H3K4me3 enrichment levels in

sperm (this study), trophectoderm (TE) (Liu *et al.*, 2016) and placenta (Shen *et al.*, 2012). B) Gene

ontology analysis of regions enriched with H3K4me3 in sperm, TE and placenta (top 75% from A

i) (i), regions enriched with H3K4me3 in sperm only (bottom 25% from A i) (ii), diet-sensitive

regions enriched with H3K4me3 in sperm, TE and placenta (top 75% from A ii) (iii), and diet-

sensitive regions enriched with H3K4me3 in sperm only (bottom 25% from A ii) (iv). Barplots

show 8 selected significant GO terms with their respective -$\log_2$(p-value). Tables S14-17 include

the complete lists of significantly enriched GO terms. C) Scatterplots showing H3K4me3

enrichment at promoters in sperm (x axis; log2 counts + 10), H3K4me3 enrichment (y axis; log2

counts + 10) and gene expression levels (color gradient; log2 FPKM + 10) in the trophectoderm

(i,ii,v,vi; (Liu *et al.*, 2016)) or in the placenta (iii,iv,vii,viii; (Shen *et al.*, 2012; Chu *et al.*, 2019)),

at either all genes with promoters enriched with H3K4me3 in sperm (i-iv) or at diet-sensitive genes

(v-viii). The top row of scatterplots includes lowly-expressed genes (bottom 50%) in

trophectoderm (i and v) or placenta (iii or vii). The bottom row includes highly-expressed genes

(top 50%) in trophectoderm (ii and iv) or placenta (vi and viii). Pearson's correlation coefficients

and associated p-values are indicated above each scatterplot, comparing H3K4me3 enrichment in

sperm versus H3K4me3 enrichment in the trophectoderm or placenta. D) Gene ontology analysis

of genes expressed in the trophectoderm (i) or the placenta (ii), overlapping with diet-sensitive

promoters in sperm. Barplots show 8 selected significant GO terms with their respective -$\log_2$(p-

value). Tables S18-19 include the complete lists of significantly enriched GO terms.

Supplemental file 1. Interactive heatmap for significant gene ontology terms enriched in livers of F0 males fed a high-fat diet across genotype, related to Figure 3A

Supplemental file 2. Interactive heatmap for significant gene ontology terms enriched in differentially expressed genes in livers of F1 wildtype mice descendants of obese sires across sex, related to Figure 3B

Supplemental file 3. Interactive heatmap for significant gene ontology terms enriched in genotype-associated differentially expressed genes in livers of animals across generation, related to Figure 3C

Supplemental file 4. Interactive bar plot for the number of significantly enriched gene ontology terms in WT HFD vs TG HFD across generation and sex, related to Figure 3C

Supplemental file 5. Interactive heatmap for significant gene ontology terms enriched in at obesity-sensitive promoters in sperm and differentially expressed genes in livers of F1 males descendants of high-fat-fed sires, related to Supplemental Figure 7C

Table S1. Diets' macronutrients composition and energy density

Table S2. Number of animals used per group per sex per generation for metabolic characterization

1387   Table S3. Significant gene ontology terms enriched in differentially expressed genes in livers of

1388   F0 males fed a high-fat diet across genotype, related to Figure 3A

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1390   Table S4. Significant gene ontology terms enriched in differentially expressed genes in livers of

1391   F1 wildtype mice descendants of obese sires across sex, related to Figure 3B

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1393   Table S5. Significant gene ontology terms enriched in genotype-associated differentially

1394   expressed genes in livers of animals across generation, related to Figure 3C

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1396   Table S6. Sperm H3K4me3 ChIP-Sequencing read numbers and alignment rates

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1398   Table S7. Significant gene ontology terms enriched at promoters with H3K4me3 gain in sperm of

1399   WT HFD, related to Figure 4Ii

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1401   Table S8. Significant gene ontology terms enriched at promoters with H3K4me3 loss in sperm of

1402   WT HFD, related to Figure 4Iii

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1404   Table S9. Significant gene ontology terms enriched at promoters with H3K4me3 gain in sperm of

1405   TG HFD, related to Figure 4Iiii

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1407   Table S10. Significant gene ontology terms enriched at promoters with H3K4me3 loss in sperm

1408   of TG HFD, related to Figure 4Iiv

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1410   Table S11. Significant gene ontology terms enriched at promoters associated with a significant

1411   linear trend, related to Figure 5F

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1413   Table S12. Significant gene ontology terms enriched at obesity-sensitive promoters of genes

1414   expressed in the 4-cell embryo, related to Figure 6Ci

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1416   Table S13. Significant gene ontology terms enriched at obesity-sensitive promoters of genes

1417   expressed in the morula embryo, related to Figure 6Cii

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1419   Table S14. Significant gene ontology terms enriched at promoters with H3K4me3 enrichment in

1420   sperm, trophectoderm and placenta, related to Figure 7Bi

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1422   Table S15. Significant gene ontology terms enriched at promoters with H3K4me3 enrichment in

1423   sperm, related to Figure 7Bii

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1425   Table S16. Significant gene ontology terms enriched at obesity-sensitive promoters with

1426   H3K4me3 enrichment in sperm, trophectoderm and placenta, related to Figure 7Biii

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1428   Table S17. Significant gene ontology terms enriched at obesity-sensitive promoters with

1429   H3K4me3 enrichment in sperm, related to Figure 7Biv

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1431   Table S18. Significant gene ontology terms enriched at obesity-sensitive promoters of genes

1432   expressed in the trophectoderm, related to Figure 7Di

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1434   Table S19. Significant gene ontology terms enriched at obesity-sensitive promoters of genes

1435   expressed in the placenta, related to Figure 7Dii

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1437   Table S20. Significant gene ontology terms enriched in at obesity-sensitive promoters in sperm

1438   and differentially expressed genes in livers of F1 males descendants of high-fat-fed sires, related

1439   to Supplemental Figure 7C

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