Ketogenic Diet Induces Anti-Tumorigenic Effects in Colorectal Cancer through Microbial Production of

Stearate

Mina Tsenkova[1], Madita Brauer[1,2], Marat Kasakin[3], Susheel Bhanu Busi[3,4], Maryse Schmoetten[1], Anthoula

Gaigneaux[5], Vitaly Pozdeev[1], Marianne Meyers[1], Eric Koncina[1], Diran Herebian[6], Fabien Rodriguez[1], Dean

Cheung[1], Martine Schmitz[1], Laura de Nies[3], Ertan Mayatepek[6], Serge Haan[1], Carine de Beaufort[7], Jérôme

Graas[8], Thorsten Cramer[9], Carole L. Linster[3], Paul Wilmes[3,5], Elisabeth Letellier[1]

[1] Molecular Disease Mechanisms Group, Department of Life Sciences and Medicine, Faculty of Science,

Technology and Medicine, University of Luxembourg, Esch-sur-Alzette, Luxembourg

[2] Institute for Advanced Studies, University of Luxembourg, Esch-sur-Alzette, Luxembourg

[3] Luxembourg Centre for Systems Biomedicine, University of Luxembourg, Esch-sur-Alzette, Luxembourg

[4] UK Centre for Ecology and Hydrology, Wallingford, United Kingdom

[5] Department of Life Sciences and Medicine, Faculty of Science, Technology and Medicine, University of

Luxembourg, Esch-sur-Alzette, Luxembourg

[6] Department of General Pediatrics, Neonatology and Pediatric Cardiology, Medical Faculty and University

Hospital Düsseldorf, Heinrich Heine University, Düsseldorf, Germany

[7] Pediatric Clinic, Centre Hospitalier de Luxembourg, Luxembourg, Luxembourg

[8] Centre d'Investigation et d'Epidémiologie Clinique, Luxembourg Institute of Health, Hesperange,

Luxembourg

[9] Molecular Tumor Biology, Department of General, Visceral and Transplantation Surgery, RWTH

University Hospital Aachen, Germany

Abstract

Colorectal cancer (CRC) patients have been shown to possess an altered gut microbiome. Diet is

a known microbiome modulator. An attenuating effect of the ketogenic diet (KD) on CRC cell growth has

been previously observed, however the role of the gut microbiome in driving this effect remains unknown.

Here, we describe a reduced colonic tumor burden upon KD consumption in a CRC mouse model with a

humanized microbiome. Importantly, we demonstrate a causal relationship through microbiome

transplantation into germ-free mice, whereby alterations in gut microbial function were maintained in the

absence of continued selective pressure from the KD. We identify stearic acid as a putative microbiome-

derived anti-cancer metabolite. Taken together, the beneficial effects of the KD are mediated by the gut

microbiome and may be dependent on a pre-existing "non-responder" or "responder" gut microbiome

profile. These results have important implications for future clinical trials evaluating the effects of the

ketogenic diet on human CRC.

Introduction

Worldwide, colorectal cancer (CRC) is the third most prevalent cancer, with over 1.9 million new cases recorded in 2020[1]. CRC incidence and mortality rates have been associated with various lifestyle-related risk factors, in particular dietary habits. Recent years have seen a rise in CRC incidence in persons aged 50 years and under, further underlining the importance of studying these factors[2]. The ketogenic diet (KD) has been shown to possess anti-cancer properties in the context of CRC, and many studies have focused on the importance of the restriction of energy to slow the growth of rapidly proliferating cells and anti-cancer signaling through ketone bodies[3]. One recently published study investigated the effects of the KD on CRC development and described a new mechanism through which KD exerts its anti-cancer effects, namely through the ketone body β-hydroxybutyrate acting on the surface receptor Hcar2, inducing the transcriptional regulator *Hopx*, thus altering gene expression and inhibiting cell proliferation[4]. These studies often focus on the effects of KD on the cancer cells themselves, and rarely on other cells of the tumor microenvironment (TME), such as immune cells[5,6] and cancer-associated fibroblasts (CAFs)[7], or on external factors, such as the gut microbiome. Specifically in CRC, cancer progression is accompanied by a state of dysbiosis of the gut microbiome[8–10]. The study of the role of the different bacteria in CRC is of particular interest, considering the affected tissue type is in contact with the gut microbiome. Until recently, few studies had investigated the effects of the KD on the gut microbiome in health and disease[11], but this has now changed, with a number of new studies published over the last three years[6,8]. These studies remain largely descriptive regarding dietary-induced gut microbiome changes and the role of the gut microbiome in maintaining the reported anti-cancer effects of the KD in the context of CRC has not yet been investigated. Therefore, we set out to investigate the importance of the gut microbiome in the context of KD consumption in CRC. We first generated a humanized gut microbiome mouse model of CRC, through the transplantation of stool samples from five healthy human donors. We then combined this model with a therapeutically administered KD and were able to confirm the cancer-suppressing properties

of the KD. Most importantly, we could demonstrate, for the very first time, the causal role of the gut

microbiome in maintaining this effect, through transplantation of the microbial community. We report

long-lasting alterations in gut microbiome function in the absence of maintained selective pressure by the

KD. In our experiments, fecal stearic acid levels were increased not only upon KD consumption, but also

upon cecal transplantation, suggesting that the shift in the microbial community contributes to the

changes in the fatty acid pool. Importantly, potential stearate-producing members were enriched in

ketogenic conditions, whereas consumers were depleted.

Results

KD leads to reduced colonic tumor burden and inflammatory response in CRC

To study the relevance of the gut microbiome in CRC development in a model relevant to human

disease, we first established a representative healthy human microbiome by mixing fecal samples from

five healthy donors (5HD; Extended Data Fig. 1a for patient metadata). The achieved 5HD mix

recapitulated the compositions of the individual donor samples, as evidenced by family, genus and species

level analysis of whole genome shotgun sequencing (WGS, Extended Data Fig. 1b-d, respectively), while

fecal metabolite levels varied across samples (Extended Data Fig. 1e). We performed fecal microbial

transplantation (FMT) of the 5HD mix into germ-free (GF) and antibiotic-treated specific-pathogen-free

(SPF) mice in an AOM/DSS CRC model (Fig. 1a and 1b, details can be found in the methods section)

followed by a switch from standard to ketogenic diet after the last cycle of DSS. No significant difference

in body weight between the standard diet (SD) and ketogenic diet (KD) groups was observed throughout

the experiments, although dips in mouse body weight were observed following the antibiotic treatment

and following each cycle of DSS (Extended Data Fig. 2a and 2b). There was no difference in colon length

between groups (Extended Data Fig. 2c, GF). KD-fed mice exhibited a lower colonic tumor burden (Fig. 1c

(GF) and Fig. 1d (SPF)) and a smaller tumor size (Fig. 1e, 1f and 1g (SPF)) than SD-fed mice.

Characterization of full-length lamina propria (LP), mesenteric lymph node (MLN) and spleen

immune cell profiles (Extended Data Fig. 2d and 2e) showed a reduction in almost all LP CD4[+] T cell

populations in KD-fed mice. Only LP natural killer T cells and type 3 innate lymphoid cells (GF LP) were

increased – both have been associated to gut homeostasis and health[12]. Finally, the expression of both

subunits of calprotectin (a biomarker of inflammation used in inflammatory bowel disease[13]) was reduced

in the spleens of GF KD-fed mice (Fig. 1h and 1i). Nevertheless, it remains unclear whether the reduction

in immune cell populations reflects reduced inflammation induced by the KD or is rather a direct

consequence of the reduced tumor development.

To further assess the importance of KD in modulating inflammation in CRC, we employed a low-

grade inflammatory model, in which mice received four doses of AOM and were randomized into one of

three subgroups - GF, 5HD mix FMT, single CRC patient FMT, each with a KD and SD branch (Extended

Data Fig. 3a, 3b (5HD) and 3c (CRC)). A single CRC donor was used for colonization, rather than a mix of

multiple samples, due to the observed dissimilarities of microbial profiles between patients in our in-

house CRC stool collection. Despite the induction of ketosis in KD-fed mice (Extended Data Fig. 3d), we

observed no significant differences in colonic tumor burden between groups (Extended Data Fig. 3e), nor

in immune cell profiles (Extended Data Fig. 3f), suggesting not only that the KD specifically exerted its anti-

cancer effect in an inflammatory setting, independent of ketosis, likely by reducing inflammation, but also

that the fecal microbiome from this CRC patient did not exhibit a higher potential for CRC induction in this

setting, in contrast to observations made by Wong et al.[14]. Of note, long-term KD feeding induced fatty

liver and fibrosis in all sub-groups (Extended Data Fig. 3g), and as previously reported for long-term KD

consumption[15]. Altogether, these results suggest that the KD exerts an anti-tumorigenic effect in CRC,

potentially by modulating the immune system.

KD induces a distinct host metabolic profile

Ordination analyses based on the underlying β-diversity among host plasma samples collected from animals undergoing ketogenic dietary intervention in the AOM/DSS inflammatory model of CRC, revealed clustering based on dietary condition (Extended Data Fig. 4a (SPF) an Extended Data Fig. 4b (GF)). β-HB plasma levels were elevated in KD-fed mice (Extended Data Fig. 4c (SPF) and 4d (GF)), confirming ketosis. KD-fed mice presented altered amino acid, fatty acid, sugar, carbohydrate, vitamin, and bile acid metabolism (Supp. Table 1 and Extended Data Fig. 4e (SPF), Supp. Table 2 and Supp Fig. 4f (GF). Furthermore, mannose was increased in KD-fed mice (Supp. Table 1 (SPF) and 2(GF)). Interestingly, mannose has been reported to possess antitumor properties[16], impairing tumor cell growth *in vitro* and *in vivo*[17], and targeting tumor-associated macrophages[18]. While treatment with β-hydroxybutyrate showed no effect, treatment with the ketone bodies acetone and sodium acetoacetate tended to reduce the differentiation of naive T cells into Th17 cells (Extended Data Fig. 4g and 4h), which play an important role in maintaining gut homeostasis[19] and are affected by KD in a dose-dependent manner[5]. Treatment with a commercially available lipid mixture mimicking KD (containing arachidonic, linoleic, linolenic, myristic, oleic, palmitic and stearic acid) led to a dose-dependent reduction in Th17 differentiation (Extended Data Fig. 4i), as did treatment with some individual fatty acids, such as palmitic and oleic acid (Extended Data Fig. 4j), suggesting that Th17 cells are susceptible to fatty acid modulation, but that different fatty acids may exhibit different effects. Collectively, these data indicate that KD induces systemic functional metabolic changes in the host, which are not limited to the induction of ketosis.

The anti-cancer effects of the KD are mediated by the gut microbiome

The gut microbiome may affect CRC development either by directly interacting with host cells (attachment, invasion and translocation), or indirectly, through bacterial metabolism (genotoxins, SCFAs and others)[20]. We first excluded bacterial translocation as a primary factor in the KD-mediated phenotype,

as mucus layer thickness (Extended Data Fig. 5a and 5b (GF)) and LPS levels in plasma (Extended Data Fig.

5c (GF) and 5d (SPF)) remained unaltered upon KD consumption, in line with Ang et al.[5]. To test the causal

role of the gut microbiome in our experimental setup, we performed a similar experiment in humanized

gut microbiome GF mice, however we housed the mice in open-top cages in a gnotobiotic flexible-film

isolator to allow for microbial exchange between groups (Extended Data Fig. 5e, 5f and 5g). Despite

confirmed ketosis, no difference in colonic tumor burden (Extended Data Fig. 5h), nor in colonic tumor

size (Extended Data Fig. 5i and 5j) was observed between groups. Furthermore, fecal microbial

compositions were similar in both groups (Extended Data Fig. 5k), with only a few taxa differentially

abundant between groups (Extended Data Fig. 5l), suggesting that microbial exchange between mice on

KD and SD was sufficient to negate the beneficial effects of the KD. Most importantly, we next performed

cecal microbial transplantation (CMT) of samples collected from the SPF diet mice (Fig. 1d) into a next

generation of SD-fed GF mice undergoing the same cancer model (Fig. 2a, Extended Data Fig. 5m).

Strikingly, KD-CMT mice, exhibited a lower colonic tumor burden than SD-CMT mice (Fig. 2b). Average

colonic tumor size per mouse did not differ between groups (Fig. 2c), however, KD-CMT mice exhibited a

smaller proportion of large tumors (Fig. 2d and e). Altogether, our results demonstrate the causal role of

the gut microbiome in mediating the previously observed KD-driven anticancer effect.

KD induces a distinct fecal microbial profile

Ordination analyses based on the underlying β-diversity among fecal samples collected from KD-

and SD-fed AOM/DSS mice revealed clustering of 5HD mix used for FMT with the individual healthy donor

stool samples and with the murine stool samples collected three days after FMT (TG, Fig. 3a (SPF) and 3d

(GF)), confirming the validity of the 5HD mix used for transplant and its engraftment. Furthermore, we

observed increasing differences between KD and SD samples over time (Fig. 3b (SPF) and 3e (GF)). Early

time points cluster together (T0, collected at diet change), while later time points diverge (T1-T4).

Differential analysis revealed *Akkermansia* spp., bacteria which can suppress colorectal tumorigenesis

through modulation of the immune system[21], *Intestimonas* spp*., Lachnoclostridium* spp*., Bilophila* spp.

(Fig. 3c (SPF)), *Phocea* spp., *Faecalitalea* spp. and others (Fig. 3f (GF), Supp. Table 3 (SPF) and 4 (GF)) to be

more abundant in KD, while *Bifidobacterium* spp*., Turicibacter* spp. (SPF)*, Barnesiella* spp*., Eisenbergiella*

spp*., Ruminococcus 1* and *2* spp. (GF) and others were depleted. Furthermore, the differential abundance

of various members of *Barnesiellaceae* spp*., Erysipelotrichaceae* spp*., Lachnospiraceae* spp. and

Ruminococcaceae spp. suggested that dietary composition affects bacterial members of the same families

in different manners.

Investigation of the engrafted gut microbial communities at experimental endpoint revealed

distinct KD- and SD-associated microbiomes (Fig. 3g and 3h, Extended Data Fig. 6a, 6b (GF), 6c and 6d), as

well as KD-CMT- and SD-CMT-associated microbiomes (Fig. 3g and 3h, Extended Data Fig. 6c and 6d).

Although a selective pressure of the KD was observed, gut microbial composition differed between cecal

donor and recipient mice, likely due to the absence of continued selective pressure from the KD, or loss

of more fragile and hard-to-engraft bacteria (Fig. 3g). Metagenome-assembled genomes (MAGs),

representing abundant members of the microbial community, allowed us to achieve species-level

resolution. Noteworthy, some MAGs annotated as CRC-associated bacteria, such as *Rikenellaceae* spp.

(light blue) and *Muribaculaceae* spp. (dark blue, Fig. 3i, Extended Data Fig. 6e (GF)), were detected in SD

groups but not the KD groups. Interestingly, various *Alistipes* spp. were differentially abundant in all

experiments. Two MAGs (*Alistipes* and *COE* species) were only identified in KD-CMT, while 12 MAGs were

only identified in SD-CMT, among which *CAG-873*, *CAG-48* and *Parabacteroides distasonis* (Fig. 3i), also

identified in the donor SPF dietary experiment.

Distinct fecal microbial functional profiles are maintained upon FMT

As microbiome-mediated effects are based on the functional and metabolic capacities of different

microbes, we also investigated KD-induced functional changes. β-diversity analysis based on KEGG and

Pfam ordinations of SPF fecal samples revealed a clear separation between groups (Fig. 4a (KEGG) and

Extended Data Fig. 7a (Pfam)), suggesting selective pressure of the diet on the intestinal microbiota. This

could also be observed in the CMT experiment, where KD-CMT clustered separately from SD-CMT, despite

being maintained on SD (Fig. 4b (KEGG) and Extended Data Fig. 7d (Pfam)). Both SPF KD-fed and KD-CMT

mice exhibited a higher number of less abundant genes/Pfams than more abundant genes/Pfams,

suggesting a KD-induced functional depletion (Extended Data Fig. 7c (SPF, KEGG), 7d (CMT, KEGG), 7e

(CMT, KEGG) and 7f (CMT, Pfam)). Accordingly, gene set enrichment analysis (Fig. 3c) and

overrepresentation analysis (Extended Data Fig. 7g) of identified KEGG orthologs revealed differences in

carbohydrate metabolism between the treatment groups in the SPF diet and CMT experiments, such as

reduced starch and sucrose metabolism under ketogenic conditions. In line with this, genes assigned to

Pfams associated with carbohydrate metabolism accounted for a large proportion of over- and under-

represented genes under ketogenic conditions (Extended Data Fig. 7i (SPF) and Extended Data Fig. 7j

(CMT)). Furthermore, we found differential abundance of several CAZymes between dietary conditions,

which are known to play a crucial role in the building and breaking down of complex carbohydrates for

use by the organism[22], with an overall increase in glycosyltransferases (GT; Extended Data Fig. 7k).

Altogether, this data underlines the selective pressure of the KD on the gut microbiome, and its capacity

to shape long-term overall gut microbial function.

The microbial metabolite stearate is elevated in ketogenic conditions and exhibits anticancer

effects

In order to investigate the link between functional alterations of the gut microbiome and the

observed cancer phenotype, we investigated fecal metabolic profiles. Analysis of fecal metabolites

revealed distinct clustering of samples by condition in both the SPF dietary and CMT experiments (Fig. 4d

and 4e, respectively). Mice in the ketogenic conditions presented altered amino acid, fatty acid,

carbohydrate and SCFA profiles (Supp. Tables 5 and 6), albeit to a lesser extent in the CMT experiment. A

single detected long-chain fatty acid, namely octadecanoic acid (also known as stearic acid), was elevated

in KD (Fig. 4f) and KD-CMT (Fig. 4g) mice. Strikingly, stearic acid levels correlated with colonic tumor

burden in the SPF dietary experiment (Fig. 4h), with a similar trend observed in the CMT experiment,

suggesting a functional relevance of long-chain fatty acid metabolism in CRC. In addition, associations

between the abundances of all identified KEGG orthologs and tumor counts in the SPF dietary experiment

identified a correlation between colonic tumor burden and some lipid-metabolism-associated KEGGs,

such as FabH, 3-oxoacyl-[acyl-carrier-protein] synthase III (K00648), FabB, 3-oxoacyl-[acyl-carrier-protein]

synthase I (K00647), FabZ, 3-hydroxyacyl-[acyl-carrier-protein] dehydratase (K02372), and FabF, 3-

oxoacyl-[acyl-carrier-protein] synthase II (K09458) (Fig. 5a and 5b, Extended Data Fig. 8a). Indeed, core

fatty acid biosynthesis KOs were less abundant in the ketogenic diet group of the SPF diet experiment,

except for the different enoyl-carrier ACPs and the thioesterases, of which one or more can be found in

most bacterial genomes (Fig. 5c). Reflecting their essential function, the core enzymes of the fatty acid

synthesis pathway correlating with tumor counts were found in both Bacteroidetes and Firmicutes

genomes. In KD, contigs carrying K00647, K00648, K09458 and K02372 were assigned to *Akkermansia*

spp., *Flavonifractor* spp. and uncharacterized Firmicutes genera, whereas many SD contigs were assigned

to Bacteroidetes genera (*Bacteroides* spp*., Parabacteroides* spp*., Muribaculum* spp. and uncharacterized

Bacteroidetes; Extended Data Fig. 8b).

Given that different bacterial taxa are known to produce and consume different fatty acids, which

are used for membrane biogenesis and as signaling molecules, we further investigated which bacterial

taxa may be responsible for the release of fatty acids, including stearic acid, and which bacteria may be

able to uptake free fatty acids. Interestingly, detection of long-chain fatty acids in different bacterial

cultures (Fig. 6a and 6b; re-analysis of the publicly available dataset from the Sonnenburg lab[23]), revealed

that – in line with the shifts in the microbial communities observed under KD (Fig. 6c and Extended Data

Fig. 8c) - the *Ruminococcaceae* and *Lachnospiraceae* families, both belonging to the class Clostridia, were

consistent producers of stearic acid, while *Tanerellaceae* and *Bacteroidaceae,* both belonging to the class

Bacteroidia, were consistent consumers (Fig. 6a). The *Clostridiaceae* family was composed of both

producers and consumers of stearic acid (Fig. 6a). The observed contrast between the abundance of fatty

acid release KOs and actual production/consumption of stearic acid by different bacteria as detected in

the Sonnenburg dataset suggests that different bacteria contribute differently to the overall fatty acid

pool. Therefore, despite no difference in the overall abundance of K10804 and K07030 between dietary

conditions (Fig. 5c), when assigned to stearate-producing bacterial families (as detected in the

Sonnenburg dataset), these KOs may result in increased levels of stearate, as we observed in ketogenic

conditions, while when assigned to stearate-consuming families, they may result in a decrease in stearate

levels, as we observed in standard conditions. Importantly, acyl-CoA thioesterase I TesA (K10804), a key

thioesterase responsible for the release of fatty acids from their acyl carrier, alongside the fatty acid kinase

FakA (K07030) used by Gram-positive bacteria to activate exogenous fatty acids, were inversely correlated

with colonic tumor burden in the SPF dietary experiment (Fig. 5d). A larger proportion of K10804 was

assigned to Clostridia in the ketogenic condition, and Bacteroidia in the standard condition in both

experiments (Fig. 5d), indicating that the lower levels of luminal stearate detected in standard conditions

may be due to the increased abundance of Bacteroidia, which, although they harbor the gene for fatty

acid release, are known stearate consumers[23]. K07030 was largely attributed to Clostridia and other

Firmicutes (Fig. 5d), suggesting that these bacteria can uptake exogenous fatty acids (for example from

the ketogenic diet) and might further elongate them into other long-chain fatty acids for downstream use

or release. To assess the putative anti-cancer properties of the long-chain fatty acid of interest identified

in the dietary and CMT experiments, we treated various CRC cell lines with increasing concentrations of

stearic acid. We observed a dose-dependent reduction in cell growth (Fig. 6d, 6e, 6f, Extended Data Fig.

8d, 8e, 8f), highlighting stearic acid as an anti-cancer metabolite. Furthermore, this observation was

specific to elevated levels of stearic acid, as treatment with other long-chain fatty acids did not exhibit

anti-cancer properties, even at higher concentrations (Fig. 6g and Extended Data Fig. 8g).

Altogether, these results suggest that KD consumption can lead to lasting functional effects on

the gut microbiome, affecting the bacterial secretome, and persisting even when the selective pressure

of the KD itself is no longer present.

Discussion

In this study we identified the gut microbiome as a driving factor in the anti-cancer effect of KD in

CRC. We observed that KD alters gut microbial function, namely bacterial carbohydrate metabolism and

the fatty acid pool. Upon KD consumption and following microbial transplantation, we observed an

increase in fecal octadecanoic acid, a long-chain fatty-acid, which exhibited anti-cancer properties *in vitro*.

The anticancer properties of the ketone body β-HB have been reported in several instances[3,4],

however, despite confirmed induction of ketosis in these mice, we observed the absence of a KD-induced

anticancer effect in the absence of robust gut microbial changes. Thus, ketosis alone seems to be

insufficient to ensure CRC suppression, similarly to other studies showing no KD benefits in the context of

cancer, despite the induction of ketosis[3,24].

Our results instead suggest that the anti-cancer effect of KD is based on gut microbial function,

rather than composition. The importance of microbial function rather than microbial composition of the

intestinal flora can be observed in other contexts as well. In melanoma, three different studies

demonstrated that the microbiome was responsible for ensuring the response to checkpoint inhibitor

therapy[25–27]. Interestingly however, these studies highlighted distinct bacterial species underlying this

response, suggesting that microbiome-encoded functions rather than individual bacterial species are

important in driving therapy response.

In regard to our own study, the depletion of dietary carbohydrates is known to provide a growth

advantage for certain bacteria, such as *Alistipes* spp., *Bilophila* spp. and mucin-degraders like *Akkermanisa*

spp., whereas *Bifidobacterium* spp. and some *Bacteroides* spp. are typically depleted[5,28], most likely due

to their preference for dietary carbohydrates over host glycans[29–31]. The shift from taxa dependent on

dietary carbohydrates taxa to taxa able to use alternative energy sources is reflected in the CAZyme profile

shift in KD and KD-CMT mice. For instance, the glycosylhydrolase GH101, enriched in all three of our

metagenomic datasets, is mucin-specific, and is required to cleave core-1 *O*-linked glycans[32]. In contrast,

the glycosylhydrolases GH50, present in the genomes of many *Bacteroides* spp. and *Proteobacteria* spp.,

and GH128, amongst others present in the genomes of the strongly reduced *CAG-485* and *CAG-873*

members, are specific for dietary carbohydrates[33] and accordingly found in reduced abundance following

KD intervention. These specific effects clearly demonstrate how diet systematically shapes the taxonomic

composition of the microbiome, driven and accompanied by a functional adaptation of the microbiome

to the new environment.

Although still an ongoing debate, the link between mucin-degrading bacteria and gut barrier

function is well-described. While overgrowth of mucin-degrading bacteria are known to damage the

epithelium[34], microbial mucin metabolism is considered beneficial as it is known to change the

glycosylation profile of the intestine[35,36], and increase mucin turnover[37]. Indeed, no mucus thinning could

be observed in KD-fed mice.

Analysis of the fecal metabolomes in the dietary intervention and CMT experiments identified

differences in the fatty acid pool. Amongst others, microbiome-derived fatty acids have an

immunomodulatory potential[38,39]. Interestingly, both *A. muciniphila* and *R. gnavus* produced higher levels

of palmitic and stearic acid when grown in the presence of mucins, linking bacterial fatty acid metabolism

to mucin physiology. In addition to their essential role in membrane biogenesis, fatty acids produced by

bacteria have signaling functions and play an essential role in host-microbe interactions[38]. The fatty acid

profile is highly species-, or even strain-, and substrate-dependent and various microbial-derived fatty

acids have different effects linking bacterial fatty acid metabolism to host health and disease[38].

Stearic acid, a long-chain fatty-acid, can originate from the diet, the host[40] and the gut

microbiome[41]. Stearic acid is normally desaturated by the host enzyme SDC1[42], is downregulated upon

reduced glucose intake and has been linked to inflammation[43–45]. Recently, Kindt et al. showed that

microbiome-derived acetate activated SDC1 and promoted fatty acid desaturation[46]. Furthermore, certain

members of the gut microbiome can directly affect stearic acid levels by consuming it as an exogenous

fatty acid for membrane lipid synthesis[23], producing it *de novo*[47], transforming it from oleic acid, or as a

product of mono- and polyunsaturated acid degradation[48,49]. In our experiments, as fecal stearic acid

levels were increased not only upon KD consumption, but also in KD-CMT, it is likely that the shift in the

microbial community is contributing to the changes in the fatty acid pool. Importantly, potential stearate-

producing members were enriched by the KD, whereas consumers were depleted (Fig. 6a and 6c).

Furthermore, several studies investigating the properties of stearic acid have demonstrated its

anti-cancer effects, both *in vitro* and *in vivo*. Stearic acid inhibited colony formation in different human

cancer cell lines[50], reduced tumor burden in rat model of mammary carcinoma[51], possibly by inducing

apoptosis via signaling through protein kinase C[52]. Finally, a recent study was able to not only validate the

suppression of colorectal adenocarcinoma by stearic acid, but also its synergy with 5-FU treatment[53]. This

effect might not be limited to stearic acid and its implications for human health and CRC in particular need

further investigation.

Based on our observations in the context of this study, the gut microbiome plays a central role in

ensuring the anti-cancer effects of the KD in the context of a murine model of inflammation-driven CRC.

Nevertheless, within this experiment, we can observe a more pronounced anti-cancer phenotype for

some mice than for others. This might indicate that the initial gut microbiome profile may determine

whether an individual is a "responder" or a "non-responder" to the KD in the context of CRC. The concept

of "responders" and non-responders" has been explored, albeit to a relatively limited extent, in epilepsy

patients who undergo KD therapy for the reduction of seizures[54]. Furthermore, the response to some

cancer treatments, such as immune checkpoint inhibition depend on gut microbial composition[55], and

ketogenic dietary regimens may be able to enhance the effects of these therapies[8]. Future studies

identifying biomarkers to predict response to dietary intervention based on the resident gut microbiome

and studies aiming to transform a "non-responder" microbiome into a "responder" microbiome would be

a significant step forward towards personalized patient care.

Figure legends

Figure 1. Ketogenic diet leads to lower colonic tumor incidence and smaller tumor size in an inflammatory model of CRC. | a. Schematic representation of the dietary AOM/DSS experimental setup in the GF (top) and SPF (bottom) facilities (created with BioRender.com). **b.** Compositions of the KD and SD, with % of calories from the indicated source. **c.** Colonic tumor burden in GF KD- and SD-fed mice. **d-f.** Colonic tumor burden (**d**), normalized average colonic tumor surface area per mouse (**e**) and tumor

surface area distribution (small= first tertile, medium=second tertile, big=third tertile; Chi-squared test χ2

(2, N = 87) = 3.4, p = 0.184; **f**) in SPF KD- and SD-fed mice. **g.** Representative images of the distal portion

of the colon from one KD- and one SD-fed mouse in the SPF facility. Scale bar = 1mm. **h-i.** Normalized

S100A8 (**f**) and S100A9 (**g**) expression in the spleens of mice from the GF diet experiment, as determined

by qPCR. Data is shown as mean±SD in (**c**), (**d**), (**e**), (**h**), and (**i**). Data in (**c**) shows n=6 mice per condition

from one experiment. Data in (**d**), (**e**) and (**f**) shows n=8 and 9 mice in the KD-fed condition and the SD-

fed conditions respectively, pooled from two independent experiments in the SPF facility. Data in (**f**) and

(**g**) shows n=4 mice per condition from one experiment in the GF facility. Two-tailed Mann-Whitney U test

in (**c**), (**d**), (**e**), (**h**), and (**i**), * p<0.05, ** p<0.01, *** p<0.001.

Figure 2. The tumor-inhibitory effect of ketogenic diet is mediated by the gut microbiome. | a.

Schematic representation of the cecal microbial transfer experimental setup in the GF facility (created

with BioRender.com). **b-e.** Colonic tumor burden (**b**), average colonic tumor surface area per mouse (in

pixels) (**c**), and tumor surface area distribution (small= first tertile, medium=second tertile, big=third

tertile; Chi-squared test χ2 (2, N = 384) = 10.3, p = 0.00586; **d**), in KC and SC recipient mice. n=16 KC

recipient mice and n=13 SC recipient mice. Cecal matter from n=8 different donor mice per condition was

used for CMT. Data shown as mean±SD in (**b**) and (**c**). Two-tailed Mann Whitney U test, **p<0.01,

***p<0.001 in (**b**) and (**c**). **e.** Representative images of the distal portion of the colon from one KC and SC

recipient mouse. Scale bar = 1mm.

Figure 3. Ketogenic diet alters gut microbiome composition. | a-f. β-diversity as assessed by PCoA (95%

confidence interval) of Bray-Curtis distance in five individual healthy donor stool samples, in a mix of the

five healthy donor stool samples (5HD mix) and in murine fecal samples three days after gavage (TG, **a**

and **d**); β-diversity as assessed by PCoA (95% confidence interval) of Bray-Curtis distance in murine fecal

samples collected over time after diet change (**b** and **e**); Abundance of selected genera which are

differentially abundant at at least one time point (using a generalized linear model on CLR, **c** and **f**) in fecal

samples collected over time after diet change from SD- and KD-fed mice in the SPF (**a**, **b** and **c**) and GF (**d**,

e, and **f**) dietary experiments (T0 at diet change, T1-T4 weeks after diet change), as analyzed by 16s rRNA

sequencing. **g-i.** β-diversity as assessed by NMDS (95% confidence interval) of Euclidean distance (**g**),

relative abundance of bacterial families (**h**), and highly characteristic bacterial MAGs (detected in at least

six mice in one condition but not more than three mice in the other (diet experiment); detected in at least

four mice in one condition but not more than three mice in the other (CMT experiment), **i**) detected in

KD, SD, KC and SC murine fecal samples at endpoint, as analyzed by WGS. In (**i**), *Rikenellaceae* are

highlighted in light blue and *Muribaculaceae* in dark blue. Data shows results from n=8 SPF KD-fed mice,

n=9 SPF SD-fed mice, pooled from two independent experiments in (**a**), (**b**), (**c**), (**g**), (**h**) and (**i**) ; n=3 GF SD

and n=6 GF KD mice from one experiment in (**d**), (**e**), (**f**) and n=8 KC and n=8 SC mice from one experiment

in (**g**), (**h**) and (**i**).

Figure 4. Ketogenic diet alters gut microbial function and metabolic profiles, leading to elevated levels of fecal stearate. | a-b. PCA (95% confidence interval) of the predicted functional features of the gut microbiome (KEGG) of SPF KD- and SD-fed mice at endpoint. **c.** Gene set enrichment analysis (GSEA, KEGG) of differentially abundant genes (threshold p.adj. < 0.05) between KD, SD, KC and SC fecal samples at endpoint. **d-e.** PCA (95% confidence interval) of identified metabolites from fecal samples from SPF KD- and SD-fed mice (**d**) and from KC and SC recipient mice (**e**), as analyzed by united GC-MS and LC-MS. **f-g.** Scaled octadecanoic acid (stearic acid) levels detected in fecal samples from SPF KD- and SD-fed mice (**f**) and from KC and SC recipient mice (**g**), as detected by LC-MS. **h.** Correlation of colonic tumor burden with fecal octadecanoic acid levels in SPF KD- and SD-fed mice (red) and in KC and SC recipient mice (blue). Two-sided Pearson correlation testing was used. Data shown in (**a**), (**c**), (**d**), (**f**) and (**h, red**) are from n=9 SPF SD-fed and n=8 SPF KD-fed mice, pooled from two independent experiments. Data shown in (**b**), (**c**), (**e**), (**g**) and (**h, blue**) are from n=8 mice per condition. Two-sided Mann-Whitney test in (**f**) and (**g**); ns p > 0.05, * p ≤ 0.05, ** p ≤ 0.01, *** p ≤ 0.001, **** p ≤ 0.0001.

Figure 5. Stearate is a microbial metabolite. |a. Schematic representation of type II bacterial fatty acid synthesis created with BioRender, adapted from Yao et Rock (2017)[41]. Core enzymes are shown with their corresponding KOs. The abundance of bolded KOs correlates with colonic tumor burden in KD- and SD-fed mice. Abbreviations: acetyl-CoA carboxylase enzyme complex (AccABCD), β-ketoacyl-ACP synthase 1 (FabB), malonyl-CoA:ACP transacylase (FabD), β-ketoacyl-ACP synthase II (FabF), β-ketoacyl-ACP reductase (FabG), β-ketoacyl-ACP synthase III (FabH), enoyl-ACP reductase enzyme isoforms (FabI, FabK, FabL and FabV), β-hydroxyacyl-ACP dehydratase (FabZ), long-chain-fatty-acid-CoA ligase (FadD), long-chain fatty acid transport protein (FadL), fatty acid kinase (FakA, FakB), acyl-ACP thioesterase (FatA), iron

transport protein (FatB), thioesterase 1/protease 1/lysophospholipase L1 (TesA), phosphate

acyltransferase (PlsX), CoenzymeA (CoA), acyl carrier protein (ACP). **b.** Correlation analysis (Pearson)

between KO abundance and colonic tumor burden in KD- and SD-fed mice. Vertical blue dotted lines

represent thresholds for correlation coefficients (r) above and below 0.65 and -0.65, respectively. The

horizontal gray dotted line represents the threshold for statistical significance -log10(0.05). KOs involved

in fatty acid metabolism appear labelled on the volcano plot and are represented in different colors

(pink=synthesis, orange=activation and blue=β-oxidation). Of those, significantly correlated KOs are

labelled in light blue font. **c.** Abundance of selected KOs of interest (summed transcripts per million (TPM))

in fecal samples from KD- and SD-fed mice, and KC and SC recipient mice, at endpoint. The abundance of

KOs highlighted in red correlates with colonic tumor burden in KD- and SD-fed mice. **d.** Correlation

(Pearson) between colonic tumor burden and the selected KOs of interest K07030 and K10804 (**top**);

Relative taxonomic assignment of contigs encoding for the selected KOs of interest K07030 and K10804

at family level (**bottom**) detected in murine fecal samples from KD-, SD-fed, KC and SC recipient mice at

endpoint. Members of the class Bacteroidia are shaded in blue, while members of the class Clostridia are

shaded in red. . Data shown in (**b**), (**c, read and black**) and (**d**) are from n=9 SPF SD-fed and n=8 SPF KD-

fed mice, pooled from two independent experiments. Data shown in (**c, gray and orange**) are from n=8

mice per condition.

Figure 6. The microbial metabolite stearate exhibits anticancer effects. | a-b. Levels of stearic acid (**a**),

and oleic (**b, left**) and palmitic acid (**b, right**) measured in bacterial cultures (in relation to sterile growth

medium, shown as log$_2$) of the Sonnenburg dataset. Members of the class Clostridia are listed in red, while

members of the class Bacteroidia are listed in blue. Total read counts detected in murine fecal samples

from KD-, SD-fed, KC and SC recipient mice at endpoint of members listed in bolded text are shown in (**c**).

c. Relative abundance (total read counts) of stearate-producing and -consuming families of interest

detected in murine fecal samples from KD-, SD-fed, KC and SC recipient mice at endpoint selected from

(**a**). **d-f.** Scaled HCT 116 (**d**), HT29 (**e**) and Caco2 (**f**) confluence at 72 hours after treatment with stearic

acid or corresponding controls (100µM, 150 µM, 200 µM, 250 µM, 300 µM). Data shows n=3 (for HCT116

and HT29) and n=2 (for Caco2) independent experiments (indicated by different datapoint shapes), each

with eight technical replicates per condition. **g.** ATP measurement (CellTiterGlo) of HT29 cells at 72 hours

after treatment with stearic acid, oleic acid, dodecanoic acid or control (200 µM). Data shows n=8

technical replicates from one experiment. Two-way ANOVA with multiple comparisons in (**c**), (**d**), (**e**) and

(**f**); **p<0.01, ***p<0.001. Data shown in (**c, red and black**) are from n=9 SPF SD-fed and n=8 SPF KD-fed

mice, pooled from two independent experiments. Data shown in (**c, gray and orange**) are from n=8 mice

per condition.

Figure 7. Functional ketogenic-diet-induced changes in the gut microbiome are responsible for its anti-

cancer properties.

Ketogenic diet consumption leads to lasting functional changes in the gut microbiome, such as alterations

in bacterial energy metabolism and in the long-chain fatty acid pool. The altered gut microbiome is

sufficient to reduce CRC development.

Extended data figure 1. | a. Metadata of fecal sample donors. M=male, F=female, N/A=not applicable,

UNKN=unknown. **b-d.** Relative abundance of the top 20 most abundant bacterial families (**b**), genera (**c**)

and species (**d**) in human stool samples (CLR units). **e.** Relative metabolite levels detected in human fecal

samples, analyzed by untargeted LC-MS.

Extended data figure 2. | a-b. Mouse body weight (grams) over time (weeks) in the SPF (**a**) and GF (**b**)

dietary experiments. Weight was not recorded between week five and ten as no scale was available in the

facility. **c.** Colon length (cm) in the GF dietary experiment at experimental endpoint. **d-e.** Heatmap of KD-

induced changes in the immune cell compartment in relation to SD (log2foldchange) in the SPF (**h**) and GF

(**i**) diet experiments. Stars overlaid on the heatmaps indicate *p<0.05, least squared means analysis. Data

is shown as mean±SD in (**a**), (**b**) and (**c**). Mann-Whitney U in (**c**), * p<0.05, ** p<0.01, *** p<0.001. Data in

(**a**) shows n=8 and 9 mice in the KD-fed condition and the SD-fed condition respectively, pooled from two

Extended data figure 3. | a. Schematic representation of the dietary AOM experimental setup in the GF

facility (created with BioRender.com). **b-c.** Mouse body weight (grams) over time (days) in mice

administered 5HD (**b**) and CRC (**c**). **d.** Ketosis levels in plasma (mmol/L), measured using a handheld

ketometer. **e.** Colonic tumor burden at endpoint. **f.** Heatmap of immune cell population phenotyping of

intra-epithelial lymphocytes (IEL), lamina propria (LP), mesenteric lymph nodes (MLN) and spleens of KD-

fed mice in relation to SD-fed mice in GF mice (GF), in mice gavaged with a mixture of stool samples from

five healthy donors (5HD), and in mice gavaged with stool from a single CRC patient (CRC). Least-squared

means analysis was performed on each combination of tissue and cell immune cell type using a linear

model, however no statistically significant differences were found. **g.** One representative image of a

section of liver stained with H&E per condition. Scale bar=500µm. Data in (**b**), (**c**), (**d**) and (**e**) shown as

mean±SD. Mann-Whitney U test in (**d**) and (**e**), not significant (ns), * $p<0.05$, ** $p<0.01$, *** $p<0.001$. Data

in (**b**), (**c**), (**d**), (**e**) and (**f**) shows n=7 and 6 mice in the GF SD and KD conditions respectively, n=6 and 4

mice in the 5HD SD and KD conditions respectively, and n=4 and 5 mice in the CRC SD and KD conditions

respectively.

Extended data figure 4. | a-b. PCA (95% confidence interval) of plasma metabolites from mice in the SPF

(**a**) and GF (**b**) diet experiments, as analyzed by united GC-MS and LC-MS analyses (**a**) and GC-MS analysis

alone (**b**). **c-d.** Relative intensity of β-HB in plasma from mice in the SPF (**c**) and GF (**d**) diet experiments,

as analyzed by GC-MS. **e-f.** Log$_2$foldchange of identified plasma bile acids in KD-fed mice in relation to SD-

fed mice in the SPF (**e**) and GF (**f**) facilities, as analyzed UHPLC-MS. **g.** Schematic representation of the

experimental setup of a Th17 cell differentiation assay (created with BioRender.com). **h-j.** Th17

differentiation upon treatment with β-HB (10mM, 50mM, 100mM), acetone (1mM, 10mM, 100mM) or

sodium acetoacetate (10mM, 100mM, 250mM) in (**h**), a lipid mixture (1%, 2%, 5%) in (**i**), BSA-complexed

palmitic and oleic acid (10μm) in (**j**). Data in (**c**), (**d**), (**h**), (**i**) and (**j**) is shown as mean±SD. Two-tailed Mann-

Whitney U test in (**c**) and (**d**); Two-tailed unpaired T test with FDR correction in (**e**) and (**f**); Paired ordinary

one-way ANOVA in (**h**), (**i**) and (**j**); ns=not significant, * $p<0.05$, ** $p<0.01$, *** $p<0.001$. Paired ordinary

one-way ANOVA comparing each set of ketone body dilutions to the control yielded no statistical

significance in (**h**). Data in (**a**), (**c**) and (**e**) shows n=9 mice in the SD-fed condition and n=8 mice in the KD-

fed condition. Data in (**b**), (**d**) and (**f**) shows n=4 mice in the SD-fed condition and n=5 mice in the KD-fed

condition. n=6 mice in (**c**) and (**d**); n=5 mice in (**e**). Abbreviations: not detected (n.d.), cholic acid (CA),

hyocholic acid (HCA), chenodeoxycholic acid (CDCA), deoxycholic acid (DCA), 7-oxo-deoxycholic acid (7-

oxo-DCA), murideoxycholic acid (MDCA), lithocholic acid (LCA), ursodeoxycholic acid (UDCA),

hyodeoxycholic acid (HDCA), muricholic acids (α-MCA, β-MCA and ω-MCA), taurocholic acid (TCA),

taurohyocholic acid (THCA), taurochenodeoxycholic acid (TCDCA), taurodeoxycholic acid (TDCA),

taurolithocholic acid (TLCA), tauroursodeoxycholic acid (TUDCA), taurohyodeoxycholic acid (THDCA),

tauro-α-muricholic acid (T-α-MCA), tauro-β-muricholic acid (T-β-MCA) and tauro-ω-muricholic acid (T-ω-

MCA).

Extended data figure 5. | a-b. Colonic inner mucus layer thickness (in pixels, **a**) and representative images

of Alcian Blue staining of colonic cryosections (**b**) in GF KD-fed and SD-fed mice. **c-d.** LPS (endotoxin units

(EU) per milliliter) in plasma from GF (**c**) and SPF (**d**) KD-fed mice and SD-fed mice measured by ELISA.

Panels **a-d** relate to experiments shown in Fig. 1. **e.** Schematic representation of the experimental setup

in the GF facility, in which mice were housed in open-top cages in a gnotobiotic flexible-film isolator

(created with Biorender.com). **f.** Ketosis levels in mouse plasma (mmol/L), measured using a handheld

ketometer. **g.** Mouse body weight (grams) over time (weeks). **h-j.** Colonic tumor burden (**h**), average

tumor surface area per mouse (pixels, **i**) and representative images of colonic tumors, scale bar=1mm (**j**)

from mice at experimental endpoint. **k.** β-diversity as assessed by PCoA of Bray-Curtis distance in mouse

fecal samples collected at two time points. **l.** Differentially abundant bacterial families (coefficient, CLR

units) in mouse fecal samples, estimated using a generalized linear model on CLR data (p.adj<0.05

(Benjamini-Hochberg correction), max. abundance>0.05), with the standard diet condition as the

reference. **m.** Mouse body weight (grams) over time (days) in the CMT experiment. Data is shown as

mean±SD in (**a**), (**c**), (**d**), (**f**), (**g**), (**h**), (**i**) and (**m**). Two-tailed Mann-Whitney U test in (**a**), (**c**), (**d**), (**f**), (**h**) and

(**i**); * p<0.05, ** p<0.01, *** p<0.001. Data in (**a**), (**c**) and (**d**) shows n=4 mice per condition. Data in (**f**), (**g**),

(**h**), (**i**), (**k**) and (**l**) shows n=9 mice in the SD-fed condition and n=8 mice in the KD-fed condition, pooled

from two independent experiments. Data in (**m**) shows 16 mice per condition.

Extended data figure 6. | a. PCA of WGS sequencing of fecal samples collected at endpoint from GF KD

and SD-fed mice. **b.** Relative abundance of bacterial families detected in fecal samples from GF KD- and

SD-fed mice at endpoint, as analyzed by WGS. **c-d.** Relative abundance of bacterial genera (**c**) and orders

(**d**) detected in fecal samples collected at endpoint from GF and SPF KD- and SD-fed mice, as well as KC

and SC recipient mice, as analyzed by WGS. **e.** Highly characteristic bacterial MAGs (detected in at least

three mice in one condition but not more than two mice in the other), detected in GF KD- and SD-fed

murine fecal samples at endpoint, as analyzed by WGS. Data shows samples collected from n=9 SPF SD-

fed mice and n=8 SPF KD-fed mice, pooled from two independent experiments in (**c**) and (**d**); n= 8 KC and

n=8 SC recipient mice from one experiment in (**c**) and (**d**); n=3 GF SD and n=6 GF KD mice from one

experiment in (**a**), (**b**) and (**e**).

Extended data figure 7. | a-b. PCA (95% confidence interval) of the predicted functional features of the

gut microbiome (Pfam) of KC and SC recipient mice at endpoint. **c-f.** Differences in gene expression profiles

mapped to the KEGG (**e** and **f**) and Pfam (**g** and **h**) databases detected in fecal samples from KD- and SD-

fed mice (**c** and **d**), and KC and SC recipient mice (**e** and **f**), at endpoint. Blue data points in (**e**) and (**f**)

represent carbohydrate-metabolism-related Pfams, solid data points represent Pfams above both defined

thresholds, while empty datapoints represent Pfams below these thresholds. Pfams named in (**e**) overlap

with those named in (**d**). **g.** Overrepresentation analysis (KEGG, threshold log2FC > 2, p.adj. < 0.05) of

genes detected in fecal samples collected at endpoint from SPF KD- and SD-fed mice, and KC and SC

recipient mice. Gene sets related to energy metabolism are shown as circular data points, while all other

gene sets are shown as triangular data points. Data point size corresponds to gene ratio. **h-i.** Differences

in gene expression profiles mapped to the DBcan database detected in fecal samples from KD- and SD-fed

mice (**h**), and KC and SC recipient mice (**i**) at endpoint. **j.** Abundance of main CAZyme families (summed

transcripts per million (TPM)) in fecal samples from KD- and SD-fed mice, and KC and SC recipient mice, at

endpoint. Boxplots show medians with 1st and 3rd quantiles. The whiskers from the hinges to the

smallest/largest values represent 1.5*inter-quartile range (IQR). Wilcoxon signed-rank test with Holm

correction, ns p > 0.05, * p ≤ 0.05, ** p ≤ 0.01, *** p ≤ 0.001, **** p ≤ 0.0001. Abbreviations: auxiliary

activities (AA), carbohydrate binding molecule (CBM), glycoside hydrolase (GH), glycosyl transferase (GT),

polysaccharide lyase (PL) and S-layer homology (SLH) families. In (**c**), (**d**), (**e**), (), (**h**) and (**j**), the horizontal

lines correspond to a three-fold increase (right) or decrease (left) in KD in relation to SD, in KC in relation

SC. The vertical lines correspond to p<0.05, the defined cutoff for statistical significance (DESeq2). Red

data points represent statistically significantly (p<0.05) differentially expressed genes with three-fold up-

or down-regulation. Data shows n=8 SPF KD-fed mice and n=9 mice SPF SD-fed mice, pooled from two

independent experiments, and n=8 KC and n=8 SC recipient mice from one experiment.

Extended data figure 8. | a. Correlation (Pearson) between colonic tumor burden of KD and SD-fed mice

and the selected KOs of interest K00647, K00648, K02372 and K09458. **b.** Relative taxonomic assignment

of contigs encoding for the selected KOs of interest at genus level in fecal samples from KD- and SD-fed

mice, and KC and SC recipient mice, at endpoint. The abundance of KOs highlighted in red correlates with

colonic tumor burden in KD- and SD-fed mice. **c.** Relative abundance (total read counts) of selected

families of interest detected in murine fecal samples from KD-, SD-fed, KC and SC recipient mice at

endpoint**.** Members of the class Clostridia are listed in red, while members of the class Bacteroidia are

listed in blue. Boxplots show medians with 1st and 3rd quantiles. The whiskers from the hinges to the

smallest/largest values represent 1.5*inter-quartile range (IQR). Wilcoxon signed-rank test with

Bonferroni correction, ns p > 0.05, * p ≤ 0.05, ** p ≤ 0.01, *** p ≤ 0.001, **** p ≤ 0.0001. **d-f.** HCT 116

(**d**), HT29 (**e**) and Caco2 (**f**) proliferation over time after treatment with stearic acid or control (100µM,

150 µM, 200 µM, 250 µM, 300 µM). Data shows mean of n=3 independent experiments (**d** and **e**), or n=2

independent experiments (**f**), each with eight technical replicates per condition. **g.** ATP measurement

(CellTiterGlo) of HT29 cells at 72 hours after treatment with stearic acid, oleic acid, dodecanoic acid or

control (200 µM). Data shows n=8 technical replicates from one experiment. Data shown in (**a**), (**b, SD and**

KD) and (**c, red and black**) are from n=9 SPF SD-fed and n=8 SPF KD-fed mice, pooled from two

independent experiments. Data shown in (**b, SC and KC**) and (**c, gray and orange**) are from n=8 mice per

condition.

Extended data figure 9. | a. Representative gating strategy of dendritic cells. **b.** Representative gating

strategy of macrophages. **c.** Representative gating strategy of regulatory T cells. **d.** Representative gating

strategy of CD8$^+$ T cells. **e.** Representative gating strategy of T helper 1 (subpanel 1) and T helper 2 cells

(subpanel 2).

Extended data figure 10. | a. Representative gating strategy of innate lymphoid cells (ILC) - ILC1 (subpanel

1), ILC2 (subpanel 2), ILC3 (subpanel 3). Transcription factors and cytokines are stained in two separate

batches. **b.** Representative gating strategy of natural killer (subpanel 1) and natural killer T (subpanel 2)

cells. **c.** Representative gating strategy of T helper 17 cells – transcription-factor-based phenotyping

(subpanel 1), cytokine-based phenotyping (subpanel 2) and the combined strategy (subpanel 3).

Acknowledgments

We acknowledge the contributions of the following people in the context of this project and thank

them for their work: Dominik Ternes, Rubens Begaj, Martin Nurmik and Cedric Gilson (MDM group,

DLSM) for assistance during organ processing at experimental endpoint; Ysaline Bossicard (MDM group,

DLSM) for tissue cryosectioning; Stephanie Willieme, Eric Grant and Mahesh Desai (LIH) for processing of

murine fecal samples; Xiangyi Dong, Floriane Gavotto and Christian Jäger (LCSB Metabolomics Platform)

for metabolite profile acquisition and raw data analysis; Aurélien Ginolhac (DLSM) for contributions to

data pre-processing; Pau Perez Escriva (DLSM) for bacterial culturing; Giulia Cesi (DLSM) for her

contributions to obtaining funding; Djalil Coowar, Jennifer Behm, Julie Virolle, Cloe Ordrenneau and all

other members of the Animal Facility Team (LCSB); Sara Gomez and Eliane Klein (DLSM) for maintenance

of organoid cultures and organoid experimentation; Rashi Halder for fecal sample 16s and WGS

sequencing. The sequencing experiments presented in this paper were carried out at the LCSB sequencing

platform (RRID: SCR_021931) at the University of Luxembourg. We also thank the patients who

contributed their samples to the national colorectal cancer cohort from which we obtained the samples

used in this study, as well as Christelle Bahlawane (CIEC), Eve Herkenne (CIEC), Laetitia Garcia (CIEC), Ingrid

Vreja (CIEC), and nurses from CIEC for contributing to this cohort. We thank Dr. Barbara Kofler for her

feedback and discussions during the course of the project. The experiments presented in this paper were

carried out using the high-performance computing facilities at the University of Luxembourg

(https://hpc.uni.lu)[56]. BioRender (BioRender.com) was used for graphical illustration.

Funding

This work was supported by the Luxembourg National Research Fund (FNR) (grant nos.

CORE/C16/BM/11282028 (E.L.), PoC/18/12554295 (E.L.), PRIDE17/11823097 (M.T., M.K., L.d.N.) and

CORE/15/BM/10404093 (P.W.)), by the Luxembourg National Research Fund and the Fondation Cancer

Luxembourg (grant no. CORE/C20/BM/14591557 (E.L.)) as well as by the Fondation du Pélican de Mie and

Pierre Hippert-Faber under the aegis of the Fondation de Luxembourg ('Pelican Grant'; M.T. and M.M.), a

FNRS-Télévie grant to M.M., no. 7.4565.21-40007364), an Internal Research Project at the University of

Luxembourg (MiDiCa—integrated analysis of the effects of microbiome-diet interactions on human

colorectal adenocarcinoma enterocytes; E.L., P.W. and S.H.), the Fondation Cancer and the Fondation

Kriibskrank Kanner Luxembourg (V.I.P), the Action LIONS Vaincre le Cancer Luxembourg and a European

Research Council grant under the European Union's Horizon 2020 research and innovation programme

(grant agreement no. 863664 to P.W.). This project was also supported by the Doctoral School in Science

and Engineering (M.T., M.K., M.M. and L.d.N.) and the Department of Life Sciences and Medicine at the

University of Luxembourg. The funders had no role in study design, data collection and analysis, decision

to publish or preparation of the manuscript.

Methods

Human sample collection

Human samples were obtained and handled in accordance with institutional guidelines. All human samples used in this project were donated freely, upon informed consent. Ethical approval was given by the Comité National d'Ethique de Recherche of Luxembourg (SOCS authorization number 201009/09 and MuSt authorization number 201110/05) and the National Commission for Data Protection in Luxembourg. Stool samples were collected at the donors' homes. The CRC patient stool sample (SOCS) was collected prior to surgery, immediately snap-frozen in a dryshipper and stored at -150°C until processing. Healthy donor stool samples (MuSt) were collected at the donors' homes in accordance with the standard practices established by the Integrated Biobank of Luxembourg (IBBL), frozen and transported on dry ice to the IBBL, then thawed for mixing and aliquoting, then refrozen and stored at -80°C until processing.

In vivo mouse experiments

Animal experiments were performed according to all applicable laws and regulations, with approval from the Animal Experimentation Ethics Committee (AEEC) and the veterinary service of the Ministry of Agriculture, Viticulture and Rural Development of Luxembourg (LUPA2019-13). They ensure that the care and the use of the animals for research purposes is conducted according to the European Union Directive 2010/63/EU and to the Grand-Ducal Regulation of the 11th of January 2013, regarding the protection of animals used for experimentation. This includes justification for the use of the animals, guidelines for their care and welfare, and the incorporation of the 3Rs (replacement, reduction and refinement). All animal protocols were reviewed by a biostatistician.

<u>Highly inflammatory mouse model of CRC</u>

SPF mice were administered a sterile-filtered antibiotic mix (vancomycin hydrochloride

(500mg/L), ampicillin (1g/L), neomycin (1g/L) and metronidazole (1g/L)) via their drinking water for one

week (refreshed every other day). GF, SPF, and CMT mice were administered a single intraperitoneal

injection of sterile-filtered AOM (10mg/kg mouse body weight in PBS, Sigma). After AOM injection, GF

mice received a gastric gavage of 5HD on two subsequent days, while SPF mice were subjected to bi-

weekly FMT during the induction of CRC to maintain enrichment of the donor fecal microbiome in relation

to the residual host mouse microbiome. FMT in SPF mice was ceased at diet change, upon removal of the

third cycle of DSS, to allow for a natural evolution of the gut microbiome in response to the diet and CRC

progression. CMT mice received a gastric gavage on two subsequent days after AOM injection, between

each cycle of DSS and once weekly after the last cycle of DSS. Three days after the first FMT/CMT, GF, SPF

and CMT mice were administered DSS via their drinking water. Mice were administered a total of three

cycles of DSS, with a two-week-long recovery period between each cycle. In the dietary experiments, half

of the mice were maintained on standard diet (A04, SAFE Lab, 40kGy irradiation) and half were randomly

allocated to the ketogenic diet (S0382-E210, ssniff Spezialdiäten, 25Gy) at the end of the last cycle of DSS.

CMT mice were all maintained on standard diet for the duration of the experiment. Collected stool

samples were snap-frozen in liquid nitrogen and stored at -80°C until use. Further details can be found in

the supplementary methods file available online.

<u>Lowly inflammatory mouse model of CRC</u>.

Mice were administered four intraperitoneal injections of sterile-filteretd AOM (15mg/kg mouse

body weight in PBS), once per week for four weeks, then gastrically gavaged with 5HD, a single CRC patient

stool sample (CRC), or fecal suspension buffer on two subsequent days. Mice gavaged with 5HD mix and

CRC were housed in individually ventilated cages, while suspension-buffer-gavaged mice were housed in

open-top cages in a gnotobiotic flexible-film isolator and were not weighed to avoid contamination. Half

of the mice were randomly allocated to the KD one week after the first injection of AOM.

16s rRNA sequencing data analysis

Raw 16S rRNA gene sequences (FASTAQ files) were cleaned and clustered as operational

taxonomic units (OTU) using the Dada2 pipeline[57] and using silvia train set (versions 132 to 138) for

taxonomy inference. Samples with no reads, amplicon sequence variants (ASV) with no identified phylum

or class and taxa present in less than 5% of samples were excluded where necessary. Data was aggregated

to genus level and relative abundances were computed, or centered log-ratio (CLR) transformation[58] was

performed. Differential analysis and graphical representation were performed in R, using the packages

from Bioconductor (DESeq2[59], phyloseq[60]) and tidyverse (ggplot).

WGS data analysis for human fecal samples

Raw genome sequences (FASTQ files) were cleaned using the Sunbeam pipeline[61]. Function

profiling was performed with HUMAnN Version 3.0[62] using the quality-controlled and host-

decontaminated FASTQ files obtained from Sunbeam. Graphical representation was performed in R, using

the packages from tidyverse, broom and RColorBrewer.

WGS data analysis for mouse fecal samples

The Integrated Meta-omic Pipeline (IMP; v3 - commitID #6f1badf7)[63] was used to process paired

forward and reverse reads using the built-in metagenomic workflow. The workflow includes pre-

processing, assembly, genome reconstruction and functional annotation of genes based on custom

databases in a reproducible manner. *De Novo* assembly was performed using the MEGAHIT (version 2.0)

assembler. Default IMP parameters were retained for all samples. MetaBAT2 and MaxBin2 in addition to

binny[64] were used for binning and genome reconstructions, i.e. MAGs. Subsequently, we obtained a non-

redundant set of MAGs using DASTool v1.1.461 with a score threshold of 0.7 for downstream analyses,

and those with a minimum completion of 90% and less than 5% contamination as assessed by CheckM

v1.1.3. Taxonomy was assigned to the MAGs using the extensive database packaged with gtdbtk v2.0.1.

For the analyses of functional potential from the assembled contigs, open-reading frames were predicted

from contigs using a modified version of Prokka that includes Prodigal gene predictions for complete and

incomplete open-reading frames. The identified genes were annotated with a hidden Markov models

(HMM) approach, trained using an in-house database including KOs derived from the Kyoto Encyclopedia

of Genes and Genomes (KEGG)[65–67], Pfam[68] and dbCAN[69] databases. All downstream analyses using the

files obtained via IMP were performed in R (version 4.2.2) using RStudio (version 2022.07.2). Differential

analysis was performed using the package *DESeq2*, microbial community analyses including non-metric

dimensional scaling (NMDS) analyses were performed using the R package *vegan* (version 2.6-4)[70]. For

further functional analysis as well as graphical representation R packages [59] *enhancedVolcano* (version

1.16.0)[71], *clusterProfiler*[72], *ggplot2*[73], *ggpubr* (version 0.6.0)[74], *tidyverse*[75] and *RColorBrewer* (version 1.1-

3)[76] were used. Details on the workflows and RMarkdowns can be found on

https://gitlab.lcsb.uni.lu/mdm/tsenkova_et_al_2024/.

Metabolomic profiling data pre-processing of untargeted LC-MS datasets

Raw data files obtained through LC-MS of human stool and murine plasma and stool samples were

processed in TraceFinder (version 5.1.203.0) for peak identification and annotation. Three different in-

house libraries, generated with reference standards, as well as one commercially available library,

mzCloud Offline for mzVault 2.3_Omics_2020A.db, in the Advanced Mass Spectral Database (AMSD)

(HighChem, from ThermoFischer Scientific), were used for peak annotation, with the adduct formulas

$[M+H]^+$ and $[M-H]^-$. Annotated features and integration tables were exported for post-processing.

Metabolomic profiling data pre-processing of untargeted GC-MS datasets

Raw data files obtained through GC-MS murine plasma and stool samples were processed in

MetaboliteDetector[77] (version 3. 220190704) for peak identification and annotation. An in-house library,

generated with reference standards was used for peak annotation. Deconvolution settings were applied

as follows: peak threshold = 5, minimum peak height = 5, bins per scan = 10, deconvolution width = 5

scans, no baseline adjustment, minimum 15 peaks per spectrum and no minimum required base peak

intensity. The data was normalized using the response ratio of the integrated peak area of each metabolite

and the integrated peak area of the IS, as described in[78]. Annotated features and integration tables were

exported for post-processing.

Metabolomic profiling post-processing data analysis

For murine plasma metabolites identified in the SPF experiment (Extended Data Fig. 4), data was

manually curated based on the pooled sample, spiked with the ISM. Features, which could not be

confirmed through MS2 data (from the commercially available database[79]) or through the ISM were

filtered out. Metabolites with missing (N/A) values were also filtered out. Single metabolite intensities

were normalized to the total metabolite area and corrected using the mean value of total metabolite

values from all samples. LC-MS and GC-MS data were unified, and duplicate metabolites were filtered out,

based on reliability and consistency of the peak areas.

Human stool sample data was similarly processed (but without the element of data unification

between methods).

For murine plasma metabolites identified in the GF experiment (GC-MS), metabolites with missing

(N/A) values were filtered out.

Murine stool SCFA content was quantified based on an IS and using the MassHunter Quantitative

Analysis Software (version 10.2.733.8). In the LC-MS and GC-MS datasets, metabolites with over 20%

missing (N/A) values were filtered out. Data from murine stool untargeted LC-MS, GC-MS and SCFA

quantification was unified and duplicate metabolites were filtered out, based on reliability and

consistency of the peak areas.

Univariate statistical analysis with Benjamini-Hochberg false discovery rate (BH FDR, performed

for all datasets), principal component analysis (PCA), scaling, centering and graphical representation in

the form of a heatmap (ComplexHeatmap R package[80]) or log2foldchanges were performed in R version

4.2.1 and Rstudio version 1.4.1717. For data scaling and centering, the standard deviation was set to a

value of 1 and the mean value was set to 0.

Other data analyses

All other data analysis, statistical analysis, and graphical representation, which is not described in

the above sections, was performed using Graphpad Prism version 9.4.1.

Data availability

Raw sequencing data files for 16S gene sequencing from murine fecal samples are available at the

ENA's sequence archive under the accession PRJEB70917 (GF) and PRJEB70920 (SPF). Raw sequencing

data files for 16S gene sequencing from human stool samples are available at the ENA's sequence archive

under the accession PRJEB70932. Raw sequencing data samples for mouse stool samples are available at

the ENA's sequence archive under the accession PRJEB66281. Raw sequencing data files for WGS from

human stool samples are available at the ENA's sequence archive under the accession PRJEB70909. Data

used to generate the figures are also provided as a 'Source Data' file.

Additional information regarding experimentation and sample processing can be found in

the Supplementary Methods file.

References

1.   Colorectal cancer statistics. *WCRF International* https://www.wcrf.org/cancer-trends/colorectal-
cancer-statistics/.

2.   Akimoto, N. *et al.* Rising incidence of early-onset colorectal cancer - a call to action. *Nat. Rev. Clin.*
Oncol. **18**, 230–243 (2021).

3.   Weber, D. D. *et al.* Ketogenic diet in the treatment of cancer – Where do we stand? *Mol. Metab.* **33**,
102–121 (2019).

4.   Dmitrieva-Posocco, O. *et al.* β-Hydroxybutyrate suppresses colorectal cancer. *Nature* **605**, 160–165
(2022).

5.   Ang, Q. Y. *et al.* Ketogenic Diets Alter the Gut Microbiome Resulting in Decreased Intestinal Th17
Cells. *Cell* **181**, 1263-1275.e16 (2020).

6.   Kong, C. *et al.* Ketogenic diet alleviates colitis by reduction of colonic group 3 innate lymphoid cells
through altering gut microbiome. *Signal Transduct. Target. Ther.* **6**, 154 (2021).

7.   Wei, R. *et al.* Ketogenesis Attenuates KLF5-Dependent Production of CXCL12 to Overcome the
Immunosuppressive Tumor Microenvironment in Colorectal Cancer. *Cancer Res.* **82**, 1575–1588
(2022).

8.   Ferrere, G. *et al.* Ketogenic diet and ketone bodies enhance the anticancer effects of PD-1 blockade.
JCI Insight **6**, 145207 (2021).

9.   Wong, C. C. & Yu, J. Gut microbiota in colorectal cancer development and therapy. *Nat. Rev. Clin.*
Oncol. **20**, 429–452 (2023).

10. El Tekle, G. & Garrett, W. S. Bacteria in cancer initiation, promotion and progression. *Nat. Rev.*
Cancer **23**, 600–618 (2023).

11. Paoli, A. *et al.* Ketogenic Diet and Microbiota: Friends or Enemies? *Genes* **10**, 534 (2019).

12. Cairo, C. & Webb, T. J. Effective Barriers: The Role of NKT Cells and Innate Lymphoid Cells in the Gut.

J. Immunol. Baltim. Md 1950 **208**, 235–246 (2022).

13. Jukic, A., Bakiri, L., Wagner, E. F., Tilg, H. & Adolph, T. E. Calprotectin: from biomarker to biological

function. *Gut* **70**, 1978–1988 (2021).

14. Wong, S. H. *et al.* Gavage of Fecal Samples From Patients With Colorectal Cancer Promotes

Intestinal Carcinogenesis in Germ-Free and Conventional Mice. *Gastroenterology* **153**, 1621-1633.e6

(2017).

15. Mu, C. *et al.* Probiotics counteract hepatic steatosis caused by ketogenic diet and upregulate AMPK

signaling in a model of infantile epilepsy. *EBioMedicine* **76**, 103838 (2022).

16. Nan, F. *et al.* Mannose: A Sweet Option in the Treatment of Cancer and Inflammation. *Front.*

Pharmacol. **13**, (2022).

17. Gonzalez, P. S. *et al.* Mannose impairs tumour growth and enhances chemotherapy. *Nature* **563**,

719–723 (2018).

18. Liu, Q., Li, X., Zhang, H. & Li, H. Mannose Attenuates Colitis-Associated Colorectal Tumorigenesis by

Targeting Tumor-Associated Macrophages. *J. Cancer Prev.* **27**, 31–41 (2022).

19. De Simone, V., Pallone, F., Monteleone, G. & Stolfi, C. Role of TH17 cytokines in the control of

colorectal cancer. *Oncoimmunology* **2**, e26617 (2013).

20. Ternes, D. *et al.* Microbiome in Colorectal Cancer: How to Get from Meta-omics to Mechanism?

Trends Microbiol. **28**, 401–423 (2020).

21. Fan, L. *et al.* A. Muciniphila Suppresses Colorectal Tumorigenesis by Inducing TLR2/NLRP3-Mediated

M1-Like TAMs. *Cancer Immunol. Res.* **9**, 1111–1124 (2021).

22. Wardman, J. F., Bains, R. K., Rahfeld, P. & Withers, S. G. Carbohydrate-active enzymes (CAZymes) in

the gut microbiome. *Nat. Rev. Microbiol.* **20**, 542–556 (2022).

23. Han, S. *et al.* A metabolomics pipeline for mechanistic interrogation of the gut microbiome. *Nature*

595, 415–420 (2021).

24. Mao, T. *et al.* Elevated serum β-hydroxybutyrate, a circulating ketone metabolite, accelerates

colorectal cancer proliferation and metastasis via ACAT1. *Oncogene* **42**, 1889–1899 (2023).

25. Gopalakrishnan, V. *et al.* Gut microbiome modulates response to anti-PD-1 immunotherapy in

melanoma patients. *Science* **359**, 97–103 (2018).

26. Matson, V. *et al.* The commensal microbiome is associated with anti-PD-1 efficacy in metastatic

melanoma patients. *Science* **359**, 104–108 (2018).

27. Routy, B. *et al.* Gut microbiome influences efficacy of PD-1-based immunotherapy against epithelial

tumors. *Science* **359**, 91–97 (2018).

28. Olson, C. A. *et al.* The Gut Microbiota Mediates the Anti-Seizure Effects of the Ketogenic Diet. *Cell*

173, 1728-1741.e13 (2018).

29. cis-Encoded Small RNAs, a Conserved Mechanism for Repression of Polysaccharide Utilization in

Bacteroides | Journal of Bacteriology. https://journals.asm.org/doi/10.1128/jb.00381-16.

30. Pudlo, N. A. *et al.* Symbiotic Human Gut Bacteria with Variable Metabolic Priorities for Host Mucosal

Glycans. *mBio* **6**, 10.1128/mbio.01282-15 (2015).

31. Milani, C. *et al.* Bifidobacteria exhibit social behavior through carbohydrate resource sharing in the

gut. *Sci. Rep.* **5**, 15782 (2015).

32. Luis, A. S. & Hansson, G. C. Intestinal mucus and their glycans: A habitat for thriving microbiota. *Cell*

Host Microbe **31**, 1087–1100 (2023).

33. Drula, E. *et al.* The carbohydrate-active enzyme database: functions and literature. *Nucleic Acids*

Res. **50**, D571–D577 (2022).

34. Desai, M. S. *et al.* A dietary fiber-deprived gut microbiota degrades the colonic mucus barrier and

enhances pathogen susceptibility. *Cell* **167**, 1339-1353.e21 (2016).

35. van der Lugt, B. *et al.* Akkermansia muciniphila ameliorates the age-related decline in colonic mucus

thickness and attenuates immune activation in accelerated aging Ercc1−/Δ7 mice. *Immun. Ageing*

16, 6 (2019).

36. Gamage, H. K. A. H. *et al.* Changes in dietary fiber intake in mice reveal associations between colonic

mucin O-glycosylation and specific gut bacteria. *Gut Microbes* **12**, 1802209 (2020).

37. Johansson, M. E. V. *et al.* Normalization of Host Intestinal Mucus Layers Requires Long-Term

Microbial Colonization. *Cell Host Microbe* **18**, 582–592 (2015).

38. Brown, E. M., Clardy, J. & Xavier, R. J. Gut microbiome lipid metabolism and its impact on host

physiology. *Cell Host Microbe* **31**, 173–186 (2023).

39. Yamada, S. *et al.* Gut microbiota-mediated generation of saturated fatty acids elicits inflammation in

the liver in murine high-fat diet-induced steatohepatitis. *BMC Gastroenterol.* **17**, 136 (2017).

40. Guillou, H., Zadravec, D., Martin, P. G. P. & Jacobsson, A. The key roles of elongases and desaturases

in mammalian fatty acid metabolism: Insights from transgenic mice. *Prog. Lipid Res.* **49**, 186–199

(2010).

41. Yao, J. & Rock, C. O. Exogenous fatty acid metabolism in bacteria. *Biochimie* **141**, 30–39 (2017).

42. Flowers, M. T. & Ntambi, J. M. Role of stearoyl-coenzyme A desaturase in regulating lipid

metabolism. *Curr. Opin. Lipidol.* **19**, 248–256 (2008).

43. Lien, E. C. *et al.* Low glycaemic diets alter lipid metabolism to influence tumour growth. *Nature* **599**,

302–307 (2021).

44. Zhou, X. *et al.* Stearoyl-CoA Desaturase-Mediated Monounsaturated Fatty Acid Availability Supports

Humoral Immunity. *Cell Rep.* **34**, (2021).

45. Grajchen, E. *et al.* Fatty acid desaturation by stearoyl-CoA desaturase-1 controls regulatory T cell

differentiation and autoimmunity. *Cell. Mol. Immunol.* **20**, 666–679 (2023).

46. Kindt, A. *et al.* The gut microbiota promotes hepatic fatty acid desaturation and elongation in mice.

Nat. Commun. **9**, 3760 (2018).

47. Kim, K. S. *et al.* Genome-wide multi-omics analysis reveals the nutrient-dependent metabolic

features of mucin-degrading gut bacteria. *Gut Microbes* **15**, 2221811 (2023).

48. McKain, N., Shingfield, K. J. & Wallace, R. J. Metabolism of conjugated linoleic acids and 18 : 1 fatty

acids by ruminal bacteria: products and mechanisms. *Microbiology* **156**, 579–588 (2010).

49. Microbial Production of Conjugated Linoleic Acid and Conjugated Linolenic Acid Relies on a

Multienzymatic System | Microbiology and Molecular Biology Reviews.

https://journals.asm.org/doi/10.1128/mmbr.00019-18.

50. Fermor, B. F. *et al.* Fatty acid composition of normal and malignant cells and cytotoxicity of stearic,

oleic and sterculic acids in vitro. *Eur. J. Cancer Oxf. Engl. 1990* **28A**, 1143–1147 (1992).

51. Habib, N. A. *et al.* Stearic acid and carcinogenesis. *Br. J. Cancer* **56**, 455–458 (1987).

52. Evans, L. M., Cowey, S. L., Siegal, G. P. & Hardy, R. W. Stearate preferentially induces apoptosis in

human breast cancer cells. *Nutr. Cancer* **61**, 746–753 (2009).

53. Mitchel, J. *et al.* Computational Identification of Stearic Acid as a Potential PDK1 Inhibitor and In

Vitro Validation of Stearic Acid as Colon Cancer Therapeutic in Combination with 5-Fluorouracil.

Cancer Inform. **20**, 11769351211065979 (2021).

54. Zhang, Y. *et al.* Altered gut microbiome composition in children with refractory epilepsy after

ketogenic diet. *Epilepsy Res.* **145**, 163–168 (2018).

55. Naqash, A. R. *et al.* The role of gut microbiome in modulating response to immune checkpoint

inhibitor therapy in cancer. *Ann. Transl. Med.* **9**, 1034 (2021).

56. Varrette, S., Bouvry, P., Cartiaux, H. & Georgatos, F. Management of an academic HPC cluster: The

UL experience. in *2014 International Conference on High Performance Computing & Simulation*

(HPCS) 959–967 (IEEE, Bologna, Italy, 2014). doi:10.1109/HPCSim.2014.6903792.

57. Callahan, B. J. *et al.* DADA2: High-resolution sample inference from Illumina amplicon data. *Nat.*

Methods **13**, 581–583 (2016).

58. Lin, H. & Peddada, S. D. Analysis of microbial compositions: a review of normalization and

differential abundance analysis. *Npj Biofilms Microbiomes* **6**, 1–13 (2020).

59. Anders, S. & Huber, W. Differential expression analysis for sequence count data. *Genome Biol.* **11**,

R106 (2010).

60. phyloseq: An R Package for Reproducible Interactive Analysis and Graphics of Microbiome Census

Data | PLOS ONE. https://journals.plos.org/plosone/article?id=10.1371/journal.pone.0061217.

61. Clarke, E. L. *et al.* Sunbeam: an extensible pipeline for analyzing metagenomic sequencing

experiments. *Microbiome* **7**, 46 (2019).

62. Integrating taxonomic, functional, and strain-level profiling of diverse microbial communities with

bioBakery 3 | eLife. https://elifesciences.org/articles/65088.

63. Narayanasamy, S. *et al.* IMP: a pipeline for reproducible reference-independent integrated

metagenomic and metatranscriptomic analyses. *Genome Biol.* **17**, 260 (2016).

64. Hickl, O., Queirós, P., Wilmes, P., May, P. & Heintz-Buschart, A. binny: an automated binning

algorithm to recover high-quality genomes from complex metagenomic datasets. *Brief. Bioinform.*

23, bbac431 (2022).

65. Kanehisa, M. & Goto, S. KEGG: Kyoto Encyclopedia of Genes and Genomes. *Nucleic Acids Res.* **28**,

27–30 (2000).

66. Kanehisa, M., Furumichi, M., Sato, Y., Kawashima, M. & Ishiguro-Watanabe, M. KEGG for taxonomy-

based analysis of pathways and genomes. *Nucleic Acids Res.* **51**, D587–D592 (2023).

67. Kanehisa, M. Toward understanding the origin and evolution of cellular organisms. *Protein Sci.* **28**,

1947–1951 (2019).

68. Mistry, J. *et al.* Pfam: The protein families database in 2021. *Nucleic Acids Res.* **49**, D412–D419

(2021).

69. Yin, Y. *et al.* dbCAN: a web resource for automated carbohydrate-active enzyme annotation. *Nucleic*

Acids Res. **40**, W445-451 (2012).

70. Oksanen, J. *et al.* vegan: Community Ecology Package. (2022).

71. Blighe, K. *et al.* EnhancedVolcano: Publication-ready volcano plots with enhanced colouring and

labeling. Bioconductor version: Release (3.18) https://doi.org/10.18129/B9.bioc.EnhancedVolcano

(2023).

72. Wu, T. *et al.* clusterProfiler 4.0: A universal enrichment tool for interpreting omics data. *Innov.*

Camb. Mass **2**, 100141 (2021).

73. ggplot2: Elegant Graphics for Data Analysis (3e). https://ggplot2-book.org/.

74. Kassambara, A. ggpubr: 'ggplot2' Based Publication Ready Plots. (2023).

75. Wickham, H. *et al.* Welcome to the Tidyverse. *J. Open Source Softw.* **4**, 1686 (2019).

76. Neuwirth, E. RColorBrewer: ColorBrewer Palettes. (2022).

77. Hiller, K. *et al.* MetaboliteDetector: comprehensive analysis tool for targeted and nontargeted

GC/MS based metabolome analysis. *Anal. Chem.* **81**, 3429–3439 (2009).

78. De Saedeleer, B. *et al.* Systematic characterization of human gut microbiome-secreted molecules by

integrated multi-omics. *ISME Commun.* **1**, 1–6 (2021).

79. Xue, J., Guijas, C., Benton, H. P., Warth, B. & Siuzdak, G. METLIN MS2 molecular standards database:

a broad chemical and biological resource. *Nat. Methods* **17**, 953–954 (2020).

80. Gu, Z., Eils, R. & Schlesner, M. Complex heatmaps reveal patterns and correlations in

multidimensional genomic data. *Bioinformatics* **32**, 2847–2849 (2016).

943