Title: Fetal programming by the maternal microbiome of offspring behavior, and DNA methylation and
gene expression within the hippocampus

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The microorganisms colonizing the gastrointestinal tract of animals, collectively referred to as the gut

microbiome, affect numerous host behaviors dependent on the central nervous system (CNS). Studies

comparing germ-free mice to normally colonized mice have demonstrated influences of the

microbiome on anxiety-related behaviors, voluntary activity, and gene expression in the CNS.

Additionally, there is epidemiologic evidence supporting an intergenerational influence of the

maternal microbiome on neurodevelopment of offspring and behavior later in life. There is limited

experimental evidence however directly linking the maternal microbiome to long-term

neurodevelopmental outcomes, or knowledge regarding mechanisms responsible for such effects.

Here we show that that the maternal microbiome has a dominant influence on several offspring

phenotypes including anxiety-related behavior, voluntary activity, and body weight. Adverse

outcomes in offspring were associated with features of the maternal microbiome including bile salt

hydrolase gene expression (*bsh*), abundance of certain bile acids, and hepatic expression of *S1pr2*. In

cross-foster experiments, offspring resembled their birth dam phenotypically, despite faithful

colonization in the postnatal period with the surrogate dam microbiome. Genome-wide methylation

analysis of hippocampal DNA identified microbiome-associated differences in methylation of 196 loci

in total, 176 of which show conserved profiles between mother and offspring. Further, single-cell

transcriptional analysis revealed accompanying differences in expression of several differentially

methylated genes within certain hippocampal cell clusters, and vascular expression of genes

associated with bile acid transport. Inferred cell-to-cell communication in the hippocampus based on

coordinated ligand-receptor expression revealed differences in expression of neuropeptides

associated with satiety. Collectively, these data provide proof-of-principle that the maternal gut

microbiome has a dominant influence on the neurodevelopment underlying certain offspring

behaviors and activities, and selectively affects genome methylation and gene expression in the

offspring CNS in conjunction with that neurodevelopment.

Main

Anxiety disorders (AD) are increasing in prevalence, affecting close to 1 in 10 children and adolescents

between the ages of 3 and 17[1]. Like most mood disorders, AD are multifactorial and often result from a

combination of genetic, environmental, and experiential factors. Similarly, one in five children in the

U.S. are obese or overweight[2], reflecting the combined influence of western diet, increasingly sedentary

lifestyles, and other factors. Moreover, AD and obesity/overweight (OO) are reciprocal risk factors,

frequently occurring as co-morbidities[3-7]. A growing body of research has linked the gut microbiome

(GM) to neurodevelopment and behavior[8-13], and growth rate or weight gain[14-17]. Work with germ-free
mice shows the importance of the GM in normative behavior and metabolism[18-20], and transfer of an
anxiety-related phenotype or increased energy harvest via fecal microbiome transfer indicates that
certain features within naturally occurring microbiomes influence these phenotypes[21-23]. There are also
developmental components to both AD and OO, raising the question of how the maternal microbiome
during pregnancy affects fetal development and subsequent behavior and energy metabolism in the
adult offspring. The maternal gut microbiome during pregnancy produces metabolites which reach
peripheral circulation and the fetal CNS[24], and maternal proteins and peptides produced by
enteroendocrine cells in response to the microbiome likely also cross the placenta and reach fetal
circulation[25-27]. Disruption of the maternal GM can affect these processes as demonstrated by increased
anxiety in the offspring of mice with antibiotic- or diet-induced dysbiosis[28-31].

There are still major gaps in our knowledge however regarding the mechanisms through which the
maternal microbiome during pregnancy programs long-lasting changes in offspring behavior and
metabolism. These intergenerational effects suggest fetal programming by an unknown mechanism,
while differences in anxiety-related behavior (and other complex behaviors) indicate a
neurodevelopmental basis. Owing to the genetic, dietary, and environmental heterogeneity, analysis of
these processes in a human population requires impossibly large sample sizes and long-term tracking of
mother-child pairs. Here, we use two groups of genotype-, age-, and sex-matched outbred mice,
colonized with one of two naturally occurring microbiomes associated with differences in anxiety-
related behavior, voluntary activity, fetal growth, food intake, and adult growth. Cross-foster studies
demonstrate the dominant influence of the maternal microbiome on offspring phenotypes. Further
analysis of hippocampal DNA revealed selective effects of the maternal microbiome on CpG
methylation, maintained in offspring independent of the postnatal microbiome. Single-nuclei RNA
sequencing (snRNA-seq) of hippocampal RNA confirmed fetal programming of several cell-specific
differentially methylated genes, including genes involved in pathways that are orexigenic in nature and
important for cell-to-cell contact.

Complex microbiome-dependent behaviors determined by maternal microbiome
To identify the developmental period in which the microbiome exerts its effects, we used an
experimental design with four groups, comprising mice born to dams harboring GM^{Low} (originating from
the Jackson Laboratory, Bar Harbor, ME) or GM^{High} (originating from Envigo, Madison, WI) and remaining
with their birth dams until weaning (control), or cross-fostered at birth to nursing dams harboring the

reciprocal microbiome (**Fig. 1a**). These groups are denoted as CF^{Low} and CF^{High}, with the microbiome

designation indicating the postnatal offspring composition acquired via cross-foster (CF). Comparisons

were then made between the two control groups, and between the two CF groups, in behavior tests

associated with anxiety-related behavior and voluntary activity between five and seven weeks of age,

and body weight (BW) at three and seven weeks of age.

In agreement with previous studies, age-, sex-, and genotype-matched mice colonized with GM^{Low} spent

less time and traveled less distance in the light portion of a light-dark transition (LDT) test (**Fig. 1b,**

Extended Data Fig. 1a), and the open arms of an elevated plus maze (EPM) test (**Fig. 1c, Extended Data**

Fig. 1b), relative to mice colonized with GM^{High}, indicating differential effects on anxiety-related behavior

of the two microbiomes. No behavioral differences were observed in the open-field exploration test

between GM^{Low} and GM^{High} mice (**Extended Data Fig. 1c-d**). To assess voluntary activity, mice were singly

housed with bluetooth wireless running wheels for a five-day acclimation period followed by seven-day

test period. Both male (**Fig. 1d**) and female (**Fig. 1e**) mice colonized with GM^{High} ran significantly more

than mice with GM^{Low} ($p < 0.0001$, F = 29.2, and $p = 0.0002$, F = 14.4, respectively). Previously reported

differences in body weight (BW) at weaning (**Extended Data Fig 1e**) and adulthood (**Fig. 1f**, $p < 0.0001$, F

= 24.7) were also reproducible. Collectively, these data confirmed microbiome-associated differences in

anxiety-related behavior, voluntary activity, and body weight, in sex-, age-, and genotype-matched

mice.

The GM-associated differences in the LDT, independent of sex, were reversed in the comparison

between CF^{Low} and CF^{High} mice, with the latter demonstrating behavior suggestive of greater anxiety (**Fig.**

1g, Extended Data Fig. 1f). Similarly, the robust GM-dependent differences in the EPM were abrogated

in the CF^{Low} and CF^{High} mice (**Fig. 1h, Extended Data Fig. 1g**) indicating that the maternal microbiome has a

substantial, if not dominant, influence on neurodevelopmental events contributing to anxiety-related

behavior in the offspring. While a significant difference of total distance traveled in the OFE test was

observed, distance traveled in the center was not found to be significant in the cross-foster groups

(**Extended Data Fig 1. h-i**). The significant GM-associated differences in voluntary activity were absent in

male and female CF mice (**Fig. 1i-j**). Comparison of BW revealed no difference at weaning (**Extended**

Data Fig. 1j) and reversal in adulthood (**Fig. 1k**), such that CF^{High} mice weighed more than age-matched

CF^{Low} mice. These findings suggest that the neurodevelopmental processes contributing to the

microbiome-associated difference in BW and voluntary activity are also subject to some degree of

influence on fetal development, presumably via the maternal microbiome. Moreover, they raise the

possibility of a connection between the anxiety-related behaviors and the behaviors underlying the

difference in BW and voluntary activity, representing a constellation of behavioral phenotypes

influenced by features within the microbiome. Bacterial 16S rRNA amplicon sequencing was used to

confirm that CF mice harbored a microbiome of comparable richness and beta-diversity to that present

in surrogate dams, in both directions of transfer (**Extended Data Fig. 2a-c**).

Taxonomic differences are associated with different levels of biologically relevant metabolites

Compositional differences between GM^{Low} and GM^{High} have been described previously[32-34], including

greater richness in GM^{High} compared to GM^{Low} (**Fig. 2a**). Families enriched in GM^{Low} included

Erysipelatoclostridiaceae, Erysipelotrichaceae, Sutterellaceae, Saccharimonadaceae, Acholeplasma-

taceae, and unresolved members of orders *Tissierellales* and RF39; while families enriched in GM^{High}

included *Prevotellaceae, Marinifilaceae, Clostridiaceae, Desulfovibrionaceae, Deferribacteraceae*, and an

unresolved family within the order *Rhodospirillales* (**Supplementary Table 1**). We next asked the

question of whether differences in the GMs are also associated with distinct metabolite profiles. To this

end, fecal samples were collected from both male and female GM^{Low} and GM^{High} mice, and a

combination of mass spectrometry (MS)-based platforms were used to measure short-chain fatty acids;

branched chain fatty acids, branched chain keto-acids, and other lipids; unconjugated primary and

secondary bile acids (BAs); all proteinogenic amino acids and several nonproteinogenic and acetylated

amino acids; tryptophan derivatives including kynurenine, serotonin, and several indoles; B vitamins;

dicarboxylic acids; glucose, fructose, and other compounds in glycolysis; all ribonucleosides and

nitrogenous bases; compounds within the pentose phosphate pathway; compounds within the classic

TCA cycle; and other biologically relevant microbial metabolites (Full list of metabolites **Supplementary**

Table 2, Supplementary Table 3). GM^{Low} and GM^{High} showed differences in sugar molecules involved in

metabolism, multiple amino acids, and bile acids (**Fig. 2b**) (**Supplementary Table 2**). Interestingly, BAs

were among the metabolites enriched in the feces of mice harboring GM^{High}. These patterns were

apparent in the feces of male mice (**Extended Data Fig. 3a**), while female mice showed a single BA

(lithocholic acid) enriched in the feces of GM^{Low} (**Extended Data Fig. 3b**). We next asked whether

differences in the fecal metabolites would translate to differences in metabolites entering vascular

circulation. Serum, concurrently collected at the time of fecal collection, was subjected to MS.

Remarkably, the only significant difference in the metabolite profiles of the serum, was a BA (**Fig.**

2c)(**Supplemental Table 3**). There were also several BAs, both primary and secondary, that did not reach

statistical significance but had high levels within the serum of individual GM^{Low} mice. This pattern was

evident in the serum of female, but not male mice (**Extended Data Fig. 3c-d**). To examine whether this

difference in bile acids may have a physiological affect, we performed quantitative RT-PCR with mRNA

from both ileal and hepatic tissue for genes known to be involved in BA cellular transport. *Asbt*, a gene

involved in transporting BAs from the ileal lumen into the ileal epithelium showed no difference in

expression (**Fig. 2d**). Expression of *Ost-ß*, a gene involved in transport of BAs from the ileal epithelium

into peripheral circulation, was increased in GM^{High} mice (**Fig. 2e**). *Gpbar1*, a G protein-coupled BA

receptor, was found to have increased expression in the ileum of GM^{Low} mice (**Fig. 2f**). In contrast, the

nuclear BA receptor *Fxr*, involved in regulation of bile acid production, showed no difference in ileal

expression (**Fig. 2g**). Accordingly, *Cyp7a1*, a gene downstream of *Fxr* that encodes the rate-limiting step

in bile acid synthesis, showed no difference in hepatic expression (**Fig. 2h**). Of note, expression of the

vascular BA transporter *Slc10a1* was increased in the liver of GM^{Low} mice (**Fig. 2i**) as was *S1pr2*, a non-

canonical G protein-coupled BA receptor (**Fig 2j**).

We examined whether bile salt hydrolase (BSH), the enzyme bacteria use to deconjugate bile acids, was

transcriptionally of functionally different between the GMs of female mice. While total gene read count

did not differ (**Extended Data Fig. 3e**), expression of *bsh* was significantly higher in GM^{Low} (**Extended**

Data Fig. 3f). The BSH family of enzymes is widely expressed among gut bacteria, and prone to

significant variations in structure with some isoforms exhibiting different deconjugation activity toward

various bile acids and possessing various levels of enzymatic activities[35, 36]. Thus, we compared BSH

enzymatic activities of both microbiomes toward various bile acids. Our results demonstrated

significantly greater BSH activity specific for cholic acid in GM^{Low}, but no other differences were detected

in BSH activities towards other BAs examined (**Extended Data Fig. 3g-k**). Collectively, these data indicate

that there are numerous differentially abundant GM associated serum metabolites including several BA

species accompanied by differences in ileal and hepatic expression of genes encoding bile acid

transporters and receptors.

Fetal programming of gene methylation in hippocampus by the maternal microbiome

Reasoning that an influence on offspring behavior by the maternal microbiome must have a biological

foundation in the CNS and a mechanism by which cellular function and gene expression are established

during fetal development, we next examined gene expression and its epigenetic regulation in offspring

hippocampus, given its central role in anxiety-related behavior[37-42]. To identify effects of the maternal

microbiome on fetal programming of DNA methylation in the hippocampus, we performed genome-

wide DNA methylation profiling in female mice.

Analysis of methylation across the entire array, and parallel comparisons between samples from GM^{Low}

or GM^{High} mice, and from CF^{Low} or CF^{High} mice, identified only 196 differentially methylated markers

(DMRs) with beta values differing by $\log_2FC > 1$ (**Supplementary Table 4**). Remarkably, 176 of those 196

sites (89.8%) showed a difference in methylation at the same site in the reciprocal contrast, such that

offspring methylation matched that of their birth dam (**Fig. 3a, R^2 = -0.644, p = 2 × 10^{-7}**). DMRs identified

in offspring hippocampi were distributed across the genome, occurring most often early in gene bodies

or enhancer/promoter regions and roughly correlating in frequency to chromosomal gene content, with

the exception of an apparent enrichment for DMRs on chromosome 14 (**Fig. 3b, p = 0.003**). Differential

methylation was detected at five contiguous markers mapped to promoters, enhancers, and exon 1 of

the *Pde1c* gene, encoding phosphodiesterase 1c, a regulator of Ca^{2+} and cGMP-dependent intracellular

signaling. This methylation pattern differed between hippocampus from GM^{Low} and GM^{High} mice, and was

conserved between birth dam and offspring, regardless of postnatal colonization (**Fig. 3c**). Similarly,

microbiome-associated differences in methylation were identified at multiple closely spaced markers on

both strands of chromosome 14, including markers associated with the genes *Ang5* and *Ang6* (**Fig. 3d**),

encoding members 5 and 6, respectively, of the angiogenin, ribonuclease A family.

To identify shared pathways or commonalities among the functional products (i.e., proteins) encoded by

protein-coding genes among the DMRs, a STRING analysis was performed using a final input of 144 gene

names. Interaction analysis resulted in assembly of one large network with 32 nodes, a smaller network

with six nodes, and four dyads (**Fig. 3e**). While enrichment analysis failed to detect greater network

connectivity than would occur at random, stratified analysis of the 32 nodes in the large network

revealed 10 significantly enriched Gene Ontology (GO) Biological Processes; five GO Molecular Functions

including TGF-β receptor binding (GO:0005160, strength 1.94, FDR-adjusted p = 0.015) and GTPase

activity (GO:0003924, strength = 1.09, FDR-adjusted p = 0.042); five KEGG pathways including Gap

junction (mmu04540, strength = 1.38, FDR-adjusted p = 0.033) and TGF-β signaling pathway

(mmu04350, strength = 1.32, FDR-adjusted p = 0.033); and four Reactome pathways including axon

guidance (MMU-422475, strength = 1.08, FDR-adjusted p = 0.048). Collectively, these data provide

evidence suggesting the inheritance of maternal DNA methylation profiles in the fetal hippocampus, in

association with differences in the maternal microbiome. The distribution and relationship of genes

affected by differential methylation reflects a semi-stochastic effect across the fetal genome, with

modest enrichment for genes with broad associations such as TGF-β signaling, GTPase activity, and axon

guidance.

Fetal programming of gene expression in hippocampus by maternal microbiome

We next performed single nuclei RNAseq on hippocampus collected from control mice and cross-fostered mice. Based on expression of cell-specific markers, 11 cell clusters were identified in the control mice and 24 cell clusters were identified in the cross-fostered mice (**Extended Data Figure 4a-b**). Based on generalized additive regression models, control mice from GM^{Low} and GM^{High} gene expression were compared, and differentially expressed genes (DEGs) within each treatment group were identified (**Supplementary Table 5**). Similarly, mice from CF^{Low} and CF^{High} were examined for DEGs within each cell cluster (**Supplementary Table 6**). After DEGs from each cell cluster had been determined using $Log_2FC >$ 1.5, STRING analysis was used to determine the protein-protein interactions of the DEGs from each treatment. The number of DEGs from each cell cluster were compared to the mean node degree received from the STRING analysis to determine which cell clusters contained a high number of DEGs that were most likely to interact within protein pathways. Interestingly the cell cluster with the highest number of DEGs, as well as the highest number of mean node degree of protein-protein interactions in both control and cross-foster mice, was identified as endothelial cells (**Extended Data Figure 5a-b**). We then performed STRING analysis to generate interaction networks using DEGs identified in the endothelial cells of control mice as well as the cross-fostered mice (**Fig. 4a-b**). Of these interactions, six DEGs (*Fas, Fzd6, Gja1, Ntng1, Pik3r3, Sox17*) showed a pattern of fetal programming. Of note, numerous DEGs identified were also found among differentially methylated genes or closely related to differentially methylated genes (**Fig. 4b**). When astrocyte and L5 IT glutamatergic neurons were examined using interaction networks, they also contained multiple DEGs that showed a pattern of fetal programming as well as DEGs that were identified as differentially methylated (**Extended Fig. 6a-b, and Extended Data Fig. 7a-b**). When we examined the Log_2FC of *Dock1* expression of CF^{Low} and CF^{High}, *Dock1* was shown to be upregulated in the clusters of endothelial cells, oligodendrocyte, microglial cells, and subsets of astrocytes and glutamatergic neurons of CF^{High} mice compared with CF^{Low} (**Fig. 4c**). Similarly, when we examined expression of *Pde1c*, it too was increased in the endothelial cell cluster of CF^{High} mice, though not consistent with the expression patterns of other cells seen with *Dock1* (**Fig. 4d**). We next used CellChat software to examine the cell-cell communication interactions of all DEGs identified in the control groups, and then in the cross-foster groups to identify cell signaling pathways that show a pattern of fetal programming. There were 42 cell-cell communication pathways that were shared between the control mice and the cross-foster mice (**Fig. 4e**). Of the 42 pathways identified, 15 showed a pattern of fetal programming including *Vegf, Igf, Il2, Tgfβ, Wnt*, and *Npy* (**Fig. 4f-g**). Interestingly, three cell-cell communication pathways that were identified in only GM^{Low} and CF^{High} were appetite-stimulating

orexigenic neuropeptide pathways, giving a possible reason for the increased weight noted in these two
groups. These findings highlight cell type-specific differences in hippocampal gene expression in genes
identified within DMRs and genes in pathways associated with growth and feeding behavior. In total, the
findings presented here demonstrate differentially abundant features within a healthy GM influence
behavior, DNA methylation, and gene expression within the central nervous system, and strongly suggest
a relationship between these events during fetal development.
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Methods
Mice
All activities described here were performed in accordance with the guidelines put forth in the Guide for
the Care and Use of Laboratory Animals and were approved by the Institutional Animal Care and Use
Committee (IACUC) of the University of Missouri, an AAALAC accredited institution. All mice tested in the
current study were outbred CD1 mice generated from breeders colonized with GM^{Low} or GM^{High},
originally obtained from the Mutant Mouse Resource and Research Center at the University of Missouri
(MU MMRRC). Colonies of mice were housed under barrier conditions in microisolator cages with
compressed pelleted paper bedding and nestlets, on ventilated racks with *ad libitum* access to irradiated
chow and acidified, autoclaved water, under a 14:10 light/dark cycle. Mice were determined to be free
of all bacterial pathogens including *Bordetella bronchiseptica*, *Filobacterium rodentium*, *Citrobacter*
rodentium, *Clostridium piliforme*, *Corynebacterium bovis*, *Corynebacterium kutscheri*, *Helicobacter* spp.,
Mycoplasma spp., *Rodentibacter* spp., *Pneumocystis carinii*, *Salmonella* spp., *Streptobacillus*
moniliformis, *Streptococcus pneumoniae*; adventitious viruses including H1, Hantaan, KRV, LCMV, MAD1,
MNV, PVM, RCV/SDAV, REO3, RMV, RPV, RTV, and Sendai viruses; intestinal protozoa including
Spironucleus muris, *Giardia muris*, *Entamoeba muris,* trichomonads, and other intestinal flagellates and
amoebae; intestinal parasites including pinworms and tapeworms; and external parasites including all
species of lice and mites, via quarterly sentinel testing performed by IDEXX BioAnalytics (Columbia, MO).
Fecal samples were collected from pregnant dams at 19 days of gestation, and from mouse pups at time
of weaning (21 days of age) using previously described methods[43]. Briefly, mice were placed in an empty
autoclaved cage within abiological safety cabinet and allowed to defecate. Freshly evacuated samples
feces were immediately collected into a sterile collection tube using autoclaved wooden toothpicks
discarded after each single usage. All samples were promptly placed on ice. Following fecal sample
collection, samples were stored in a -80°C freezer until DNA extraction was performed. Samples were
collected from all experimental mice at 50 days of age, at time of necropsy.

Cross-Foster

Mice in cross-foster groups were cross-fostered at less than 24 hours of age to a surrogate dam of the reciprocal GM. Following identification of recently birthed litters from both GMs, cages were moved to a biosafety cabinet. Litters were removed from the cage of the biological dam and placed onto clean paper towels. Bedding from the cage of the surrogate dam was gently mixed with the pups to transfer the surrogate dam's scent to the pups and reduce the possibility of cannibalism. The pups were then placed into the surrogate dam cage, and cages were returned to the appropriate housing rack.

Behavior testing

Open Field Exploration. The open field exploration test was used to evaluate anxiety-related behavior and locomotor function. Environmental control chambers (Omnitech Electronics, Inc., Columbus, OH) consisting of 4 separate environmental isolation chambers containing a plexiglass box (41cm × 41cm × 30cm) placed onto an infrared grid (41cm × 41cm) to track locomotion. Lighting for each isolation chamber was set to 159 lux. Mice were allowed to acclimate to the behavior room for 1 hour prior to testing. Before starting each test, the plexiglass was cleaned with 0.25% bleach, followed by 70% ethanol to remove any residual olfactory cues. Each mouse was placed into the middle of the open field exploration test and recorded for 30 minutes by the Fusion behavior monitoring software (Omnitech Electronics, Inc., Columbus, OH). The first 20 minutes of the test were considered acclimation time, and the final 10 minutes were analyzed following completion of the test. Total distance traveled (cm), time spent in the center zone (seconds), distance traveled in the center zone, and vertical activity (rearing) were measured.

Light/Dark Transition. The light/dark transition test was performed within the environmental control chambers (Omnitech Electronics, Inc., Columbus, OH, USA). The apparatus consisted of a plexiglass box within the environmental chambers (41cm × 41cm × 30cm) that were partitioned into two equal sections by a black plexiglass insert with a door that allowed one half to be a dark zone, and a second half to be a light zone. The light zone was illumination was set to 200 lux. Mice were allowed to acclimate to the behavior room for 1 hour prior to testing. Before the start of each test, the plexiglass box and insert were cleaned with 0.25% bleach, followed by 70% ethanol to remove any residual olfactory cues. Mice were placed into the light zone facing away from the dark zone and monitored by Fusion behavior monitoring software (Omnitech Electronics, Inc., Columbus, OH, USA) for 15 minutes. Time spent in the light zone

(sec), distance travelled in the light zone (cm), and number of transitions between light and dark zones

were measured.

Elevated Plus Maze. The elevated plus maze test consisted of an apparatus with two open arms (32.5 × 5

cm, with 2-mm ledges) and two closed arms (32.5 × 5 cm, with 14.5 cm high walls). The open arms were

arranged perpendicular to the closed arms so the apparatus formed the shape of a plus sign with a

center square (5 × 5 cm). The entire apparatus was raised 50 cm above the floor. The center zone of the

apparatus was illuminated to 50 lux. Mice were allowed to acclimate to the behavior room for 1 hour

prior to testing. Prior to testing, the apparatus was cleaned with 0.25% bleach followed by 70% ethanol

to remove olfactory cues. Each mouse was placed in the center square facing an open arm and was

recorded and monitored for 5 minutes. Distance Traveled in the open arms (cm), time spent in the open

arms (sec), and number of entries into the open arms was calculated from distance measurements and

entry counts obtained by Any-Maze monitoring software (Stoelting Co., Wood Dale, IL, USA).

Voluntary running. Litters for running wheel experiments were culled to six pups per litter (3 male, 3

female) at birth, and then weaned into same-sex trios at weaning. During wheel set-up at seven weeks

of age, mice were transferred from their home cage to a new static microisolator cage containing a

wireless running wheel (Med Associates, ENV-047) connected to a wireless hub and laptop computer in

the animal room. Mice were singly housed during the experiment, assigned to running wheel cages using

a random number generator, and were placed in alternating order on the shelf such that microbiome

group and sex were consistently alternated. Following five days of acclimation, data were collected

continuously for seven consecutive days using Wheel Manager software, v2.04.00 (Med Associates, SOF-

860). Data were analyzed using Wheel Analysis software, v2.02.01 (Med Associates, SOF-861). No other

mice were housed in the room containing running wheels, traffic was limited to daily checks by

laboratory staff, and no cage changes were performed during the acclimation and test period.

Necropsy

Mice were transported to the necropsy room at 50 days of age, and allowed to acclimate to the room for

1 hour. Mice were then euthanized one at a time by CO_2 asphyxiation out of sight of other mice. The

euthanasia chamber was cleaned with 70% ethanol between mice to eliminate olfactory cues. Following

loss of paw pinch and righting reflexes, blood was collected by cardiac puncture and placed into serum

separator tubes. The brain was then removed, and the hippocampus was gently dissected out, placed in

a 2 mL tube, and promptly plunged into liquid nitrogen to flash freeze. Liver and ileum were isolated,

placed in a 2mL tube, and promptly plunged into liquid nitrogen. Two fecal pellets collected from the

colon for 16S rRNA gene analysis. Blood was allowed to clot for 30 minutes at room temperature, and

was then centrifuged at 4,000 RPM for 15 minutes, and serum placed into a 1.5 mL microcentrifuge

tube. Hippocampus, feces, and serum were promptly placed into -80°C freezer for storage.

Metabolite analyses

GC-MS. Fecal and plasma samples were diluted in 18 volumes of ice-cold 2:2:1

methanol/acetonitrile/water containing a mixture of internal standards (D4-citric acid, D4-succinic acid,

D8-valine, and U13C-labeled glutamine, glutamic acid, lysine, methionine, serine, and tryptophan;

Cambridge Isotope Laboratories), where the 1-part water was composed of sample volume + water.

Sample extraction mixtures were vortexed for 10 minutes at RT and rotated for 1 hour at -20°C.

Mixtures were centrifuged for 10 minutes at 21,000 × g, and 150 µL of the cleared metabolite extracts

were transferred to autosampler vials and dried using a SpeedVac vacuum concentrator (Thermo). Dried

metabolite extracts were reconstituted in 30 µL of 11.4 mg/mL methoxyamine (MOX) in anhydrous

pyridine, vortexed for 5 minutes, and heated for 1 hour at 60°C. Next, to each sample 20 µL of N,O-

Bis(trimethylsilyl)trifluoroacetamide (TMS) was added, samples were vortexed for 1 minute, and heated

for 30 minutes at 60°C. Derivatized samples were analyzed by GC-MS. One µL of derivatized sample was

injected into a Trace 1300 GC (Thermo) fitted with a TraceGold TG-5SilMS column (Thermo) operating

under the following conditions: split ratio = 20:1, split flow = 24 µL/minute, purge flow = 5 mL/minute,

carrier mode = Constant Flow, and carrier flow rate = 1.2 mL/minute. The GC oven temperature gradient

was as follows: 80°C for 3 minutes, increasing at a rate of 20°C/minute to 280°C, and holding at a

temperature at 280°C for 8 minutes. Ion detection was performed by an ISQ 7000 mass spectrometer

(Thermo) operated from 3.90 to 21.00 minutes in EI mode (-70eV) using select ion monitoring (SIM).

LC-MS SCFA analysis. 18-fold (w/v) extraction solvent (Acetonitrile:Methanol:Water (2:2:1)) containing

deuterated SCFA standards (D3-acetate, D7-butyrate, and D5-propionate) was added to each sample

and rotated at -20°C for 1 hr and then centrifuged at 21,000 × g for 10 min. Supernatant was used for

LC-MS SCFA analysis. LC-MS data was acquired on a Thermo Q Exactive hybrid quadrupole Orbitrap mass

spectrometer with a Vanquish Flex UHPLC system or Vanquish Horizon UHPLC system. The LC column

used was a ZIC-pHILIC guard column (20 × 2.1 mm). The injection volume was 2 µL. For the Mobile

phase, Solvent A consisted of 20 mM ammonium carbonate [(NH4)2CO3] and 0.1% ammonium

hydroxide (v/v) [NH4OH] at pH ~9.1] and Solvent B consisted of Acetonitrile. This method was run at a

flow rate of 0.1 mL/min, and the injection volume was 2 µL. Linear gradient was used at 70% solvent B

with a 5 min elution time. The mass spectrometer was operated in targeted selected ion-monitoring

(tSIM) mode from 1 to 5 minutes. An inclusion list for the three short chain fatty acids and their

deuterated versions were used in tSIM method.

LC-MS bile acid analysis. Extraction solvent (methanol:acetonitrile:water, 2:2:1) was spiked with (5

µLI/mL) deuterated bile acids MaxSpec Mixture (Cayman Chemicals Item no. 33506). 18-fold volume

extraction buffer was added to each sample. The samples were placed in a -20°C freezer for 1 hour while

rotating. The samples were then centrifuged at 21,000 × g for 10 minutes. Supernatant was transferred

to LC-MS autosampler vials for analysis. LC-MS data was acquired on a Thermo Q Exactive hybrid

quadrupole Orbitrap mass spectrometer with a Vanquish Flex UHPLC system or Vanquish Horizon UHPLC

system. A Thermo Hypersil GOLD (2.1 × 150 mm, 1.9 µm) UHPLC column was used with a column

Temperature of 30°C. For the Mobile Phase, solvent A consisted of 1% acetonitrile in water with 0.1%

formic acid, and solvent B is 99% acetonitrile with 0.1% formic acid. The gradient started at 50% Solvent

B and was held for 2.5 minutes; then increased to 100% B at 10 minutes and held for 0.5 minutes before

re-equilibration to 50% solvent B for 5.5 min. Flow Rate was 0.4 mL/min, and injection volume was 3 µL.

The mass spectrometer was operated in full-scan negative mode, with the spray voltage set to 3.0 kV,

the heated capillary held at 275°C, and the HESI probe held at 350°C. The sheath gas flow was set to 40

units, the auxiliary gas flow was set to 15 units, and the sweep gas flow was set to 1 unit. MS data

acquisition was performed in a range of m/z 70–1,000, with the resolution set at 70,000, the AGC target

at 1 × 106, and the maximum injection time at 200 ms.[44].

Metabolomic Data Analysis. GC-MS Raw data were analyzed using TraceFinder 5.1 (Thermo). Metabolite

identification and annotation required at least two ions (target + confirming) and a unique retention

time that corresponded to the ions and retention time of a reference standard previously determined

in-house. A pooled-sample generated prior to derivatization was analyzed at the beginning, at a set

interval during, and the end the analytical run to correct peak intensities using the NOREVA tool[45].

NOREVA corrected data were then normalized to the total signal per sample to control for extraction,

derivatization, and/or loading effects. Acquired LC-MS data were processed by Thermo Scientific

TraceFinder 4.1 software, and metabolites were identified based on the University of Iowa

Metabolomics Core facility standard-confirmed, inhouse library. NOREVA was used for signal drift

correction[45]. For bile acids, data were normalized to one of the d4-bile acid standards. For SCFA, analyte

signal was corrected by normalizing to the deuterated analyte signal and the signal obtained from

processing blank was subtracted.

Microbiome analysis

DNA extraction. Fecal DNA was extracted using QIAamp PowerFecal Pro DNA kits (Qiagen), according to the manufacturer's instructions, with the exception that the initial sample disaggregation was performed using a TissueLyser II (Qiagen), rather than a vortex and adaptor as described in the protocol.

16S rRNA amplicon library preparation and sequencing. Extracted fecal DNA was processed at the University of Missouri DNA Core Facility. Bacterial 16S rRNA amplicons were constructed via amplification of the V4 region of the 16S rRNA gene using previously developed universal primers (U515F/806R), flanked by Illumina standard adapter sequences[46, 47]. Oligonucleotide sequences are available at proBase[48]. Dual-indexed forward and reverse primers were used in all reactions. PCR was performed in 50 μL reactions containing 100 ng metagenomic DNA, primers (0.2 μM each), dNTPs (200 μM each), and Phusion high-fidelity DNA polymerase (1U, Thermo Fisher). Amplification parameters were $98°C^{(3\ min)}$ + [$98°C^{(15\ sec)}$ + $50°C^{(30\ sec)}$ + $72°C^{(30\ sec)}$] × 25 cycles + $72°C^{(7\ min)}$. Amplicon pools (5 μL/reaction) were combined, thoroughly mixed, and then purified by addition of Axygen Axyprep MagPCR clean-up beads to an equal volume of 50 μL of amplicons and incubated for 15 minutes at room temperature. Products were washed multiple times with 80% ethanol and the dried pellet was resuspended in 32.5 μL EB buffer (Qiagen), incubated for two minutes at room temperature, and then placed on a magnetic stand for five minutes. The final amplicon pool was evaluated using the Advanced Analytical Fragment Analyzer automated electrophoresis system, quantified using quant-iT HS dsDNA reagent kits, and diluted according to Illumina's standard protocol for sequencing on the MiSeq instrument.

Bioinformatics. DNA sequences were assembled and annotated at the MU Informatics Research Core Facility. Primers were designed to match the 5' ends of the forward and reverse reads. Cutadapt[49] (version 2.6) was used to remove the primer from the 5' end of the forward read. If found, the reverse complement of the primer to the reverse read was then removed from the forward read as were all bases downstream. Thus, a forward read could be trimmed at both ends if the insert was shorter than the amplicon length. The same approach was used on the reverse read, but with the primers in the opposite roles. Read pairs were rejected if one read or the other did not match a 5' primer, and an error-rate of 0.1 was allowed. Two passes were made over each read to ensure removal of the second primer. A minimal overlap of three bp with the 3' end of the primer sequence was required for removal. The QIIME2[50] DADA2[51] plugin (version 1.10.0) was used to denoise, de-replicate, and count ASVs (amplicon sequence variants), incorporating the following parameters: 1) forward and reverse reads were

truncated to 150 bases, 2) forward and reverse reads with number of expected errors higher than 2.0

were discarded, and 3) Chimeras were detected using the "consensus" method and removed. R version

3.5.1 and Biom version 2.1.7 were used in QIIME2. Taxonomies were assigned to final sequences using

the Silva.v132[52] database, using the classify-sklearn procedure.

Real-time reverse transcription-polymerase chain reaction (qRT-PCR)

Total RNA was isolated from tissues using the Qiagen RNeasy Mini Kit per manufacturer's instructions.

RT-PCR was performed using the BioRad iTaq Universal SYBR Green One-Step Kit following the

manufacturers instructions. Briefly, each reaction consisted of 5μL of SYBR Green Supermix, 0.125μL

iScript reverse transcriptase, 0.45μL of forward and reverse primers, 1.475μL of water, and 2.5μL of

template RNA. The reaction was run on a BioRad C1000 Touch thermal cycler with a BioRad CFX384 Real-

Time System with the following parameters: 50˚C for 10 min for reverse transcription, 95˚C for 1 min for

DNA Polymerase activation and DNA denaturation, and 40 cycles of 95˚C for 10 sec and 60˚C for 30 sec.

Melt-curve analysis was performed using the following parameters: 65-95˚C with 0.5˚C increments for 5

sec/step. Primers used can be found in **Supplementary Table 7**.

Bile salt hydrolase metagenomic and metatranscriptomic analysis of mouse feces

Metagenomic and metatranscriptomic *bsh* (K01442) read counts were acquired from previous multi-

omic analysis of GM^{Low} (GM1) and GM^{High} (GM4)[53]. Expression counts from metatranscriptomic analysis

were normalized to *bsh* metagenomic reads.

Measurement of BSH activity in mouse feces

BSH activity in the mouse feces was measured using previously reported bioluminescent bile acid

activatable luciferin probes (BAL) protocol[54] with major modification by replacing whole-cell

bioluminescence readout with the recombinant luciferase enzymatic assay[55]. Mouse fecal samples were

soaked in PBS (pH 7.4, Gibco, ref# 10010-023) supplemented with 2-mercaptoethanol (Acros Organics,

20 mM) at a concentration of 10 mg/mL on ice for 30 min. The mixtures were homogenized by

sonication in ultrasound cleaner (Elmasonic Easy 40 H, 340 W) at 0°C for 30 min, stirring every 10 min.

Resulting mixtures along with blank buffer (3 replicates by 50 μL) were mixed with working solutions of

BAL probes (50 μL, 20 μM in PBS) along with a solution of luciferin (50 μL, 2 μM in PBS) in a 96-well assay

plate (Corning, ref# 3595) and incubated at 37°C for 1 h. After incubation, the mixtures were diluted with

2% Triton X-100 in PBS (100 μL) to stop the reaction. In a separate 96-well flat bottom black plate

(Corning, ref# 3650), resulting mixtures (5 µL) were diluted with PBS (50 µ). A luciferase solution

containing recombinant luciferase from Photinus pyralis (Sigma-Aldrich, 20 µg/mL), ATP disodium

trihydrate (Fisher Scientific, 2 mM), and magnesium sulfate heptahydrate (Fisher Scientific, 2 mM) in PBS

(50 µL) was added to each well simultaneously. Bioluminescence was measured immediately in an IVIS

Spectrum (Xenogen) imaging system for 20 min with 1 min intervals using automatic settings. Raw data

were processed using Living Image 4.2 software (Caliper LifeSciences), further data processing was

carried out in Excel (Microsoft 365), and finally visualization and statistical calculations were performed

in Prism 9 (GraphPad software). Deconjugation potentials or percentage of probe hydrolysis were

calculated as the ratio of the signal from the BAL probe to the signal from luciferin in the corresponding

fecal extract and reported as the mean value of 3 replicates. The signals from incubation of BAL probes in

blank buffer provided a background result of nonspecific hydrolysis of the probes.

Isolation of hippocampal nuclei

Single nuclei were isolated from mouse hippocampal tissue samples as follows. Briefly, Nuclei Lysis

Buffer was prepared by adding 12 mL of Nuclei EZ Prep Lysis Buffer (Sigma-Aldrich, St. Louis, MO, USA) to

a 15mL tube and adding 1 cOmplete Ultra tablet (Sigma-Aldrich, St. Louis, MO, USA) and allowing tablet

to dissolve. Two 4-mL aliquots of the Nuclei EZ Prep Lysis Buffer + cOmplete Ultra tablets were then

placed in 15 mL tubes. Twenty (20) µL of Protector RNase inhibitor (Sigma-Aldrich, St. Louis, MO, USA)

and 20uL of Superase-In (MilliporeSigma, Burlington, MA, USA) were added to one 4 mL aliquot to make

Nuclei Lysis Buffer 1 (NLB1). Four (4) µL of Protector RNase inhibitor (Sigma-Aldrich, St. Louis, MO, USA)

and 4 µL of Superase-In (MilliporeSigma, Burlington, MA, USA) were added to the second -mL aliquot to

make Nuclei Lysis Buffer 2 (NLB2). Suspension Buffer (SB) was prepared by adding 1 mL of fetal bovine

serum (Sigma-Aldrich, St. Lous, MO, USA) to 9 mL of 1× phosphate-buffered saline with 4 µL of Protector

RNase inhibitor (Sigma-Aldrich, St. Louis, MO, USA). Eight (8) hippocampi halves from eight individual

mice were pooled and homogenized to a single cell suspension in a 2 mL dounce homogenizer with 2 mL

of NBL1. The sample was then strained through a 200 µm strainer (pluriSelect Life Science, El Cajon, CA,

USA) and the strained cell suspension returned to the 2 mL dounce and homogenized to a nuclei

suspension. The nuclei were strained through a 40 µm strainer (pluriSelect Life Science, El Cajon, CA,

USA) and centrifuged at 500 RCF at 4°C for 5 minutes. Supernatant was removed, and pellet was

resuspended with NLB2 and incubated at 4°C for 5 minutes. Nuclei were then centrifuged at 500 RCF at

4°C for 5 minutes, supernatant was removed, and nuclei were resuspended in suspension buffer.

10x Genomics single cell 3' RNA-Seq library preparation

Libraries were constructed by following the manufacturer's protocol with reagents supplied in 10x Genomics Chromium Next GEM Single Cell 3 Kit v3.1. Briefly, nuclei suspension concentration was measured with an Invitrogen Countess II automated cell counter. Nuclei suspension (1,200 nuclei per microliter), reverse transcription master mix, and partitioning oil were loaded on a Chromium Next GEM G chip with a nuclei capture target of 8,000 nuclei per library. Post-Chromium controller GEMs were transferred to a PCR strip tube and reverse transcription performed on an Applied Biosystems Veriti thermal cycler at 53°C for 45 minutes. cDNA was amplified for 13 cycles and purified using Axygen AxyPrep MagPCR Clean-up beads. Fragmentation of cDNA, end-repair, A-tailing and ligation of sequencing adaptors was performed according to manufacturer specifications. The final library was quantified with the Qubit HS DNA kit and the fragment size determined using an Agilent Fragment Analyzer system. Libraries were pooled and sequenced on an Illumina NovaSeq 6000 to generate 50,000 reads per nuclei.

Single cell bioinformatics

FASTQ files were generated from the raw base call outputs using Cell Ranger (10X Genomics) pipeline, *mkfastq* v3.0. Using default parameters, a UMI (gene-barcode) count matrix per sample was obtained using the built-in Cell Ranger count pipeline. To reduce noise, we only kept genes that were detected in at least three barcodes, and subsequently removed ribosomal-encoded genes from the count matrix. Scrublet[56] was then used to identify potential multiplet-barcodes and only those with a doublet score of less than 0.15 were used for downstream analyses. The files were then combined in a single embedding for the control and CF groups separately, following the Seurat v3 integration workflow[57]. SCTransform was used to normalize each sample, followed by the identification of integration anchors and variable features using the Seurat workflow. Dimension reduction was performed scaled data after 4000 highly variable genes across the samples were identified (*SelectIntegrationFeatures* function). The *IntegrateData* function was then used to obtain a combined and centered matrix, where the top 30 components were used to carry out ordination analyses. These components were used to build a SNN (shared nearest neighbour) graph which was subsequently clustered using the *Louvain* algorithm for speed and computational efficiency. The principal components were then mapped into two dimensions using the default uniform manifold approximation and projection (UMAP) algorithm, where the n = 30 neighbours was set, with a minimum distance of 0.4. Finally, the *FindAllMarkers* function was used to identify marker genes for each cluster. The top marker genes were used manually based on literature

searches to assign cell type annotations for each cluster. This was further corroborated by cluster

annotations using the Azimuth mouse reference datasets[57]. The cell types across samples and groups

were combined with their pseudo bulk profiles, and the resulting gene-cell type matrix was normalized

by estimating transcripts per million and transformed (log2) for downstream analyses. To obtain

statistically enriched differential gene expression, we used generalized additive regression models,

where in the control or CF variables, alongside the GM^{Low} or GM^{High} status were encoded as independent

variables. The models were analyzed for each cluster independent of the other, where per gene log2

fold-change was determined. Significance was identified as those genes with an adjusted p-value of less

than 0.05, following Benjamini-Hochberg correction. All figures and statistical analyses were performed

using R v4.1[58].

Cell-to-cell communication was inferred using log10-transformed gene expression data collected from

snRNA-seq of the mouse hippocampus using CellChat[59, 60]. Cell clusters as identified above were grouped

into the following cell types based on Azimuth classification: Glutamatergic and GABAergic neurons,

Periendothelial Cells, Microglia, Astrocytes, and Oligodendrocytes. Ligand-receptor interactions were

inferred using the mouse reference database provided by CellChat (Accessed May 25, 2023).

Overexpressed genes and interactions were determined using default settings. Cell-cell communication

probability was inferred using default settings. Information flow was determined by the summation of

communication probability for each pathway.

Methylome analysis

Hippocampal genomic DNA was isolated from adult female cross-foster (CF) and control (non-CF)

offspring samples using the DNAeasy kit (Qiagen, Valencia, CA) following the manufacturer's

instructions. For studying Genome-wide DNA methylation profiles, 1 μg of genomic DNA was treated

with sodium bisulfite (Zymo Research, Irvine, CA). Converted DNA was analyzed using Infinium Mouse

Methylation BeadChip assay (Illumina, San Diego, CA). This array includes over 285,000 CpG sites

covering all RefSeq genes, including CpG islands, translation start sites, enhancers, imprinted loci, and

other regions[61]. All data analyses were conducted using the R environment version 4.2.0. Microarray

data was processed using the *ENmix* version.1.34.02[62] and *minfi* v.1.44.0[63] packages. Quantile

normalization of U or M intensities for Infinium I or II probes were performed, respectively. A model-

based correction was performed, and a dye-bias correction was conducted using *RELIC* [64]. β-values

representing the averaged total intensity value per CG position was calculated as unmethylated intensity

(U) + methylated intensity (M) [M / (U + M + 100)]. Probes with a detection $p < 1 \times 10^{-6}$ and less than 3

beads were defined as low quality. Samples with low quality methylation measurements > 5% or low

intensity bisulfite conversion probes were removed from further analysis. Differentially methylated

positions (DMPs) between the experimental groups were determined using the *ENmix* version.1.34.02[62]

package. For each position, the magnitude of the DNA methylation difference was expressed as Fold

Changes in the logarithmic scale (logFC) and the significance of the difference as a FDR-corrected p-Value

(q value).

Statistics

Two-way ANOVA followed by Tukey's post-hoc analysis was used to compare differences in groups across

all behavior testing parameters. Specific parameters analyzed included time spent in center zone,

distance travelled in center zone, total distance travelled (OFE), time spent in light chamber, distance

travelled in light chamber, number of entries into light chamber (LDT), and time spent in open arms,

distance travelled in open arms, number of entries into open arms (EPM). All univariant data analysis

was performed using SigmaPlot 14.0 (Systat Software, Inc, San Jose, CA). For multivariate data (e.g.,

microbiome beta-diversity), two-way permutational multivariant analysis of variance (PERMANOVA) was

used with main effects of age and GM.   PERMANOVA analysis was performed using the PAST 4.03

software and was based on Bray-Curtis dissimilarities. All diversity and richness indices were calculated

using PAST 4.03 software, followed by two-way ANOVA for main affects of age and GM using SigmaPlot

14.0 (Systat Software, Inc, San Jose, CA). Due to uniform lack of normality across metabolites, a Mann-

Whitney U test was used to test for statistical differences in metabolite concentrations between

treatment groups.

Statement of data availability

All data supporting our analyses and reported conclusions have been deposited in the appropriate data

repositories and are publicly available. Metagenomic, metatranscriptomic, and 16S rRNA amplicon

sequencing data are available at the National Center for Biotechnology and Informatics (NCBI) Sequence

Read Archive (SRA) under the BioProject accession number PRJNA885816. Mouse Methylation

BeadChip array data are available at the Gene Expression Omnibus (GEO) under accession GSE239371.

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Center, and the University of Missouri Office of Animal Resources.

Figure legends

Figure 1. Anxiety-related behavior and other outcomes in offspring are influenced by the maternal gut

microbiome. a. Schematic showing the experimental groups and timing of outcome measures. **b-e.**

Behavior outcomes in male (M) and female (F) mice colonized with GM^{Low} or GM^{High}, including time

spent in the light portion of a light/dark test (**b**), time spent in the open arms of an elevated plus maze

(**c**), and distance run per day (Km) by male (**d**) and female (**e**) mice. **f.** Body weight per mouse (grams) at

day 50 in control mice. **g-j.** Same behavior outcomes in CF^{Low} and CF^{High} mice as those shown in panels **b-**

e. **k.** Body weight per mouse at day 50 in cross-fostered mice. p and F values represent effect of GM in

two-way ANOVA with Tukey post hoc. Significant sex-dependent differences were detected in distance

on running wheels and body weight in both control and cross-fostered mice, with no significant

interactions between GM and sex in any tests. * $p<0.05$, ** $p<0.01$, **** $p<0.0001$

Figure 2. Microbiomes linked to fetal programming of complex behaviors differ in synthesis or

catabolism of several metabolites including bile acids. a. Hierarchical clustering of data from adult

GM^{Low}- or GM^{High}-colonized mice, demonstrating segregation of GMs by richness and composition

(legend at right). **b,c.** Volcano plots showing metabolites enriched in GM^{Low} (red dots) or GM^{High} (blue

dots) feces (**b**) or serum (**c**). **d-g.** Normalized ileal expression of *Asbt* (**d**), *Ostβ* (**e**), *Gpbar1* (**f**), and *Fxr* (**g**)

male (M) and female (F) mice colonized with GM^{Low} (red dots) or GM^{High} (blue dots). **j.** Normalized

hepatic expression of *Cyp7a1* (**h**), *Slc10a1* (**i**), and *S1pr2* (**j**) in the same groups of mice. Gene expression

normalized to *β-Actin* expression. Results indicate main effect of GM in one- or two-way ANOVA,

following correction for multiple tests. * $p<0.05$, ** $p<0.01$, **** $p<0.0001$. Abbreviations: 2-HBA (2-

hydroxybutyrate), α-MCA (alpha-Muricholic Acid), β-ALA (beta-Alanine), BUTY (Butyrate), CA (Cholic

Acid), CDCA (Chendeoxycholic Acid), CYS (Cysteine), DCA (Deoxycholic Acid), F6P (Fructose-6-Phosphate),

G6P (Glucose-6-Phosphate), GCA (Glycocholic Acid), GLY (Glycerate), INO (Inositol), LAC (Lactate), LEU

(Leucine), MVA (Mevalonic Acid), R5P (Ribulose-5-Phosphate), SUC (Succinate), TCA (Taurocholic Acid),

TCDCA (Taurochenodeoxycholic Acid), TDCA (Taurodeoxycholic Acid), TLCA (Taurolithocholic Acid), UDCA

(Ursodeoxycholic Acid).

Figure 3. Maternal microbiome is associated with gene methylation in offspring hippocampus. a. Dot
plot showing normalized difference [Log_2(FC)] in mean methylation between GM^{Low} and GM^{High}, and
between CF^{Low} and CF^{High}, of all CpG markers achieving a Log_2(FC) > 1 in either comparison. **b.** Ratio of
observed to predicted differentially methylated regions (DMRs), and locations of DMRs relative to gene
bodies, on each chromosome. **c.** Mean beta values of 27 CpG sites spanning the enhancers, promoters,
introns and exons across the *Pde1c* gene in all four groups, with specific sites indicated above (upper);
and log_2(FC) between control and cross-fostered groups (lower). **d.** Mean beta values (upper) and
Log_2(FC) between groups (lower) across adjacent regions of the positive (left) and negative (right) strand
of a region of chromosome 14 containing genes for *Ang5*, *Ang6*, and other genes. **e.** Protein interaction
networks among products of DMRs, with node color indicating Log_2(FC) in methylation between GM^{Low}
and GM^{High}.

Figure 4. a, b. Interaction networks constructed using differentially expressed genes (DEGs) identified in
hippocampal endothelial and perivascular cells of control (**a**) and cross-fostered (**b**) mice. Highlighted
nodes include DEGs identified in both comparisons and showing a pattern of fetal imprinting, and genes
that are also differentially methylated (*Pde1c*, *Dock1*), or closely related (PDE cluster, *Dcc*, *Elmo1*, *Dock4*,
Dock5). **c, d.** Log_2FC in expression of Pde1c (**c**) and Dock1 (**d**) in hippocampal cell clusters of male and
female CF^{Low} and CF^{High} mice, as determined via real-time snRNAseq. **e.** Venn diagram showing number of
inferred cell-to-cell communication pathways identified in hippocampus of GM^{Low}, GM^{High}, CF^{Low}, and
CF^{High} mice. Pathways listed above and below the diagram were selectively identified in the indicated
groups. **f, g.** Bar charts showing the relative degree of cell-to-cell communication between GM^{Low} and
GM^{High} (**f**), and CF^{Low}, and CF^{High}, (**g**) mice in the indicated pathways.

Extended Data

Extended Data Figure 1. a-e. Dot and bar plots showing other results of behavior tests in adult male (M)
and female (F) GM^{Low} and GM^{High} mice including total distance traveled (**a**) and time spent in the center
zone (**b**) during OFE, and distance traveled in the light portion of the light/dark test (**c**) or open arms of
the elevated plus maze (**d**), and body weight at 21 days of age (**e**). f-j. Same outcomes in CF^{Low} and CF^{High}
mice as those shown in panels **a-e**. * p<0.05, ** p<0.01, **** p<0.0001

Extended Data Figure 2. Dot and bar plots showing differences in richness (**a**) and principal coordinate
analysis (PCoA) plots showing differences in beta-diversity based on Jaccard (**b**) and Bray-Curtis distances
(**c**), between adult male (M) and female (F) mice colonized with GM^{Low} or GM^{High}, and similarities in all of

the above metrics between CF mice at seven weeks of age and their cognate birth dams. **d.** Cladogram

showing results of differential abundance (DA) testing, performed in parallel using ALDEx2 and ANCOM-

BC2. Concentric rings at periphery indicate significant DA with enrichment indicated by color (legend

upper right) using ALDEx2 (outer); ANCOM-BC2, which first identifies DA based on structural zeros (SZ)

or sequences that are absent from one group (middle); and phylum (inner, legend at right). ****

p<0.0001

Extended Data Figure 3. Volcano plots showing the metabolites enriched in feces of GM^{Low} (red dots) and

GM^{High} (blue dots) males (**a**), and females (**b**). Volcano plots showing the metabolites enriched in serum

of GM^{Low} (red dots) and GM^{High} (blue dots) males (**c**), and females (**d**) and Dot plots representing gene (**e**)

and transcript (**f**) copy numbers specific for bile salt hydrolase (Bsh), and the normalized

(transcript/gene) expression (**g**) in the feces of adult female mice colonized with GM^{Low} or GM^{High} (n =

3/GM). Box plots and individual data showing hydrolytic activity of bile salt hydrolase (BSH) in adult male

and female mice colonized with GM^{Low} or GM^{High}, determined using five different bile acid-conjugated

bioluminescent probes specific for cholic acid (CA, **h**), deoxycholic acid (DCA, **i**), chenodeoxycholic acid

(CDCA, **j**), ursodeoxycholic acid (UDCA, **k**), and lithocholic acid (LCA, l). * p<0.05, **** p<0.0001.

Abbreviations: 2-HGA (2-hydroxygluterate), 3-HPA (3-Hydroxyproprionate), α-KGA (alpha-Ketogluterate),

α-KIC (alpha-Ketoisocaproate), ASP (Asparagine), β-ALA (beta-Alanine), CDCA (Chendeoxycholic Acid),

CYS (Cysteine), DCA (Deoxycholic Acid), F6P (Fructose-6-Phosphate), G6P (Glucose-6-Phosphate), GLY

(Glycerate), IAA (Indoleacetic Acid), ISO (Isocitrate), LAC (Lactate), LCA (Lithocholic Acid), LEU (Leucine),

MAL (Malate), MET (Methionine), ORN (Ornithine), PHEN (Phenylalanine), PRO (Proline), PTA

(Pantothenic Acid), R5P (Ribulose-5-Phosphate), SUC (Succinate), TDCA (Taurodeoxycholic Acid), TRY

(Tryptamine), VAL (Valine).

Extended Data Figure 4. UMAP projections of hippocampal cell clusters in control GM^{Low} (**a**) and GM^{High}

(**b**), and cross-foster CF^{Low} (**c**) and CF^{High} (**d**) mice.

Extended Data Figure 5. a, b. Dot plot correlation between the number of differentially expressed genes

(DEGs) and the mean node degree determined by protein interaction analysis of those DEGs, in

comparisons of GM^{Low} and GM^{High} offspring (**a**) and in CF^{Low} and CF^{High} offspring (**b**). Marker shapes

denote cell type including endothelial/perivascular cells (Endo, red squares); astrocytes and

oligodendrocytes (Glial, grey diamonds); GABAergic neurons (GABA, dark blue triangles); and

glutamatergic neurons (Gluta, brown triangles).

Extended Data Figure 6. a, b. Interaction networks constructed using differentially expressed genes
(DEGs) identified in hippocampal level five intratelencephalon (L5 IT)-projecting glutamatergic neurons
from control (**a**) and cross-fostered (**b**) mice. Labeled nodes include DEGs identified in both comparisons
and showing a pattern of fetal imprinting, and genes that are also differentially methylated (*Dock1*), or
closely related (PDE cluster, *Adcy8, Dcc, Ntn1*).

Extended Data Figure 7. a, b. Interaction networks constructed using differentially expressed genes
(DEGs) identified in hippocampal astrocyte subsets from control (**a**) and cross-fostered (**b**) mice. Labeled
nodes include DEGs identified in both comparisons and showing a pattern of fetal imprinting, and genes
that are also differentially methylated (*Dock1*), or closely related (PDE cluster, *Adcy8, Dcc, Ntn1*).

Supplementary Table 1. Enriched bacterial family taxa harbored by either GM^{Low} or GM^{High}.

Supplementary Table 2. Results of fecal metabolite concentrations from GM^{Low} and GM^{High} mice.

Supplementary Table 3. Results of serum metabolite concentrations from GM^{Low} and GM^{High} mice.

Supplementary Table 4. Differentially methylated regions identified within the genomes of female GM^{Low}
and GM^{High} mouse hippocampi.

Supplementary Table 5. Differentially expressed genes identified within the hippocampal cells of GM^{Low}
and GM^{High} control mice.

Supplementary Table 6. Differentially expressed genes identified within the hippocampal cells of CF^{Low}
and CF^{High} mice.

Supplementary Table 7. Primer pairs used for qRT-PCR analysis.

1. Prevention CfDCa. Anxiety and depression in children: Get the facts. Children's Mental Health.
Volume 2023: cdc.gov, 2023.
2. Prevention CfDCa. Prevalence of Childhood Obesity in the United States. Overweight and
Obesity. Volume 2023. cdc.gov, 2023.
3. Gariepy G, Nitka D, Schmitz N. The association between obesity and anxiety disorders in the
population: a systematic review and meta-analysis. Int J Obes (Lond) 2010;34:407-19.
4. Grundy A, Cotterchio M, Kirsh VA, Kreiger N. Associations between anxiety, depression,
antidepressant medication, obesity and weight gain among Canadian women. PLoS One
2014;9:e99780.
5. Lindberg L, Hagman E, Danielsson P, et al. Anxiety and depression in children and adolescents
with obesity: a nationwide study in Sweden. BMC Med 2020;18:30.
6. Sharafi SE, Garmaroudi G, Ghafouri M, et al. Prevalence of anxiety and depression in patients
with overweight and obesity. Obesity Medicine 2020;17:1-5.

7.   Wang S, Sun Q, Zhai L, et al. The Prevalence of Depression and Anxiety Symptoms among
Overweight/Obese and Non-Overweight/Non-Obese Children/Adolescents in China: A
Systematic Review and Meta-Analysis. Int J Environ Res Public Health 2019;16.
8.   Bercik P, Denou E, Collins J, et al. The intestinal microbiota affect central levels of brain-derived
neurotropic factor and behavior in mice. Gastroenterology 2011;141:599-609, 609 e1-3.
9.   Bravo JA, Forsythe P, Chew MV, et al. Ingestion of Lactobacillus strain regulates emotional
behavior and central GABA receptor expression in a mouse via the vagus nerve. Proc Natl Acad
Sci U S A 2011;108:16050-5.
10. Buffington SA, Di Prisco GV, Auchtung TA, et al. Microbial Reconstitution Reverses Maternal Diet-
Induced Social and Synaptic Deficits in Offspring. Cell 2016;165:1762-1775.
11. Hsiao EY, McBride SW, Hsien S, et al. Microbiota modulate behavioral and physiological
abnormalities associated with neurodevelopmental disorders. Cell 2013;155:1451-63.
12. Catron TR, Swank A, Wehmas LC, et al. Microbiota alter metabolism and mediate
neurodevelopmental toxicity of 17beta-estradiol. Sci Rep 2019;9:7064.
13. Kim E, Paik D, Ramirez RN, et al. Maternal gut bacteria drive intestinal inflammation in offspring
with neurodevelopmental disorders by altering the chromatin landscape of CD4(+) T cells.
Immunity 2022;55:145-158 e7.
14. Cho HM, Gonzalez-Ortiz G, Melo-Duran D, et al. Stimbiotic supplementation improved
performance and reduced inflammatory response via stimulating fiber fermenting microbiome
in weaner pigs housed in a poor sanitary environment and fed an antibiotic-free low zinc oxide
diet. PLoS One 2020;15:e0240264.
15. Everard A, Belzer C, Geurts L, et al. Cross-talk between Akkermansia muciniphila and intestinal
epithelium controls diet-induced obesity. Proc Natl Acad Sci U S A 2013;110:9066-71.
16. Lee H, Lee Y, Kim J, et al. Modulation of the gut microbiota by metformin improves metabolic
profiles in aged obese mice. Gut Microbes 2018;9:155-165.
17. Rodrigues RR, Greer RL, Dong X, et al. Antibiotic-Induced Alterations in Gut Microbiota Are
Associated with Changes in Glucose Metabolism in Healthy Mice. Front Microbiol 2017;8:2306.
18. Desbonnet L, Clarke G, Shanahan F, et al. Microbiota is essential for social development in the
mouse. Mol Psychiatry 2014;19:146-8.
19. Diaz Heijtz R, Wang S, Anuar F, et al. Normal gut microbiota modulates brain development and
behavior. Proc Natl Acad Sci U S A 2011;108:3047-52.
20. Rabot S, Membrez M, Bruneau A, et al. Germ-free C57BL/6J mice are resistant to high-fat-diet-
induced insulin resistance and have altered cholesterol metabolism. FASEB J 2010;24:4948-59.
21. Collins SM, Kassam Z, Bercik P. The adoptive transfer of behavioral phenotype via the intestinal
microbiota: experimental evidence and clinical implications. Curr Opin Microbiol 2013;16:240-5.
22. De Palma G, Lynch MD, Lu J, et al. Transplantation of fecal microbiota from patients with irritable
bowel syndrome alters gut function and behavior in recipient mice. Sci Transl Med 2017;9.
23. Turnbaugh PJ, Ley RE, Mahowald MA, et al. An obesity-associated gut microbiome with
increased capacity for energy harvest. Nature 2006;444:1027-31.
24. Pessa-Morikawa T, Husso A, Karkkainen O, et al. Maternal microbiota-derived metabolic profile
in fetal murine intestine, brain and placenta. BMC Microbiol 2022;22:46.
25. Deng X, Guarita DR, Pedroso MR, et al. PYY inhibits CCK-stimulated pancreatic secretion through
the area postrema in unanesthetized rats. Am J Physiol Regul Integr Comp Physiol
2001;281:R645-53.
26. Cabral A, Cornejo MP, Fernandez G, et al. Circulating Ghrelin Acts on GABA Neurons of the Area
Postrema and Mediates Gastric Emptying in Male Mice. Endocrinology 2017;158:1436-1449.

27.   Yamamoto H, Kishi T, Lee CE, et al. Glucagon-like peptide-1-responsive catecholamine neurons in
the area postrema link peripheral glucagon-like peptide-1 with central autonomic control sites. J
Neurosci 2003;23:2939-46.

28.   Arslanova A, Tarasova A, Alexandrova A, et al. Protective Effects of Probiotics on Cognitive and
Motor Functions, Anxiety Level, Visceral Sensitivity, Oxidative Stress and Microbiota in Mice with
Antibiotic-Induced Dysbiosis. Life (Basel) 2021;11.

29.   O'Connor R, Moloney GM, Fulling C, et al. Maternal antibiotic administration during a critical
developmental window has enduring neurobehavioural effects in offspring mice. Behav Brain
Res 2021;404:113156.

30.   Sun Y, Zhu H, Cheng R, et al. Outer membrane protein Amuc_1100 of Akkermansia muciniphila
alleviates antibiotic-induced anxiety and depression-like behavior in mice. Physiol Behav
2023;258:114023.

31.   Bruce-Keller AJ, Fernandez-Kim SO, Townsend RL, et al. Maternal obese-type gut microbiota
differentially impact cognition, anxiety and compulsive behavior in male and female offspring in
mice. PLoS One 2017;12:e0175577.

32.   Cheatham CN, Gustafson KL, McAdams ZL, et al. Standardized Complex Gut Microbiomes
Influence Fetal Growth, Food Intake, and Adult Body Weight in Outbred Mice. Microorganisms
2023;11.

33.   Ericsson AC, Davis JW, Spollen W, et al. Effects of vendor and genetic background on the
composition of the fecal microbiota of inbred mice. PLoS One 2015;10:e0116704.

34.   Ericsson AC, Hart ML, Kwan J, et al. Supplier-origin mouse microbiomes significantly influence
locomotor and anxiety-related behavior, body morphology, and metabolism. Commun Biol
2021;4:716.

35.   Song Z, Cai Y, Lao X, et al. Taxonomic profiling and populational patterns of bacterial bile salt
hydrolase (BSH) genes based on worldwide human gut microbiome. Microbiome 2019;7:9.

36.   Abdulrab S, Al-Maweri S, Halboub E. Ursodeoxycholic acid as a candidate therapeutic to alleviate
and/or prevent COVID-19-associated cytokine storm. Med Hypotheses 2020;143:109897.

37.   Adhikari A, Topiwala MA, Gordon JA. Synchronized activity between the ventral hippocampus
and the medial prefrontal cortex during anxiety. Neuron 2010;65:257-69.

38.   Baksh RA, Ritchie CW, Terrera GM, et al. The association between anxiety disorders and
hippocampal volume in older adults. Psychol Aging 2021;36:288-297.

39.   Jimenez JC, Su K, Goldberg AR, et al. Anxiety Cells in a Hippocampal-Hypothalamic Circuit.
Neuron 2018;97:670-683 e6.

40.   Mineur YS, Obayemi A, Wigestrand MB, et al. Cholinergic signaling in the hippocampus regulates
social stress resilience and anxiety- and depression-like behavior. Proc Natl Acad Sci U S A
2013;110:3573-8.

41.   Revest JM, Dupret D, Koehl M, et al. Adult hippocampal neurogenesis is involved in anxiety-
related behaviors. Mol Psychiatry 2009;14:959-67.

42.   Satpute AB, Mumford JA, Naliboff BD, Poldrack RA. Human anterior and posterior hippocampus
respond distinctly to state and trait anxiety. Emotion 2012;12:58-68.

43.   Wolfe AE, Moskowitz JE, Franklin CL, et al. Interactions of Segmented Filamentous Bacteria
(Candidatus Savagella) and bacterial drivers in colitis-associated colorectal cancer development.
PLoS One 2020;15:e0236595.

44.   Cantor JR, Abu-Remaileh M, Kanarek N, et al. Physiologic Medium Rewires Cellular Metabolism
and Reveals Uric Acid as an Endogenous Inhibitor of UMP Synthase. Cell 2017;169:258-272.e17.

45.   Li B, Tang J, Yang Q, et al. NOREVA: normalization and evaluation of MS-based metabolomics
data. Nucleic Acids Res 2017;45:W162-w170.

46. Walters WA, Caporaso JG, Lauber CL, et al. PrimerProspector: de novo design and taxonomic
analysis of barcoded polymerase chain reaction primers. Bioinformatics 2011;27:1159-61.

47. Caporaso JG, Lauber CL, Walters WA, et al. Global patterns of 16S rRNA diversity at a depth of
millions of sequences per sample. Proc Natl Acad Sci U S A 2011;108 Suppl 1:4516-22.

48. Loy A, Maixner F, Wagner M, Horn M. probeBase--an online resource for rRNA-targeted
oligonucleotide probes: new features 2007. Nucleic Acids Res 2007;35:D800-4.

49. Martin M. Cutadapt removes adapter sequences from high-throughput sequencing reads.
EMBnet.journal 2011;17:10-12.

50. Bolyen E, Rideout JR, Dillon MR, et al. Reproducible, interactive, scalable and extensible
microbiome data science using QIIME 2. Nat Biotechnol 2019;37:852-857.

51. Callahan BJ, McMurdie PJ, Rosen MJ, et al. DADA2: High-resolution sample inference from
Illumina amplicon data. Nat Methods 2016;13:581-3.

52. Pruesse E, Quast C, Knittel K, et al. SILVA: a comprehensive online resource for quality checked
and aligned ribosomal RNA sequence data compatible with ARB. Nucleic Acids Res
2007;35:7188-96.

53. Zachary L McAdams SBB, Kevin L Gustafson, Nathan Bivens, Craig L Franklin, Paul Wilmes, Aaron
C Ericsson. Multi-omics analysis of mouse fecal microbiome reveals supplier-dependent
functional differences and novel metagenome-assembled genomes. bioRxiv 2022.

54. Khodakivskyi PV, Lauber CL, Yevtodiyenko A, et al. Noninvasive imaging and quantification of bile
salt hydrolase activity: From bacteria to humans. Sci Adv 2021;7.

55. Vorobyeva AG, Stanton M, Godinat A, et al. Development of a Bioluminescent Nitroreductase
Probe for Preclinical Imaging. PLoS One 2015;10:e0131037.

56. Wolock SL, Lopez R, Klein AM. Scrublet: Computational Identification of Cell Doublets in Single-
Cell Transcriptomic Data. Cell Syst 2019;8:281-291 e9.

57. Stuart T, Butler A, Hoffman P, et al. Comprehensive Integration of Single-Cell Data. Cell
2019;177:1888-1902 e21.

58. Team RDC. R: A Language and Environment for Statistical Computing. 2010.

59. Jin S, Guerrero-Juarez CF, Zhang L, et al. Inference and analysis of cell-cell communication using
CellChat. Nat Commun 2021;12:1088.

60. Suoqin J, Maksim VP, Qing N. CellChat for systematic analysis of cell-cell communication from
single-cell and spatially resolved transcriptomics. bioRxiv 2023:2023.11.05.565674.

61. Zhou W, Hinoue T, Barnes B, et al. DNA methylation dynamics and dysregulation delineated by
high-throughput profiling in the mouse. Cell Genom 2022;2.

62. Xu Z, Niu L, Li L, Taylor JA. ENmix: a novel background correction method for Illumina
HumanMethylation450 BeadChip. Nucleic Acids Res 2016;44:e20.

63. Aryee MJ, Jaffe AE, Corrada-Bravo H, et al. Minfi: a flexible and comprehensive Bioconductor
package for the analysis of Infinium DNA methylation microarrays. Bioinformatics 2014;30:1363-
9.

64. Xu Z, Langie SA, De Boever P, et al. RELIC: a novel dye-bias correction method for Illumina
Methylation BeadChip. BMC Genomics 2017;18:4.

a

Gad1
Sema5a
Bdnf
Dab2
Ly6c1
Sgcd

p = 0.118

p = 1 × 10⁻¹⁶

b

Gad1
Dock1
Dcc
Ntn1
Bdnf
Sema5a
Ly6c1

Pde1a
Pde3a
Pde4b
Pde5a
Pde7b
Pde8a
Pde10a

Adcy8

Sgcd
Dab2