Complex system modelling reveals oxalate homeostasis is driven by diverse oxalate-degrading bacteria

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Running head: Oxalate metabolism within a complex system framework

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Summary

Decades of research have made clear that host-associated microbiomes touch all facets of health. However, effective therapies that target the microbiome have been elusive given its inherent complexity. Here, we experimentally examined diet-microbe-host interactions through a complex systems framework, centered on dietary oxalate. Using multiple, independent molecular, animal, and *in vitro* experimental models, we found that microbiome composition influenced multiple oxalate-microbe-host interfaces. Importantly, administration of the oxalate-degrading specialist, *Oxalobacter formigenes,* was only effective against a poor oxalate-degrading microbiota background and gives critical new insights into why clinical intervention trials with this species exhibit variable outcomes. Data suggest that, while heterogeneity in the microbiome impacts multiple diet-host-microbe interfaces, metabolic redundancy among diverse microorganisms in specific diet-microbe axes is a critical variable that may impact the efficacy of bacteriotherapies, which can help guide patient and probiotic selection criteria in probiotic clinical trials.

Introduction

Research into the host-associated microbiome is at an inflection point. Decades of research have revealed that host-associated microbiomes are intimately linked to host health and touch all aspects of host physiology[1,2]. The first phase of microbiome research was focused on descriptive studies that characterized differences in the microbiome by host species, body site, and disease phenotypes[3-5]. Clinical case:control metagenome wide association studies that found differences in microbiome composition between healthy and disease cohorts gave rise to the ambiguous term "dysbiosis" and much of the literature is focused on "balancing" the gut microbiota[6]. In the second, and current, phase of research, studies have moved towards gaining more mechanistic insight into specific microbe-host interactions that influence host physiology and disease[6-9]. However, it is increasingly being recognized that, given the wide variability in microbiome composition, host genetics, and lifestyles, understanding mechanisms and causal relationships between gut bacteria and host physiological responses is not enough for the development of effective bacteriotherapies that target the gut microbiota[10,11]. In fact, many probiotic clinical trials, with known mechanistic links between the probiotics and host physiology, have exhibited wide variability in results[12-15]. It is currently unclear what sources of variability may drive the response to targeted bacteriotherapies. Some variables that have been proposed include heterogeneity in microbiome composition, alcohol consumption, and bowel movement quality[10].

Complex system theory is one means to potentially constrain hypotheses and bridge the gap between mechanistic studies and effective bacteriotherapies[16,17]. Studies of the host-associated microbiome often casually acknowledge that these systems are complex and, while, there has been progress made in developing mathematical approaches to complex modelling of host-microbiome relationships[16-19], few studies have bridged the gap between experimental biology and complex system theory. Mammals and their gut microbiome, are often considered as a holobiont[20], defined as a discrete unit that exhibits collective action and evolves as a unit. Using evolutionary theory approaches, it is hypothesized that the form and function of the microbial part of the holobiont is driven primarily by host-microbe influences, but which require microbe-microbe interactions to help manage the enormous burden of microbiome constraint, which is termed an "ecosystem on a leash"[21]. Under this hypothesis, microbe-host interactions, in which host-associated microbes evolve to produce metabolic by-products for the sole benefit of the host, are necessarily rare. Essential features of complex systems include functional redundancy[21,22] and cooperation through chains of direct interactions[21-23], distinct functional nodes that process and transfer resources[22,23], fractality[22,23], and adaptability through specific homeostatic feedback mechanisms to maintain relatively consistent internal conditions given a dynamic external environment[21,24]. While considerable progress has been made in understanding the nature of complex systems, there is a lack of consensus on basic terminology and broadly applicable analytical or experimental models[25]. This limitation is due in part because complex systems necessarily transect many divergent entities in nature and is thus studied in diverse scientific disciplines[25]. Thus, while some essential features of complexity have been elucidated within specific real-world systems, such as the conversion of polysaccharides to butyrate by multiple species in the gut[26], or feedback

98   loops in blood pressure regulation[27], experimental evidence of multiple features of
99   complexity within a single system is sparse, especially in microbe-host systems.
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To overcome the limitations of applying complex systems theory to the microbe-host
holobiont, new models and experimental frameworks are needed that balance
complexity with tractability. Antinutrients, produced in plants to deter herbivory, disrupt
homeostasis by targeting the function of the microbiome, host, or both[28], and provide an
effective focal point to study complexity. Oxalate is an antinutrient present in many
plant-based foods, which typically provides the majority of oxalate in circulation[29], but is
also produced as a terminal metabolite in the liver[30]. While some host genetic
mutations increase endogenous production of oxalate[31], mammals do not produce
enzymes capable of degrading oxalate[32]. However, multiple oxalate-degrading bacteria
exist in the gut, which degrade oxalate through one of a handful of simple metabolic
pathways involving one or two genes[33-35], which isolates this function to the gut
microbiota. As such, oxalate degradation as a function, exhibits a moderate amount of
complexity compared to other gut microbiota functions, such as the production of
trimethylamine N-oxide (TMAO), that requires host input[36].   Beyond the moderate
complexity, it is known that oxalate-degrading bacteria are susceptible to antibiotics and
that antibiotic use decreases oxalate degradation[37-41]. Elevated levels of oxalate induce
oxidative stress, activates the inflammasome, and disrupts epithelial barrier function
through tight junction proteins[42-44]. This molecule has been linked to diseases including
kidney stones and chronic kidney disease[45-47], breast cancer[48], and cardiometabolic
disorders such as atherosclerosis[49], obesity[50], and diabetes[50]. *Oxalobacter formigenes,*
which uses oxalate as a sole carbon and energy source[33], is a well-studied oxalate-
degrading species of bacteria. The negative, at times lethal, effects of oxalate, along
with the identification and mechanisms of oxalate-degrading bacteria in the gut, have
been worked out for several decades[33,51-54], pre-dating the current microbiome era.
Despite this knowledge, clinical intervention trials involving *Oxalobacter formigenes,*
which is perhaps the most effective oxalate-degrading species known, have
successfully resulted in a significant reduction in urine oxalate levels in only 43% of
studies[15,55]. Oxalate-degrading lactic acid bacteria have been successful in 37.5% of
studies[15]. Both treatments led to a wide variability in patient responses. Given these
data and the well worked out mechanisms of oxalate metabolism, it is clear that having
an understanding of the mechanistic links between the gut microbiota and host
physiology, alone, is demonstrably not sufficient to develop effective bacteriotherapies.
Therefore, even though the history of oxalate-microbe-host interactions is much greater
than most other microbe-host systems, oxalate degradation represents an accurate
reflection of the challenges faced by microbiome research and is a prime candidate for
complex system modelling to understand the critical variables that determine
responsiveness to bacteriotherapies.
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The objectives of the current study were to evaluate oxalate-microbe-host interactions,
within the framework of complex systems. We used multi-omic approaches utilizing
multiple independent *in vivo* and *in vitro* models to understand the critical variables that
influence the gut microbiota's maintenance of oxalate homeostasis and its impact on the
host. We targeted several potential oxalate-microbe-host interfaces that include the gut

microbiota itself, which is one of the first lines of defense against antinutrients[56,57],
intestinal epithelium, which is an important barrier between microbe and host[21], the liver,
which is important for the biotransformation of dietary or microbial metabolites[58], along
with the kidneys and vasculature, where calcium oxalate can potentially form calcified
deposits or induce inflammation[49,59-61]. Collectively, data indicate that multiple oxalate-
microbe-host interfaces are influenced significantly by gut microbiota composition and
that harboring diverse microorganisms capable of degrading oxalate can limit the impact
of *O. formigenes* as a probiotic. Based on results from this study, we propose a phased
approach for the development of bacteriotherapies whereby clinical case:control studies
determine whether or not a clinical phenotype is associated with the microbiome and
the microbial taxa/functions associated with specific phenotypes (Phase I).
Hypothesized taxa and/or microbial functions should be mechanistically resolved
through *in vitro* and germ-free animal studies (Phase II). Finally, mechanistic insights
should be applied to a complex systems theoretical framework to identify those
variables that most impact the potential success of bacteriotherapies (Phase III). Such a
phased approach would have broad implications for patient and probiotic selection in
the development of targeted bacteriotherapies.
161
162   **Results**
163
Defining the oxalate-microbe-host as a complex system
To use complex system modelling as a means to identify the most pertinent variables
that impact oxalate-microbe-host interactions, we first had to define the system as a
series of nodes, whereby oxalate is processed, connections, where the end-product of
one node is transferred to another node, and fractals, which are autonomous subunits
or layers that exhibit analogous, but unique, functions to other layers. For antinutrients,
such as oxalate, we can define four unique nodes where these molecules can either be
transformed or where they can transform the host. The first node is the stomach where
the low pH can biotransform some molecules, such as glucosinolates[62]. Some
proportion of the molecules can be absorbed into the circulation in the stomach.
Stomach contents are then transferred to the intestines, the second node, where they
are first exposed to high densities of gut bacteria, particularly in the colon. Within the
gut microbiota, there are two fractal layers that include microbial species and the genes
within each species. In each of these fractal layers, there are three hypotheses that can
be generated about how microbes can degrade oxalate or other antinutrients. These
include a) one species/gene, one function; b) multiple species/genes, one function; or c)
multiple species, multiple functions. Canonically, the hypothesis is that one single
species, *O. formigenes,* is primarily responsible for oxalate degradation[63], which is
achieved through a two gene metabolic pathway (oxalyl-CoA decarboxylase and formyl-
CoA transferase)[53,54]. However, more recent studies show that many species of gut
bacteria degrade oxalate and multiple metabolic pathways can be used to degrade
oxalate that comprise of one or two genes[34,35,64,65]. Furthermore, studies have shown
that there are broad interactions between the gut microbiota and oxalate degradation[66-
72]. Finally, two of the most common by-products of oxalate degradation are CO_2 and
formate. Importantly, these by-products can be used in downstream metabolic
pathways such as acetogenesis, methanogenesis, and sulfate-reduction[73-76]. Given the

inconsistent results in *O. formigenes* trials and the recognition that there are broad gut
microbiota-oxalate interactions that maintain oxalate homeostasis, we can hypothesize
that, instead of relying on a single species, oxalate homeostasis is maintained either by
diverse oxalate-degrading bacteria or by cooperative networks whereby a small number
of oxalate-degrading bacteria produce substrates to be used in downstream metabolic
pathways (i.e. multiple species, one function or multiple species, multiple functions).
Again, some proportion of oxalate in the intestines gets absorbed into circulation or is
excreted in the stool. However, oxalate can also be secreted back into the gut through
transporters such as SLC26a6[77,78]. Another proportion of the molecule can be
transported through the portal vein to the liver for hepatic biotransformation[79].
Importantly, for oxalate, the liver is a source, rather than a sink[32]. However, for other
molecules, such as trimethylamine that is produced by gut bacteria, the liver is critical
for converting the molecule to the more pathogenic TMAO form[36]. Some complex
antinutrients, such as creosote, require both the gut microbiota and the liver[80]. The liver
can also be divided into fractal layers based on cell type and genes. Oxalate or other
antinutrients that are neither excreted in the stool, nor degraded by the gut microbiota,
nor degraded by the liver, can impact one or more organs and interact with the host
through localized immune responses, with the remaining being excreted in the urine.
As such, this model sets up multiple testable hypotheses, which are explored in depth,
below.
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Constitutive and oxalate-dependent effects of the microbiome impact host hepatic gene
expression
Both the gut microbiota and the liver are important organs for the neutralization of
antinutrients[58,81], indicative of functional redundancy, cooperation, and fractality. While
it is known that the liver does not degrade oxalate itself, it could still be impacted by
oxalate, in gut microbiota dependent ways. To determine the effects of oxalate
exposure and microbiome on host hepatic gene expression, we used a fecal transplant
model to examine different host microbiomes with the same host genetics. Specifically,
a five-day course of neomycin was used to suppress the native gut microbiota of Swiss-
Webster mice (SWM)[38], followed by fecal transplants either from SWM (allograft; SW-
SW) or *N. albigulia* (NALB)*,* which has a highly effective and transferable oxalate-
degrading gut microbiota[68,69,72], (xenograft; SW-NALB). Subsequently, animals were
fed either a 0% or 1.5% oxalate diet (Evigo, Fig. 1A, Table S1). Liver tissue was
obtained after three weeks and processed for bulk RNAseq. The RNAseq data analyses
revealed constitutive microbiome and microbiome-dependent oxalate effects (Fig.
1B,C), whereby SW-SW mice exhibited an oxalate-dependent alteration of 219 hepatic
genes, with a net increase in activity, while the SW-NALB mice exhibited an oxalate-
dependent alteration of 21 genes with a net decrease in activity (Fig. 1C, Table S2). In
the SW-NALB mice, the primary response was a decrease in sulfation activity with
oxalate exposure, which is involved in the deactivation, detoxication, and excretion of
xenobiotics (Fig 1C), and suggests oxalate may be beneficial for this host-microbe
system[82]. The primary response in the SW-SW mice was an increase in mitochondrial
activity, translation, protein regulation, and ribosome biogenesis, indicative of oxalate-
induced hepatic stress[49,83]. Since hosts only differed by gut microbiota composition,
these data demonstrate causative interactions between the gut microbiota and liver

activity through oxalate-dependent and independent pathways. Within the framework of
complex systems, results show microbe-host cooperation whereby oxalate effectively
processed within the SW-NALB gut microbiota reduced overall liver activity, indicative of
a beneficial impact. Data also suggest that both the gut microbiota and the immune
system are involved in oxalate remediation (redundancy), such that if oxalate cannot be
neutralized in the gut microbiota or liver, then the molecule will be processed through
host immune response mechanisms (fractality), in this case indicated through an overall
increase in hepatic activity and specifically in mitochondrial activity.
244
Constitutive and oxalate-dependent effects of the microbiome impact microbial
metabolic activity in the gut
Microbe-microbe interactions are important features of the microbe-host holobiont within
the conext of complex systems, both in terms of constraining the microbiome and in
processing dietary components[21,22,26,56]. To assess changes to microbial metabolic
output with oxalate exposure, we used the same animals as above. Following the diet
trial, colon stool was collected post-necropsy and processed for untargeted
metabolomics, which is a measure of total microbial metabolic output. Collectively,
results are indicative of constitutive microbiome and microbiome-dependent oxalate
effects (Fig. 2A,B). The SW-SW mice exhibited an alteration of 162 microbial
metabolites upon oxalate exposure, with a net decrease in activity compared to the no
oxalate group, whereas the SW-NALB mice exhibited an alteration of 83 microbial
metabolites, with a net increase in activity compared to the no oxalate group (Fig. 2B,
Table S3). In SW-NALB mice, the primary response was an increase in lipid metabolism
and a shift (increase/decrease) in fatty acid, secondary metabolite, and alkaloid profiles.
In the SW-SW mice, the primary response was an increase in fatty acid synthesis and
phenylalanine metabolism, and a decrease in synthesis of secondary metabolites,
cholesterol, and alkaloids (Fig. 2B). Therefore, while oxalate had a much greater impact
on gut microbial metabolism in SW-SW mice overall, the metabolic pathways impacted
were similar. Net changes in microbial metabolites produced are indicative of a
negative impact of oxalate on microbial activity in SW-SW and positive impact in SW-
NALB mice. Integration of host hepatic gene expression and gut metabolomic data
shows that oxalate induces a small decrease in hepatic activity overall for SW-NALB
mice and a large increase in hepatic activity for SW-SW mice (Fig. 2C, Table S4). From
a complex systems perspective, data reflect a causative effect of oxalate for the shift in
microbial metabolic output. Specifically, the SW-NALB mice exhibit hallmarks of
homeostatic feedback with oxalate exposure to maintain a consistent metabolic output,
defined by the relatively small, net negative, microbial metabolite-hepatic gene network
compared to the large, net positive, network of SW-SW mice. Additionally, data further
support the cooperation, redundancy, and fractality of the gut-liver axis. While SW-
NALB exhibit a small increase in microbial metabolic activity and decrease in liver
activity, the SW-SW mice saw a large decrease in microbial metabolic activity, coupled
with a large increase in hepatic activity, which is reflected in the multi-omic network
profiles (Fig. 2C).
279
Oxalate stimulates the growth of microbial populations involved in oxalate metabolism,
formate metabolism, and their precursors

To gain a deeper understanding of microbe-microbe interactions associated with
oxalate exposure and to identify specific microorganisms that positively respond to
oxalate exposure, NALB with their native microbiota were pair-fed increasing amounts
of oxalate, from 0.2% to 6% (Fig. 3A). Stool was sampled after 5 days on the 0.2% and
6% diets and processed for shotgun metagenomics. Analysis of metagenomic data
revealed that oxalate had a significant impact on metagenome composition (Fig. 3B),
with a significant increase of 1073 gene populations and decrease of 382 gene
populations (Fig. 3C; Table S5). Changes in gene abundance included four oxalate
metabolism gene populations, a shift in 48 gene populations involved in formate
metabolism (32 +/16 -), and a shift in genes related to glycine and
glyoxylate/dicarboxylate metabolism (6+/4-), which are precursors to oxalate (Fig. 3D).
A total of 128 differentially abundant genes were involved in sugar metabolism. Altered
gene populations primarily belonged to *O. formigenes* and *Alistipes senegalensis,* with
many genes belonging to the *Muribaculum* genus (Fig. 3E). *Muribaculum spp* harbor
oxalate-degrading genes, which suggests oxalate metabolic redundancy in the gut
microbiota[84]. The oxalate-dependent metagenomic divergence of the NALB gut
microbiota (Fig. 3), combined with the lack of change in the microbial metabolomic
profile with oxalate exposure (Fig. 2), suggest that oxalate stimulates taxonomically
diverse, but metabolically redundant microorganisms, in support of maintaining
homeostasis. Given that data came from the same hosts sampled longitudinally, these
data also reflect a microbiota that is adaptive to oxalate exposure, which is another
important characteristic of complex systems.
304
Oxalate and formate metabolism are highly redundant functions in the NALB gut
To investigate the hypothesis that oxalate stimulates a taxonomically diverse,
metabolically redundant community, 248 full length genomes were extracted from
shotgun metagenomic data (Fig. S1). Genes for oxalate metabolism, formate
metabolism, or the formate metabolic pathways of acetogenesis, methanogenesis, and
sulfate reduction, were derived from the KEGG pathway database[85] and mapped to full
length genomes. This analysis provides a targeted assessment for metabolic
redundancy aimed at oxalate metabolism and pathways associated with the by-products
of oxalate metabolism (potential cooperation). A total of 59.3% of genomes contained
at least one gene associated with oxalate metabolism or handling (Fig. 4A), most
represented by oxalyl-CoA decarboxylase, glycerate dehydrogenase, and formyl-
CoA:oxalate CoA transferase (Fig. 4B). However, only 27.8% of genomes harbored a
complete metabolic pathway for oxalate degradation (Fig. 4C). Taxa with oxalate genes
were dominated by *Bacteroides, Muribaculaceae, Clostridium, Ruminococcus,* and
Lachnospiraceae (Fig. 4D). Formate metabolism genes were found in 97.18% of
genomes, which was dominated by serine hydroxymethyltransferase, and formate-
tetrahydrofolate ligase (Fig. S2A-C). Acetogenic genes were also present in 97.18% of
genomes, dominated by acetate kinase and formate-tetrahydrofolate ligase (Fig. S3A-
C). Methanogenic genes were present in 100% of genomes, dominated by
phosphoserine phosphatase, atp-dependent 6-phosphofructokinase, and phosphate
acetyltransferase (Fig. S4A-C). Sulfate-reducing genes were present in 31.05% of
genomes, dominated by bifunctional oligoribonuclease and PAP phosphatase, FMN
reductase, and cysteine synthase (Fig. S5A-C). Data show highly redundant oxalate-

associated metabolic pathways and thus provide evidence for very robust homeostatic
feedback mechanisms to handle oxalate and metabolic by-products within the NALB gut
microbiota. Additionally, the broad diversity of species that contain oxalate-related
genes suggest that the distribution of metabolic genes is somewhat independent of the
distribution of microbial species, which suggests that microbial genes exist in an
autonomous fractal layer, to some degree. This hypothesis is supported by studies
which show a high degree of horizontal gene transfer within the gut microbiota as a
means of adaptation[86].
336
Oxalate metabolism is driven both by substrate availability and microbiota composition
Adaptability and homeostatic feedback within complex systems is driven by the
convergence of system components and resource availability[24]. To examine the
confluence of resource availability and oxalate metabolism, a custom medium based on
previously published gut microbiota media[87] was modified by adding substrates
associated with metabolic pathways enriched by oxalate (Fig. 3C, Table S6). The
oxalate-degrading species *Enterococcus gallinarum,* previously isolated from NALB[70]
and the whole NALB community were assessed. Chosen substrates impacted oxalate
metabolism and the impact of oxalate on growth, particularly at the community level
(Fig. 5A,B). A minimal media with the same substrates added as sole carbon and
energy sources (Table S7) allowed for quantification of the proportion of the NALB
microbiota that could use each substrate as sole carbon and energy sources.
Culturomic data recapitulates molecular data to show a considerable amount of
redundancy surrounding oxalate metabolism (Fig. 5C). Isolates generated from this
assay were used for subsequent study (metabolic cohort; Figure 5D). Additionally, a
second cohort was defined and commercially purchased based both on known
metabolic functions and the proportion of studies that saw an increase in their
taxonomic population with oxalate consumption (Fig. 5D; taxonomic cohort). Where
possible, isolates from human sources were obtained. Cohorts, defined in the STAR
methods, were used to delineate hypotheses that either carbon and energy substrates
are sufficient to explain known effects of the oxalate-degrading microbial network or that
additional aspects of taxa commonly stimulated by dietary oxalate are required to
explain past results (taxa defined through previous meta-analysis of studies)[15]. Oxalate
metabolism with the metabolic and taxonomic cohorts was assessed *in vitro* in minimal
media with oxalate as a sole carbon and energy source (Fig. 5E,F). There were
considerable differences in oxalate metabolism in both cohorts, dependent on the
microbes present. However, significant oxalate metabolism occurred even in the
absence of *O. formigenes,* indicative of metabolic redundancy. Collectively, data show
that both resource availability and community composition impacts oxalate metabolism,
which helps to define the adaptive nature of the NALB gut microbiota. Additionally,
results further bolster evidence for redundancy surrounding oxalate metabolism.
368
Severity of oxalate-induced microbe-host effects is dependent on microbial oxalate
metabolism, independent of taxonomy
To delineate hypotheses of metabolic redundancy or cooperation for mitigating the
negative effects of oxalate on the gut microbiota and host, two independent diet trials
were conducted with analogous microbial communities derived from the metabolic and

taxonomic cohorts. Following antibiotic suppression of the gut microbiota, SWM were
given microbial transplants from either the metabolic or taxonomic cohorts in a
longitudinal, crossover experimental design with either a 0% or 3% oxalate diet (Envigo;
Fig. 6A, S8A; Table S1). The 0% oxalate diet was designed to test the stability of
oxalate-degraders since *O. formigenes* is often lost when oxalate is removed from the
diet[15]. Transplanted microbial communities included the same as those for *in vitro*
studies (Fig. 5D-F). Animal metrics and microbial were tracked over the course of the
trial as was urinary/fecal oxalate, urinary formate, inflammatory cytokines, and
creatinine. Renal calcium oxalate (CaOx) deposition, cardiac fibrosis, and colitis was
assessed through histopathology. CaOx deposition and cardiac fibrosis was quantified
through a semi-automated process, based on stain color that differentiates calcium
deposits (Von Kossa) or collagen (Mason's Trichrome). Colitis severity was assessed
by two independent reviewers in hematoxylin and eosin stained tissues through a
standardized, multi-factorial assessment[88].

Using microorganisms from the taxonomic cohort, while the change in urinary and fecal
oxalate levels were greatest in mice given *O. formigenes,* the change in oxalate levels
were significantly greater than the no bacteria controls (Group 1) even in the absence of
O. formigenes, consistent with *in vitro* results (Fig. 6B,C). Interestingly, the change in
urinary formate levels was not different in any microbial group for the taxonomic cohort
(Fig. 6D). While IL1β was below detection levels, IL6 exhibited levels consistent with
oxalate induction, which decreased over the course of the trial (Fig. 6B, S6A).
Differences in IL18 were only seen as an increase over time in the No_ox (Group 5)
(Fig. S6B). The only changes in urinary creatinine seen was an increase and decrease
in the NALB and All (Group 4) (Fig. S6C), respectively, which indicates that while the
NALB bacteria may induce some inflammation, the minimal community present in the
All (Group 4) group may limit these effects and actually improve kidney health under
conditions of oxalate exposure. While some differences were seen in water or food
metrics, these can largely be explained by batch effects of the two trials conducted (Fig.
S6D-G). We did see a greater increase in body mass in animals receiving the No_ox
(Group 5) microorganisms than when *O. formigenes* was administered alone (Group 2)
, which can not be explained by batch effects. Renal CaOx deposition, cardiac fibrosis,
and colitis severity all closely tracked oxalate levels (Fig. 6E-J, S6H-I) and did not
depend on *O. formigenes* if the other probiotic microbes were present. Collectively,
data suggest that oxalate homeostasis and oxalate-induced pathologies are mitigated
by the presence of diverse oxalate-degrading bacteria and that adding *O. formigenes* on
an already effective oxalate-degrading microbiota will not improve oxalate homeostasis.

The microbiota composition of colon contents from this diet trial was significantly
different from excreted feces (Fig. S7A). The microbiome composition in stool from
mice was not different based on probiotic administration (Fig. S7B), but within group
differences for the All (Group 4) group was significantly lower than other groups (Fig.
S7C), indicative of a protective effect against oxalate exposure. This conclusion is
corroborated by the change in alpha diversity in which the microbiota of animals given
the All (Group 4) group exhibited the greatest post-antibiotic recovery and is the only
group that saw recovery beyond a marginally significant increase in diversity, post-
antibiotics (Fig. S7D). In general, there was not much loss of the inoculated bacteria
throughout the study, in any group (Fig. S7E).

Overall, metabolic cohort transplants were less effective than the taxonomic cohort in
terms of inducing oxalate metabolism, particularly in the group without bacteria (Group
1) isolated against oxalate (Figs. 6B,C, S8B,C). However, there was a much greater
change in format metabolism, dependent on the microbes present (Fig. S8D). Despite
the more moderate change in oxalate levels, there were similar oxalate-associated
effects on renal calcium oxalate deposition (Fig. S8F,G), which was not dependent on
formate levels (Fig. S8H). With the metabolic cohorts, the presence of known oxalate
degraders appeared to be more important for oxalate homeostasis than the taxonomic
cohort, since absence of known oxalate-degraders led to oxalate levels similar to the
No_bact (Group 1) controls (Figs. 6B,C; S8B,C). Collectively, data show that while the
taxa chosen for the taxonomic cohort enabled efficient oxalate even in the absence of
O. formigenes, the bacteria present in the metabolic cohort had a greater influence on
formate levels. In both diet trials, urinary oxalate, but not formate correlated with CaOx
deposition (Fig. S8G,H – metabolic, data not shown - taxonomic). The effects of oxalate
and transplant group differed between the two cohort studies with mice in the metabolic
cohort exhibiting higher levels of IL-6 of microbial transplant groups compared to the
negative controls. However, similar to the taxonomic cohort, there were no differences
in IL18. Urinary creatinine increased significantly over time for all groups receiving a
microbial transplant, in contrast with the taxonomic cohort (Figs. S6A-C,S9A-C). For the
metabolic cohort, there similar group-based differences observed in water based
metrics. However, animals in the taxonomic cohort exhibited greater positive changes
in food intake and body mass than the metabolic cohort (Fig. S9D-G).

In the metabolic cohort, we did not observe the same trends in the microbiota
composition, antibiotic recovery, or persistence as we did in the taxonomic trial
indicative of less effective microbial communities at protecting the community as a
whole (Fig. S10A-D), though probiotic bacteria were generally persistent (Fig. S10E).
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447   Overall, data from the taxonomic and metabolic cohorts indicate that oxalate
448   metabolism results from a defined community of microorganisms that includes
449   redundancy in oxalate metabolism as the primary driver. Importantly, the efficacy of *O.*
450   *formigenes* was apparent when administered alone, but the effect was diminished when
451   co-inoculated with other oxalate-degrading microbes.
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Discussion
While research in the last two decades have made clear that the gut microbiota is
intimately tied to all facets of host health, translating those insights into actionable
biotherapies has been difficult due to the inherent complexity and heterogeneity present
in the microbe-host system. The study of complex systems holds enormous potential to
constrain hypotheses and offer insight into effective bacteriotherapy development[23].
However, the field is limited by inconsistent terminologies, concepts, and tractable
experimental frameworks[25]. The objective of the current study was to examine oxalate-
microbe-host interactions within a complex systems framework. Collectively, results of
the study offer quantifiable and generalizable metrics of diet-microbe-host systems that
can be used to guide more effective patient and probiotic selection criteria for clinical
trials involving bacteriotherapies that target the gut microbiota.
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Microbial oxalate metabolism, which has been researched for several decades, pre-
dating the current microbiome era, is an ideal focal point to understand pertinent
variables that impact probiotic success. Here, we found that heterogeneity in
microbiome composition, independent of host genetics, significantly impacted multiple
diet-microbe-host interfaces that included hepatic activity (Figs. 1,2), gut microbiota
metabolism (Figs. 2,3), renal mineralization (Fig. 6E,F; S8E,F), intestinal inflammation
(Fig. 6H,I), and cardiac fibrosis (Fig. S6H,I). Importantly, we found that oxalate
degradation was highly redundant among diverse species in the gut of *N. albigula,*
which consumes a high oxalate diet in the wild (Fig. 4). Consistent with past studies,
administering *O. formigenes* led to a significant reduction in both stool and urine oxalate
(Fig. 6B,C). However, when co-administered with other oxalate-degrading
microorganisms, there was no additive effect. Oxalate-based results were similar, but
to a lower degree, in the metabolic cohort (Fig. S8B,C). In taxonomic cohort studies, we
did not see significant differences in the change in urine formate, based on microbial
transplant group (Fig. 6D), in contrast to metabolic cohort studies (Fig. S8D).
Collectively, data offer strong support for the hypothesis that metabolic redundancy
among diverse taxa, is the primary driver of oxalate homeostasis, rather than metabolic
cooperation in which the by-products of oxalate degradation are used in downstream
pathways such as acetogenesis, methanogenesis, and sulfate reduction. However,
data on the metabolic cooperation hypothesis were inconclusive and there are multiple
known microbe and host sources of formate, which may confound results in these
studies[74,89-91].

Modelling the microbe-host system through an evolutionary perspective, it has
previously been suggested that while host control over the microbiome is the primary
driver of the form and function of the gut microbiota, given the enormous biomass and
diversity of the gut microbiota, microbe-microbe competition is also required to constrain
the microbiota in mammalian microbe-host systems[21]. In the current (Figs. 2B, 5B) and
previous studies[33,34,64,65], we and others have found that oxalate can differentially exhibit
positive or negative effects on microbial growth and metabolism dependent on the
species and environment present. These data provide two alternative ecological
pressures to degrade oxalate. The first is to use oxalate as a carbon and energy source
for growth, as is the case with *O. formigenes[33].* The second is to degrade oxalate to
remove it as a toxin, as is the case with some *Lactobacilli* and *Bifidobacteria[64,65].* The
data showing oxalate degradation as a metabolically redundant function among multiple
diverse microorganisms that maintains oxalate homeostasis (Figs. 4, 6, S8), suggest
that the amount of oxalate consumed or produced by the liver is too great for a single,
slow-growing oxalate-degrading specialist can handle alone, in contrast to prevailing
hypotheses[63], and in support of the ecosystem on a leash hypothesis. Importantly, the
near universal presence of formate metabolism genes suggest that formate may be an
even greater source of ecological pressure (Figs. S2-S5). Collectively, data from the
current and previous studies on the effect of oxalate exposure on the gut microbiota[68,71]
support the hypothesis that the gut microbiota serves as an adaptive organ[92-94] in which
specific, metabolically redundant microbes respond to and eliminate dietary
components, for the benefit of themselves, but which can residually protect or harm host
health depending on the dietary molecules and gut microbiota composition[6,92-94].

Oxalate degradation, as a focal point in diet-microbe-host interactions, is a special case
in which the effects of oxalate on host health and the mechanisms of microbial oxalate
degradation have largely been worked out for decades[33,51-54]. Furthermore, oxalate
degradation exhibits moderate complexity, both in that it is isolated to the gut microbiota
and is performed through a handful of simple metabolic pathways[31-35]. Despite this
knowledge, clinical trials designed to reduce systemic oxalate using either *O.*
formigenes or other oxalate-degrading bacteria have exhibited a wide variety of patient
and trial responses[15]. However, knowledge about other diet-microbe-host links are
largely in their infancy. Many of the other known features exhibit much greater
complexity than oxalate degradation. For instance, while the production of short chain
fatty acids are widely viewed as beneficial for both the gut microbiota and host health[95-
100], many short chain fatty acids are known and are produced by a wide variety of
species[101,102]. Other important diet-microbe-host links, such as the production of
secondary bile acids or TMAO[6,36,103-105], also involve host hepatic activity, increasing the
complexity further. Given the complexity of diet-microbe-host interactions and the fact
that understanding the mechanisms through which the gut microbiota modifies the diet
to influence host health is demonstrably insufficient for the development of effective
bacteriotherapies[12-15], we propose a three-phase, pre-clinical experimental workflow for
the development of targeted bacteriotherapies. In the first phase of research,
case:control metagenome-wide studies and research into other factors that modify the
microbiome, such as prior antibiotic exposure, can identify disease phenotypes that are
influenced by the microbiome, along with the microbial taxa and genes responsible for
this association. In the second phase of research, hypothesized taxa and/or metabolic
functions can be explored through *in vitro* and germ-free animal studies, using
appropriate models to determine the mechanistic links that drive disease phenotypes
through diet-microbe-host interactions. Finally, in phase three, these mechanistic links
can be applied to a complex system theoretical framework, as done in the current study,
to identify those variables most pertinent to successfully influence specific phenotypes
through targeted changes to the gut microbiota. Such a phased research structure will
provide for much more effective probiotic and patient selection criteria prior to clinical
trials.
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There were some important limitations to the current study. First, while we did conduct
one study with *N. albigula,* most animal studies here sought to eliminate host genetics
from the equation, as a means of simplification. Host genetics are another layer of
complexity that were not examined here and may have an impact on oxalate
homeostasis beyond the gut microbiota. Second, in animal studies with the refined
communities of microorganisms, the taxonomic and metabolic cohorts studies were
conducted separately and some batch effects are apparent, such as with the change in
creatinine values or urine output. Finally, it is apparent from our data and the literature
that there are multiple host and microbial sources of formate. As such, data pertaining
to formate utilization by our transplant communities are inconclusive.
554
555   In conclusion, using a complex systems theoretical framework, we examined the
556   oxalate-microbe-host interactions of multiple oxalate-microbe-host interfaces and found
557   multiple microbiome-dependent effects of oxalate. The negative effects of oxalate were

mitigated by metabolically redundant oxalate-degrading bacteria, more so than by metabolic cooperation or a single oxalate-degrading species. Critically, we found that while *O. formigenes* can lower urine oxalate when placed on a background of a poor oxalate-degrading community, as current theory predicts, this effect is lost when co-administered with other oxalate-degrading bacteria. Collectively, data help to resolve why the gut microbiota of the white throated woodrat, *Neotoma albigula,* effectively responds to and degrades even very high dietary oxalate levels[68,69,72] and offer a clear pathway for more effective patient and probiotic selection for future clinical trials to reduce urine oxalate. More importantly, the conceptual and experimental framework developed in this study, based on complex systems theory, paves the way for a phased approach to microbiome research in which clinical microbiome insights (Phase I) drive mechanistic insights between the gut microbiota and host physiology (Phase II), that can be applied to a complex system model to constrain hypotheses and identify the most pertinent variables that drive microbe-host interactions that influence host physiology and health (Phase III). Such an approach will allow for much more efficacious probiotic and patient selection criteria in clinical intervention trials.

Data availability Sequence reads from the animal study are available at the Sequence Read Archive under Accession numbers for gut microbiota genomes: PRJNA833303, Shotgun metagenomics: PRJNA839366, Liver transcriptomics: PRJNA1018952 Gut microbiota data: 16SPRJNA1018559

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Author contributions: SM, DD, MM and AWM conceived and designed the study. SM, CAB, AA, AN, and AWM designed and performed most *in vitro* and animal-based biological experiments. JA, MS, AZ, TO performed addtional animal and *in vitro* experiments and contributed to data analysis. SM and AWM wrote the manuscript with input from all authors. AWM supervised the study. All authors reviewed the manuscript.

Declaration of interests: The authors declare no conflict of interest

Figure titles and legends

Fig. 1

Fig. 1. Oxalate exposure impacted host hepatic activity in a microbiota dependent fashion. A) Swiss Webster mice were given neomycin, followed by an allograft (SWM) or xenograft (NALB) fecal transplant, then maintained on a 0% or 1.5% oxalate diet prior to necropsy for fecal metabolomics (Fig. 2) and hepatic transcriptomics. B) PCoA of normalized, whole-transcriptome data. p=0.02 for microbiome composition, p=0.07 for dietary oxalate content, p=0.3 in 2-way analysis; 2-way PERMANOVA. C) Total number of hepatic genes significantly stimulated or inhibited by dietary oxalate. Significant genes are plotted by Log2FoldChange. Positive values reflect genes increased with oxalate exposure and negative values are genes decreased with exposure. FDR < 0.05, Wald test. Hepatic genes are annotated to pathway (Kegg, Uniprot, PubChem,

609   Metacyc) and the total number of genes that exhibit a positive or negative shift with
610   oxalate exposure are listed in the legend. Complete gene list is in Table S2.
611

A

PCoA2 (16.13% of variance)

0.1

0.0

-0.1

• SW-NALB 0% oxalate
♦ SW-NALB 1.5% oxalate

0.0   0.1   0.2

A1 (24.55% of variance)

B   **Fig. 2**

Xenobiotic metabolism
Vitamin D3 synthesis
Unknown
Tyrosine metabolism
Tryptophan metabolism
Tropane alkaloid synthesis
Sphingolipid synthetic pathway
Serotonin metabolism
Quorum-sensing
Pyruvate metabolism
Pyrimidine metabolism
Purine metabolism
Proline degradation pathway
Primary bile acid biosynthesis
Phosphatidylcholine biosynthesis
Phenylalanine metabolism
Nicotine and cotinine degradation
N-benzylformamide degradation
Melanin synthesis
Lysine metabolism
Lipid metabolism
Leucine metabolism
L-kynurenine degradation
Isoleucine metabolism
Histidine degradation
Guanine degradation
Glycine, serine, and threonine
Glycerophospholipid metabolism
Futalosine pathway
Fatty acid synthesis
Fatty acid metabolism
Ethylbenzene degradation
Cholesterol synthesis
Carotenoid biosynthesis
Carnitine metabolism
Calystegine biosynthesis
Brassinosteroid synthesis
Biotin metabolism
Biosynthesis of secondary metabolites
Beta-ketoadipate pathway
Benzylisoquinoline alkaloid synthesis
Arachidonic acid metabolism

0   5

Log2foldchange

Microbiome

SW-NALB (+46/-37)
SW-SW (+64/-98)

Hepatic genes

SparCC correlation

-0.88   0.88

NALB
58 Metabolites
22 Hepatic genes
122 Negative
Interactions
60 Positive
Interactions

SWM
162 Metabolites
207 Hepatic genes
1048 Negative
Interactions
3114 Positive
Interactions

613
614
Fig. 2. Oxalate exposure impacted microbial me________________biota
dependent fashion. A) PCoA of protein normaliz______________ibolomic data.
p=0.001 for microbiome composition, p=0.1 for o____________=0.3 in 2-way
analysis; 2-way PERMANOVA. B) Total numbe______________ificantly
stimulated or inhibited by dietary oxalate. Signifi____________ed by
Log2FoldChange. Positive values reflect metab______________late exposure

and negative values are metabolites decreased with exposure. FDR < 0.05, Mann-

Whitney U or Fisher's exact test. Metabolites are annotated to pathway (Kegg, Uniprot,

PubChem, Metacyc) the total number of metabolites that exhibit a positive or negative

shift with oxalate exposure are listed in the legend. Complete list is in Table S3. C)

Change in the host-microbe interaction network upon exposure to oxalate, quantified as

hepatic gene-microbe metabolite correlations R > +/- 0.3 and FDR < 0.05 with SparCC,

visualized in Cytoscape. All host-microbe interactions are listed in Table S4.

Fig. 3. Oxalate exposure stimulates taxonomically diverse microorganisms, with a few
strains that dominate the response. A) *Neotoma albigula* with native microbiota were
given increasing amounts of dietary oxalate up to 6% w/w. *indicates sampling

timepoints. B) PCoA of normalized metagenomic data. p=0.02; PERMANOVA. C) Total
number of microbial genes significantly stimulated or inhibited by dietary oxalate,
annotated to pathway (Kegg, UniProt, PubChem, Metacyc) and listed by
Log2FoldChange. The total number of genes stimulated or inhibited by oxalate are
listed in the legend. Genes with unknown annotation are not listed. The complete list of
annotated genes is listed in Table S5. D) Number of significantly differentiated genes
involved in oxalate degradation, sulfate reduction, acetogenic, methanogenic, or sugar
metabolic pathways or utilization of by-products of those pathways stimulated (positive)
or inhibited (negative) by dietary oxalate. Genes are listed by their Log2FoldChange
between no and high oxalate diets. FDR < 0.05, Wald test. E) The number of
genes/genome significantly altered by oxalate, mapped to microbial genomes extracted
from *N. albigula.* Number of genes/genomes are log10-transformed to show the
distribution more clearly. A total of 92% of genomes had at least one significantly
altered gene population mapped to them.

Fig. 4. Genes related to the metabolism or handling of oxalate are present in >50% of 248 full length NALB microbial genomes from the gut. A) Proportion of the genomes extracted from *N. albigula* that had at least one oxalate-related gene. B) Relative distribution of oxalate-handling genes by gene function. C) Proportion of genomes that have a complete pathway for oxalate degradation, specifically. oxdd=oxalate oxidoreductase; acec=acetyl-CoA:oxalate CoA-transferase; oxc=Oxalyl-CoA decarboxylase; succ=succinyl-CoA:coenzyme A transferase; frc=Formyl-CoA transferase; D) Number of oxalate-handling genes by genome.

Fig. 5

C

Substrate	No. of Isolates	% of Community
Oxalate	70	14.58%
Cellulose	68	14.17%
Sucrose	65	13.54%
D-Glucose	45	9.38%
Aspartic acid	38	7.92%
Galactose	19	3.96%
Formate	16	1.67%
Mannose	12	1.25%
Fructose	10	1.04%
Acetate	7	0.73%
Methylvaric/butyric acid	4	0.42%
Glutamic acid	1	0.10%

D

Group	Substrate usage	Metabolic cohort	Taxonomic cohort	% of studies
All, No_ox	Fructose	Ruminococcus sp.	Lactobacillus helveticus	71%
All, No_ox	Galactose	Bacteroides acidofaciens	Lactobacillus helveticus	71%
All, No_ox	Sucrose	Bacteroides acidofaciens	Bacteroides thetaiotaomicron	86%
All, No_ox, Ox_form	Formate	Enterobacter sp.	Desulfovibrio piger, Methanobrevibacter smithii, Ruminococcus gnavus	71%, 71%, 86%
All, Ox, Ox_form	Oxalate	Bacteroides vulgatus	Oxalobacter formgienes	86%
All, No_ox	Glucose	Bacteroides vulgatus	Coprococcus comes	100%
All, No_ox	Mannose	Bacteroides acidofaciens	Lactobacillus plantarum	71%
All, No_ox	Methyl	Bacteroides dorei	Bacteroides thetaiotaomicron	86%
All, No_ox	Acetate	Bacteroides dorei	Bacteroides thetaiotaomicron	86%
All, No_ox	Aspartic	Bacteroides dorei	Bacteroides thetaiotaomicron	86%

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Fig. 5. Microbial community composition and available substrates impact oxalate
metabolism and the impact of oxalate on growth. A) Substrates associated with
metabolic pathways enriched by exposure to dietary oxalate *in vivo* differentially impact
oxalate metabolism. $p < 0.001$ in one-way and two-way ANOVA against bacterial group
and substrate; +/- reflects $p < 0.05$, Holm's-corrected, pairwise t-test compared to base
media for an increase (+) or decrease (-) in oxalate degradation. B) Substrates
differentially impact the influence of oxalate on microbial growth; $p < 0.001$ in two-way
ANOVA against substrate and bacterial group, and one-way analysis against substrate;
+/- reflects $p < 0.05$, Holm's-corrected, one-sample t-test compared 0 (no impact of
oxalate) for an increase (+) or decrease (-) in growth due to oxalate exposure. The
impact of oxalate on growth was not calculated for cellulose or Media B. C) Culture-
based means to quantify proportion of the NALB community that can use substrates
identified through shotgun metagenomics as sole carbon and energy sources. D)
Defined microbial communities to assess oxalate metabolism *in vitro* and *in vivo*. Listed
are the microbial consortia, which substrate the microbes utilize that corresponds to the
shotgun metagenomic data, taxonomic classification of microorganisms used in the two
cohorts, and the proportion of studies in which microorganisms in the taxonomic cohort
were stimulated by oxalate exposure. E,F) Oxalate metabolism in minimal media with
20mM oxalate from the microbial communities listed in 5D, in comparison to the NALB
community. $p < 0.001$, ANOVA comparing microbial groups. *$p < 0.05$, **$p < 0.01$;
***$p < 0.001$; Holm's corrected, one sample t-tests against 0 (no oxalate metabolism).
Blue letters reflect statistical groups between microbial groups for oxalate metabolism.
693
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Fig. 6

A

n=16 animals/group, pooled by cage (4 animals/sample)

SW mouse
1. No_bact
2. Ox
3. Ox_form
4. All
5. No_ox

	T1	T2	T3	T4
Days	0-6	7-12	13-18	19-25
Treatment	Neomycin 3% Oxalate	Microbial Transplant 3% Oxalate	0% Oxalate	3% Oxalate

Group 1	No_bact
Group 2	Ox
Group 3	Ox_form
Group 4	All
Group 5	No_ox

B, C, D, E, F, G, H, I, J — figure panels

Fig. 6. Microbial community composition (taxonomic cohort) impacted the effect of exogenous oxalate on host health. A) Swiss Webster mice were given neomycin, followed by inoculation of microbial consortia that included either no bacteria or the taxonomic cohort listed in Figure 5C. B,C) The effect of microbial transplants on urinary (B) or fecal (C) oxalate levels over the course of the diet trial, compared to baseline.

ANOVA p<0.001 for microbial group, but was not significant by timeperiod or 2-way
analyses for both B & C. D) The effect of microbial transplants on urinary formate levels
over the course of the diet trial, compared to baseline. ANOVA was not significant in
one-way and two-way analyses. E) Renal calcium oxalate deposition. Arrows show
stained calcium deposits, which were quantified through an automated algorithm in
QuPath. F) Quantification of renal calcium oxalate deposition by group. p<0.001,
ANOVA. Blue letters reflect statistical groups between microbial groups for renal
calcification by Holm's corrected paired t-tests. G) Pearson correlation between urinary
oxalate and renal calcium oxalate deposition. R=0.22, p=0.32 with NALB samples
included (blue circle); R=0.7, p=0.001 excluding the NALB group. H) Representative
colon tissues from the No_bact (Group 1) and All (Group 4) groups, exhibiting high and
low colitis severity scores, respectively. Tissues were stained with hematoxylin and
eosin and scored based on standardized, multifactorial metrics. I) Quantification of
colitis severity by group. p<0.001, ANOVA. Blue letters reflect statistical groups
between microbial groups for renal calcification by Holm's corrected paired t-tests. J)
Pearson correlation between colitis severity and renal calcium oxalate deposition. R=
0.7, p=0.002. Colitis severity was not quantified for the NALB group.
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Star Methods

Animal studies.

Tracking animal health

Throughout all diet trials, animals were monitored for evidence of trauma, dehydration, pain, or other forms of suffering. Additionally, water and food intake, urine output, and body mass was monitored daily (i.e., Figs. S6, S9). If animals lost >10% of their baseline body mass, they were removed from the diet trial and placed back onto standard mouse chow.

Effect of oxalate on the native gut microbiota of Neotoma albigula

To determine the impact of dietary oxalate on *N. albigula* with their native microbiota, 14 adult *N. albigula* woodrats were collected from Castle Valley, UT (38.63′N, 109.41′W) in September 2014, using Sherman live traps. Animals were transported to the University of Utah and housed in individual cages (48 by 27 by 20 cm) with a 12-h/12-h light/dark cycle, at 28°C and 20% humidity. Animals were initially maintained on a 0.2% oxalate, high-fiber rabbit chow (Harlan Teklad formula 2031; Envigo) for 7 months prior to experimentation. This diet reduces the overall detectable diversity of the microbiota of these animals but maintains the members of the native microbiota overall [1]. All methods were approved by the IACUC under protocol no. 12-12010.

Subsequently, *N. albigula* woodrats were placed in a diet trial in which the oxalate concentration of the food was gradually increased over time along a gradient from 0.2% (for days 1 to 5; herein referred to as 0%), 3% (days 6 to 10), and 6% (days 11 to 15; Fig. 3A). The oxalate concentration of the diet was adjusted by adding the appropriate amount of sodium oxalate (Fisher Scientific, Pittsburgh, PA) into the powdered rabbit chow on a dry weight basis. The schedule for each concentration of dietary oxalate was chosen to ensure that the gut microbiota had time to respond to the specific diet [2,3]. During diet trials, oxalate did not have a negative impact on *N. albigula* health and neither fecal nor urinary oxalate levels increased significantly[4].

During the diet trial, animals were placed in metabolic cages to separate urine and feces into sterile 50-ml conical tubes. A subsample of feces was collected from each animal every 4 to 5 days on the 0% and 6% oxalate diets for shotgun metagenomic sequencing. Samples were frozen at −80°C until DNA extraction.

Stool collection for bacterial isolations and fecal transplant studies

Feces for fecal transplants were collected from two sources. For the Swiss-Webster
feces, 20 individual animals (Taconic Farms, female, six weeks old) were placed on a
0% oxalate diet in cages with a custom-designed insert to separate urine and feces at
the Cleveland Clinic (IACUC #2016-1653) [5]. For the *N. albigula* feces, 14 individual
animals (mixed sex and age) were placed on a 3% oxalate diet in a metabolic chamber
at the University of Utah (IACUC #12-12010) to acclimate the microbiome to oxalate
metabolism[5]. After 3 days of acclimation on the respective diets, feces were collected
from animals within 2 h of defecation, submerged in sterile 15% glycerol and flushed
with CO_2 prior to freezing at −80 °C until use in animal studies approximately 12 months
after receipt (IACUC #2016-1653) or for bacterial isolations.
1093
Microbiota-dependent effects of oxalate on liver and gut microbiota
All animal studies were approved through the Cleveland Clinic's IACUC (IACUC #'s
2016-1653, 2020-2312). To examine the host-independent effects of oxalate on gut
microbiota with either a low or high efficiency at degrading oxalate, two distinct host-
microbe model systems were developed. For both models, equal numbers of male and
female Swiss-Webster mice were used as the host. For the low oxalate-degrading gut
microbiota, Swiss-Webster mice were given fecal transplants using feces from other
Swiss-Webster mice (allografts), as discussed below. A 1.5% oxalate diet is sufficient to
induce hyperoxaluria in Swiss-Webster mice, defined as a 50% increase in urinary
oxalate excretion[6-8]. For the high oxalate-degrading gut microbiota, Swiss-Webster mice
were given fecal transplants from *N. albigula* (xenografts). We have previously shown
that fecal transplants from *N. albigula* are sufficient to induce significant and persistent
oxalate metabolism[7,8]. During and after fecal transplants, animals were grouped four to
a cage, with four cages assigned to each treatment group, for a total of 16 animals per
experimental group. To minimize individual variability and eliminate any cage effect in
subsequent metrics, samples and data collected from all animals in a cage were pooled
together into an individual sample. To develop the two different mouse models, the
conversion of the gut microbiota from the native microbiota to the grafted microbiota
(allografts or xenografts) was completed in two stages. First, the native microbiota was
depleted with a five-day course of neomycin (0.5g/L water, combined with 2g/L
sucralose), while on a 0% oxalate diet. Mice were given *ad libitum* access to water
during this time and throughout the experiment. Neomycin is a broad spectrum antibiotic
that is poorly absorbed across the gut, and effectively reduces gut microbiota density by
up to 90%[9]. After antibiotic depletion, mice were given the respective fecal transplants
by first thawing feces, then aseptically mixing 32 g feces per kg body weight directly into
powdered mouse chow. Fecal transplants were performed daily for 6 days (Fig. 1A), as
previously described[5], during which animals were switched to either a 0% or 1.5%
oxalate diet. All animals were maintained on their respective diets for two weeks
following fecal transplants (Table S1). A total of four treatment groups were defined
based on allografts/xenografts and oxalate diet.
1124
1125   Following diet trials, animals were sacrificed through CO_2 asphyxiation and cervical
1126   dislocation. Upon necropsies, liver tissue from each animal was dissected out and
1127   placed into RNAlater on ice, prior to freezing at -80ºC, within two hours of necropsies.

1128 Additionally, colon feces were collected and placed into screw-cap tubes with o-rings,
1129 on ice, prior to freezing at -80ºC.
1130
Microbial cohort-dependent effects on mitigating the systemic effects of oxalate on host
and microbiome
To determine the effect of specific microbial cohorts at mitigating the systemic host-
microbiome effects of oxalate, different combinations of two microbial cohorts were
established. First, based on the metabolic pathways enriched by oxalate in the *N.*
albigula gut microbiota (Fig. 3D,5C, Table S5), assessed through comparative shotgun
metagenomics (described below), we hypothesized that microorganisms that engage in
those metabolic pathways help to mitigate the systemic effects of oxalate. To test this
hypothesis, we isolated bacteria from *N. albigula* stool (described below) and grouped
microorganisms into four cohorts (Fig. 5D). These included oxalate-degrading bacteria
alone (Ox; Group 2), microorganisms that can utilize formate or oxalate (Ox_form;
Group 3), oxalate and formate users, in addition to the metabolism of selected sugars
(All; Group 4), or the complete cohort except for oxalate degraders (No_ox; Group 5).
Microorganisms isolated from *N. albigula* stool and used in microbial transplants were
termed the "metabolic cohort". In addition to the metabolic cohort, a "taxonomic cohort"
was defined by cross-referenced metabolic pathways enriched by oxalate with microbial
taxa previously reported to be stimulated by oxalate (Fig. 5D)[10]. Microorganisms from
this cohort were purchased commercially from the ATCC or DSMZ (Table S8). In
addition to these cohorts, we also examined a negative control in which animals were
inoculated with sterile media (No_bact (Group 1); Group 1), and a positive control in
which animals were inoculated with the whole gut microbiota of *N. albigula,* extracted
from stool by first vortexing in a 1:1 mixture of stool and sterile PBS, followed by
centrifuging at 8000RPM for 2 minutes. The supernatant was inoculated into gut
microbiota media with 20mM sodium oxalate (Table S6) overnight prior to microbial
transplant.
1156
To prepare each isolate for transplants, an overnight culture of each species was grown
and mixed in equal proportions by volume for each cohort. The community was then
centrifuged and supernatant was decanted. After antibiotic depletion of the native gut
microbiota in Swiss-Webster mice, 38mg of pelleted bacteria of each preparation was
added directly to the food and administered over the course of six days (Figs. 6, S8), as
done previously[6,7]. Preparations corresponded to approximately 5×10^8 microorganisms
for each isolate in the appropriate transplant groups. Quantification of bacterial numbers
was performed through absorbance of the microbial preparations on a
spectrophotometer at 600 nm, calibrated to direct microscopic counts.
1166
As above, animals were grouped four to a cage, with samples from each cage pooled
together prior to collection and analyses. Similarly, animals were maintained on custom
inserts that mimic metabolic cage for the effective separation of urine and stool prior to
collection. During the microbial transplant animal studies, stool and urine was collected
daily and inserts disinfected. For oxalate and formate quantification, samples were
collected at the end of the antibiotic depletion, microbial transplants, a 0% oxalate
washout period, and after return to a 3% oxalate diet (Figs. 6B-D, S8B-D). Prior to

biochemical assays, urine was frozen ($-20°C$) and feces were dried at 45°C overnight.
Prior to freezing, aliquots of urine were equally divided into six fractions for each of the
biochemical assays performed (discussed below). Fractions for oxalate quantification
were collected into 4N HCl prior to freezing to prevent the non-enzymatic conversion of
ascorbic acid into oxalate [2]. For microbial inventories, a portion of feces and colon feces
(discussed below) were frozen at $-80°C$. All animals were maintained on a 3% oxalate
diet, except during the washout period (Table S1).
1181
Following diet trials, animals were sacrificed through CO_2 asphyxiation and cervical
dislocation. Necropsies were performed to aseptically remove colon feces, colon,
kidneys, and heart tissue. Colon tissue was longitudinally bisected, swiss-rolled, and
placed into 4% paraformaldehyde overnight for fixation at 4ºC for histopathology [11].
Kidney and heart tissues were placed into 4% paraformaldehyde overnight for fixation at
4ºC prior to histopathology. Hearts were first perfused with paraformaldehyde solution
prior to immersion.
1189
After fixation, colon, kidney, and heart tissue were placed in 70% ethanol at 4ºC prior to
paraffin embedding, serial sectioning, and staining. To quantify colitis, colon tissue was
stained with hematoxylin and eosin and imaged with light microscopy (Fig. 6H). Whole
colons were scored for colitis by two blinded, independent reviewers using a semi-
quantitative protocol that considers inflammatory infiltrates, goblet cell loss, crypt
density, crypt hyperplasia, muscle thickening, submucosal inflammation, crypt
abcesses, and ulcerations[12]. To quantify calcium oxalate deposition, kidney tissue was
stained with Von Kossa staining[13], which turns calcium deposits black and the
remaining tissue pink (Figs. 6E, S8E). Kidneys were imaged under light microscopy
and calcium oxalate deposition was quantified using an automated process in QuPath,
based on stain color. The area of the black calcium oxalate deposits was normalized to
total kidney area. To quantify cardiac fibrosis, heart tissue was stained with Masson's
trichrome stain, which stains collagen fibrosis blue and the remaining tissue red (Fig.
S6H). Hearts were imaged under light microscopy and fibrosis was quantified with an
automated process in QuPath, quantifying the blue and red stained areas[14]. Fibrosis
was normalized to total heart surface area.
1206
Biochemical assays.
Urinary creatinine (Fisher Scientific), formate (VWR), IL-6 (R&D Systems), IL-18 (Fisher
Scientific), and IL-1β (R&D Systems) were quantified with ELISA-based assays,
following manufacturer's instructions. Positive controls that included a known amount of
substrate along with no substrate negative controls were included in all batches of
ELISA assays. Samples, standards and controls were all run in duplicate and values
averaged. Urinary and fecal oxalate were quantified with an ELISA-based assay
(Sigma-Aldrich), with a modified protocol, as follows. Upon initial testing of oxalate and
formate assays using solutions of sodium oxalate and sodium formate in water, it was
discovered that while formate assays only had affinity for formate, the oxalate assays
had equal affinity for both oxalate and formate (Figs. S11A). Specifically, when oxalate
alone was added to solution, the quantified concentration of oxalate matched the
amount added. However, when oxalate and formate was added at equal

concentrations, the quantified oxalate was approximately twice as high as what was
added (Fig. S11B). Furthermore, when adding 300uM of formate or oxalate to human
urine specimens, the amount of oxalate quantified was approximately 300uM higher
than urine without any modifications (Fig. S11C). To eliminate the formate
contamination on oxalate measurements, oxalate was extracted by first acidifying to pH
3 with 3M HNO_3. Acidified urine was centrifuged, and supernatant collected. The pH
was then brought up to 7 with NaOH. Subsequently, 5M $CaCl_2$ was added to solution to
precipitate calcium oxalate. The precipitates were extracted by centrifugation and
decanting. Finally, calcium oxalate solution was acidified in 1:4 parts of 4N HCl prior to
enzymatic assay, as previously described[2]. When oxalate was extracted from urine
specimens in this way, prior to quantification, we saw a significant decrease in
quantified oxalate (Fig. S11C), as expected given the assay affinity for formate. When
solutions containing formate alone went through the extraction process, no oxalate was
quantified. Given these results, urinary and fecal oxalate was extracted prior to ELISA-
based assays using the manufacturer's recommendations, post-extraction. For fecal
oxalate, samples were acidified with 6N H_2SO_4 to solubilize oxalate prior to following the
extraction protocol above. For creatinine, cytokines, and oxalate, values generated on
a 0% oxalate diet were substracted from all other values, matched by cage, with the
assumption that this would isolate oxalate-induced molecule generation. For urinary
formate, this substraction was not done since formate can come from multiple sources
other than oxalate degradation and values on a 0% oxalate diet were not clearly lower
than on a 3% oxalate diet. For all values, data are presented as the change from
baseline. Data were statistically compared with two-way analyses and post-hoc,
Holm's-corrected, paired t-tests.
1244
1245   **Culturomic assays.**
1246   All assays were conducted under strict anaerobic conditions (90% N_2, 5% H_2, 5% CO_2)
1247   in an anaerobic chamber (Bactron 300).
1248
The stool from *N. albigula* were used to determine the impact of environmental factors
on oxalate metabolism *in vitro* and to isolate bacteria for the metabolic cohort.
Enterococcus gallinarum, an oxalate-degrading species previously isolated from *N.*
albigula, was also used in culturomic assays to determine the impact of environmental
factors on oxalate metabolism[15]. To test environmental factors on oxalate metabolism,
gut microbiota media, previously designed to support a broad array of gut bacteria[16],
was used as a base media. From there, compounds were added to the media based on
metabolic pathways enriched by dietary oxalate in the *N. albigula* gut microbiota (Fig.
3D, Table S6). Concentrations of added chemicals were based on previously published
media recipes where necessary. To assess oxalate metabolism in different culture
conditions, oxalate was quantified by extracting oxalate and quantification through
titration with $KMnO_4$, as we have done previously[15].
1261
To isolate bacteria for the metabolic cohort and to validate the metabolic redundancy of
oxalate metabolism and other pathways stimulated by oxalate, a minimal media with the
same substrates from above were added as sole carbon and energy sources (Table
S7). In this medium, oxalate was added at 50mM to specifically select for bacteria that

can use oxalate as a carbon and energy source. Subsequently, the NALB microbiota
from the stool was first diluted to ~1 bacterium/100ul and then inoculated into 5 or 10
96-well plates, depending on the rarity of positive hits, and quantifying growth through
spectrophotometry. Wells in which the absorbance values at 600nm for greater than
one standard deviation above the average for all well were considered positive for
growth. Wells with positive growth had bacteria isolated by streaking on rich media,
transferred to broth cultures, and had stocks made in 15% glycerol that were frozen at -
80ºC until needed. Those isolates grown in oxalate or formate containing media were
subsequently enriched in the minimal media and oxalate or formate degradation was
validated through broth cultures and ELISA-based assays.
1276
Metabolomics.
For untargeted metabolomic assays, fecal samples were re-suspended in Optima
LC/MS grade water (50mg stool to 150ul water. The samples were then placed briefly in
a water bath at 37°C and placed on dry ice. An aliquot of each sample was taken out for
protein concentration measurement. Then, 150 µL of chilled acetonitrile containing
internal standards (Betaine-d9, Carnitine-d9, Orinithine-d6, Valine-13C3, Tyrosine-13C,
15N, Estrone-13C3, and Cholesterol-13C3) was added to the remaining samples
followed by centrifugation at 14,000g for 10 minutes to precipitate out the protein pellet.
The supernatants were recovered and transferred to fresh tubes. The samples were
dried briefly and re-suspended in 2% acetonitrile and 0.1% formic acid for subsequent
LCMS analysis. One-microliter aliquots taken from each sample were pooled and this
QC standard was analyzed every 10 injections. The untargeted metabolomics was
performed by injecting 0.5uL of each sample onto a 10 cm C18 column (Thermo Fisher
CA) coupled to a Vanquish UHPLC running at 0.35mL/min using water and 0.1% formic
acid as solvent A and acetonitrile and 0.1% formic acid as solvent B. The 15-min
gradient used is given below. The Orbitrap Q Exactive HF was operated in positive and
negative electrospray ionization modes in different LC-MS runs over a mass range of
50-750 Da using full MS at 120,000 resolution. The data dependent acquisitions were
obtained on the pooled QC sample. The DDA acquisition (DDA) include MS full scans at
a resolution of 120,000 and HCD MS/MS scans taken on the top 10 most abundant ions
at a resolution of 30,000 with dynamic exclusion of 4.0 seconds and the apex trigger set
at 2.0 to 4.0 seconds. The resolution of the MS2 scans were taken at a stepped NCE
energy of 20.0, 30.0 and 45.0.
1300
XCMS was used to deconvolute the data using 5 ppm consecutive scan error, 7 to 75
seconds as minimum and maximum peak width, S/N threshold of 10, and span of 0.2 in
positive and negative electrospray ionization modes for retention time correction. The
resulting peak table was normalized to total protein concentration and further analyzed
via MetaboLyzer [17]. Briefly, the ion presence threshold was set at 0.7 in each study
group. Data were then log-transformed and analyzed for statistical significance via non-
parametric Mann-Whitney U test. Ions present in just a subset of samples were to be
analyzed as categorical variables for presence status via Fisher's exact test. All p-
values were set to be corrected via the Benjamini-Hochberg step-up procedure for false
discovery rate (FDR < 0.05). The data could then be utilized for PCA, putative
identification assignment, and pathway enrichment analysis via KEGG[18], HMDB[19],

LIPIDMAPS[20], and BioCyc[21] databases. In addition to differential abundance analysis
provided by MetaboLyzer, whole metabolome comparisons were made as a Binomial
dissimilarity matrix, which is optimal for metabolomic datasets[22], with statistical analysis
provided by PERMANOVA with 999 permutations and a principal component
visualization in Vegan[23].

1317

Transcriptomics.
For transcriptomic analysis, RNA was extracted from liver tissue with a TRIzol RNA
purification kit (Invitrogen), following manufacturer's recommendations. Extracted RNA
was converted to cDNA using a cDNA synthesis kit (Fisher Scientific) and stored at -
20ºC. The cDNA quality was checked on a bioanalyzer and libraries were prepared with
the TruSeq stranded mRNA library prep kit. Sequencing occurred on an Illumina HiSeq
2500 at the Genomics Core (Cleveland Clinic) for paired 100bp sequencing.

1325

The raw sequencing files, with 33.5 million +/- 950,000 reads per sample, were pre-
processed using an established protocol[24]. Specifically, FastQC and SortMeRNA was
used to remove low quality reads, remove rRNA reads, and merge paired reads[25,26].
Subsequently, trimmomatic was used to remove adapter sequences[27] and the
remaining high quality reads were mapped to the mm10 mouse reference genome for
annotation, using HISAT[28,29]. The annotated gene counts were normalized to fragments
per kilobase of transcript per million mapped reads. Comparative whole transcriptome
analyses were conducted as a Bray-Curtis dissimilarity index and principal components
visualization with statistical analysis provided by PERMANOVA with 999 permutations,
in the Vegan package of R statistical software[23,30]. Differential abundance analysis was
conducted in Cuffdiff2, with significance defined at a false discovery rate <0.05 [31].
Sequences mapping to mouse genes were annotated to metabolic pathway with the
gene ontology database[32].

1339

To integrate transcriptomic and metabolomic data, the normalized metabolite
concentrations and normalized transcript counts of metabolites and genes that were
significantly different between the SWM-SWM and SWM-NALB groups were correlated,
within each group, using SPARCC correlations in R[33]. Significant positive and negative
correlations were calculated at an R greater or less than 0.4 or -0.4, respectively and an
FDR <0.05. Significant correlations were visualized in Cytoscape version 3.3.0[34].

1346

Shotgun metagenomics.
For shotgun metagenomic analysis, DNA from *N. albigula* stool was extracted with the
QIAmp DNA stool minikit (Qiagen). The extracted DNA was submitted to Argonne
National Laboratory (Chicago, IL) for 150bp paired-end shotgun metagenomic
sequencing on an Illumina HiSeq 2500. The low quality reads were trimmed from raw
sequencing data and paired ends were merged using default parameters in BBMerge[35].
Reads were first mapped to the *Neotoma* genome [36] with BWA mem with default
settings[37], and removed. Paired, non-rodent sequences were assembled in
MetaSpades with default parameters[38].

1356

Full-length microbial genes were extracted and annotated from the assembled contigs
using PROKKA software[39]. Gene annotation was achieved by mapping to the UniProt
and Hamap protein databases[40,41]. To dereplicate genes, ensure common
nomenclature across samples, and build a reference gene catalog for the quantification
of gene counts, full-length genes were clustered at 90% homology in CD-hit[42]. After the
creation of a non-redundant gene catalogue, high quality reads for each sample were
mapped to the annotated gene catalog to generate gene-level count tables with BWA
mem.
1365
Gene count tables were normalized and differential abundance analysis was conducted
with a negative binomial Wald test in DESeq2[43]. Significantly different genes were
considered at an FDR <0.05. The normalized count tables were also used to generate a
weighted Bray–Curtis dissimilarity matrix in the Vegan R package, with statistical
comparisons with a PERMANOVA at 999 permutations[23]. To annotate differentially
abundant genes to taxonomy, genes were mapped to full length genomes extracted
directly from the shotgun metagenomic data, as described below.
1373
de novo *genome construction and calculation of metabolic redundancy*
For the *de novo* construction of genomes, the metaspades assembled contigs were
binned to genomes with Autometa software[44], as previously described[45]. The Autometa
algorithm takes assembled contigs as input, bins the data to genomes using contig
coverage values, GC content, and the Barnes-Hut t-Distributed Stochastic Neighbor
Embedding (BH t-SNE) distribution of the contigs. Taxonomy is assigned based on the
consensus classification of all contigs in a genomic bin. Completeness and purity
calculations are based on the presence of known, unique universal single copy genes in
Autometa. After genomic binning, the contigs were oriented and scaffolded in CSAR[46],
which compares the genomic bins to reference genomes of close relatives. Gaps within
the genomes were filled with Abyss-Sealer[47] using the original raw sequencing reads as
input. The completeness and purity of genomes were recalculated and taxonomic
assignment was validated through phylogenetic analysis of the *de novo* constructed
genomes in comparison with all complete NCBI genomes (Fig S1), achieved through
Phylophlan, using the "—accurate" parameter which considers more phylogenetic
positions at the cost of computational speed[48]. Phylophlan allows for the phylogenetic
analysis of bacteria and archaea using complete genomes rather than gene amplicons,
which provides greater resolution on phylogenetic analysis. Collectively, we extracted
248 high quality, full length genomes, defined as being >80% complete and >90% pure,
based on current standards[49].
1394
To quantify the proportion of the *N. albigula* microbiota that contained genes related to
oxalate metabolism, formate metabolism, acetogenesis, methanogenesis, or sulfate
reduction, all genes that contribute to those metabolic pathways were extracted from the
KEGG database[50]. Subsequently, PROKKA[39] was run on the 248 full length genomes
to extract and annotate full length genes. The PROKKA extracted genes were then
cross-referenced with the gene databases from KEGG to determine the proportion of
genomes that contained at least one gene in the target pathways and determine which
taxa had those genes.

1403
16S rRNA metagenomics.
Fecal DNA from mice in the SWM-NALB and SWM-SWM studies, underwent DNA
extraction through a semi-automated protocol on a KingFisher Duo Prime System
(Thermo Scientific) following the manufacturer's protocol for stool. The protocol
includes mechanical lysis with bead-beating, piston driven lysis, and proteinase K
chemical lysis. The extracted DNA, which attaches to magnetic beads in a proprietary
salt solution, is removed from solution and eluted in buffer. Duplicate samples of a
commercial DNA positive of known composition (Zymboiomcs, USA) were included as
positive controls, as well as the DNA reagents that went through the entire workflow,
sterile water, and a PCR negative as negative controls.
1414
The fecal DNA was submitted to the Microbial Sequencing and Analytics Core at
Cleveland Clinic for high throughput sequencing of the 16S rRNA gene on an Illumina
MiSeq. The DNA was first PCR amplified with the 515F and 806R primers that target
the V4 hypervariable region of the 16S gene. The DNA concentrations were quantified
before and after PCR amplification on a Qubit and normalized prior to library prep with
the Illumina Nextera XT library prep kit. The sequence run was conducted to generate
150bp, paired-end sequences.
1422
The raw sequencing data were processed in the R statistical package (4.2.0)[30]. Quality
control, removal of bimeras, and assignment of amplicon sequence variants (ASV) were
completed in dada2[51]. For ASV taxonomic assignment, a combined, non-redundant
database of the Silva 138 SSURef and NCBI 16S rRNA databases were used[52]. Taxa
assigned to mitochondria or chloroplasts were removed from subsequent analysis. The
resulting ASV's were aligned in MSA[53] and arranged into a maximum likelihood
phylogeny in phangorn[54]. The resulting phylogenetic tree and ASV table were merged
with sample data for loading into PhyloSeq[55]. The sequencing depth threshold required
to adequately capture microbial diversity was calculated with a rarefaction analysis in
Vegan[23]. Non-control samples below the depth threshold were removed from further
analysis.
1434
1435 The raw count table of 16S rRNA sequences was normalized with the DESeq2
1436 algorithm and α-diversity was calculated as phylogenetic diversity in Phyloseq, along
1437 with beta-diversity as a weighted UniFrac distance[56]. Alpha diversity was analyzed with
1438 a paired t-test with a Holm's correction where applicable, while beta-diversity analyses
1439 were conducted with a PERMANOVA after 999 permutations.
1440
1441
1442 **Supplementary figure legends:**
1443
1444 Fig. S1. Phylogeny of genomes extracted from the *N. albigula* metagenome, in
1445 comparison to >3000 full length microbial genomes. Stars indicate taxonomic
1446 placement of extracted genomes. All other points indicate reference genomes.
1447

Fig. S2. Representation of formate metabolism genes in the NALB metagenome derived
from 248 full length genomes. A) Proportion of the genomes extracted from *N. albigula*
that had at least one formate metabolism gene. B) Representation of formate
metabolism genes among the metagenome, broken down by gene function and
proportion of total formate metabolism genes. C) Representation of formate metabolism
genes broken down by taxon.

1454

1455   Fig. S3. Representation of acetogenic genes in the NALB metagenome derived from
1456   248 full length genomes. A) Proportion of the genomes extracted from *N. albigula* that
1457   had at least one acetogenic gene. B) Representation of acetogenic genes among the
1458   metagenome, broken down by gene function and proportion of total acetogenic genes.
1459   C) Representation of acetogenic genes broken down by taxon.

1460

Fig. S4. Representation of methanogenic genes in the NALB metagenome derived from
248 full length genomes. A) Proportion of the genomes extracted from *N. albigula* that
had at least one methanogenic gene. B) Representation of methanogenic genes
among the metagenome, broken down by gene function and proportion of total
methanogenic genes. C) Representation of methanogenic genes broken down by
taxon.

1467

Fig. S5. Representation of sulfate-reducing genes in the NALB metagenome derived
from 248 full length genomes. A) Proportion of the genomes extracted from *N. albigula*
that had at least one sulfate-reducing gene. B) Representation of sulfate-reducing
genes among the metagenome, broken down by gene function and proportion of total
sulfate-reducing genes. C) Representation of sulfate-reducing genes broken down by
taxon.

1474

Fig. S6. Microbial transplant composition impact on urinary inflammation, renal health,
and overall mouse health for the taxonomic cohort. A-G) The effect of microbial
transplants on urinary IL-6 (A), IL-18 (B), and creatinine (C) levels, along with water
intake (D), urine output (E), food intake (F) and body mass (G). H) Masson's Trichrome
staining of heart tissue reveals fibrosis. Shown are representative images from the
No_bact (Group 1) and All (Group 4) groups. I) Quantification of cardiac fibrosis from
different microbial transplant groups. Statistical significance - 2-way ANOVA (shown on
charts) and post-hoc, Holm's corrected, paired t-tests. Blue letters reflect statistical
groups between microbial transplants and $*p<0.05$, $**p<0.01$; $***p<0.001$ for longitudinal
comparisons within each microbial transplant group.

1485

Fig. S7. Effect of microbial transplants on microbial community composition for the
taxonomic cohort. A,B) Beta-diversity analysis based on a weighted UniFrac
dissimilarity matrix of colon feces collected at the end of the study period vs. stool (A; .
$p=0.006$, PERMANOVA) or in the endpoint stool samples by group (B; no significant
differences). Similar results for (B) were obtained with colon feces. Statistical
differences shown by blue letters in legend. C) Within group beta-diversity distance of
colon feces. $p=0.006$, one-way ANOVA. Blue letters represent statistical groups, based
on post-hoc, Holm's corrected, paired t-tests. Similar results were found with endpoint

stool samples. D) Change in phylogenetic diversity of stool for each microbial transplant
group. Stats, shown on graph, are based on Pearson correlations. E) Normalized
counts of transplanted microorganisms in the stool across timepoints and in the colon
feces at the end of the diet trial.
1498
Fig. S8. Microbial community composition (metabolic cohort) impacted the effect of
exogenous oxalate on kidney health. A) Experimental design. Swiss Webster mice were
given neomycin, followed by inoculation of one of five microbial consortia that included
either no bacteria, the NALB community, or the metabolic cohort listed in Figure 5C.
Animals were maintained on a 3% oxalate diet throughout the trial except for a 0%
oxalate washout period after the microbial transplant period. B,C) The effect of microbial
transplants on urinary (B) or fecal (C) oxalate levels over the course of the diet trial,
compared to baseline. ANOVA $p<0.001$ for microbial group (B&C), and $p<0.01$ for both
timeperiod and in 2-way analysis for (B only). D) The effect of microbial transplants on
urinary formate levels over the course of the diet trial. ANOVA $p<0.001$ for microbial
group and timeperiod. E) Renal calcium oxalate deposition based on Von Kossa
staining of renal tissue sections. Arrows show calcium deposits stained black, which
were quantified through an automated algorithm in QuPath. F) Quantification of renal
calcium oxalate deposition by group. $p=0.014$; ANOVA. G,H) Pearson correlation
between urinary oxalate ($R=0.7$, $p<0.001$) (G) or formate ($R=0.026$, $p=0.9$) (H) and renal
calcium oxalate deposition. Where applicable, statistical significance was assessed
through an ANOVA and post-hoc, Holm's corrected, paired t-tests. Statistical groups
shown by blue letters.
1517
Fig. S9. Microbial transplant composition impact on urinary inflammation, renal health,
and overall mouse health for the metabolic cohort. A-G) The effect of microbial
transplants on urinary IL-6 (A), IL-18 (B), and creatinine (C) levels, along with water
intake (D), urine output (E), food intake (F) and body mass (G). Statistical significance -
2-way ANOVA (shown on charts) and post-hoc, Holm's corrected, paired t-tests. Blue
letters reflect statistical groups between microbial transplants and *$p<0.05$, **$p<0.01$;
***$p<0.001$ for longitudinal comparisons within each microbial transplant group.
1525
Fig. S10. Effect of microbial transplants on microbial community composition for the
metabolic cohort. A,B) Beta-diversity analysis based on a weighted UniFrac
dissimilarity matrix of colon feces collected at the end of the study period vs. stool (A; .
$p=0.006$, PERMANOVA) or in the endpoint stool samples by group (B; no significant
differences). Similar results for (B) were obtained with colon feces. Statistical
differences shown by blue letters in legend. C) Within group beta-diversity distance of
colon feces. $p=0.006$, one-way ANOVA. Blue letters represent statistical groups, based
on post-hoc, Holm's corrected, paired t-tests. Similar results were found with endpoint
stool samples. D) Change in phylogenetic diversity of stool for each microbial transplant
group. Stats, shown on graph, are based on Pearson correlations. E) Normalized
counts of transplanted microorganisms in the stool across timepoints and in the colon
feces at the end of the diet trial.
1538

Fig. S11. Effect of oxalate and formate on oxalate quantification using an enzymatic,
ELISA-based assay. A) Correlation between oxalate or oxalate + formate, added to
water, on oxalate concentration quantified through the enzymatic kit. B) Ratio of the
calculated oxalate vs. the added concentration of oxalate and formate. C) The effect of
adding oxalate or formate to urine, or of extracting oxalate from urine. R values and p-
values (A) or p-values from one-way ANOVA (B,C) shown on chart. Blue letters
represent statistical groups, based on pairwise t-tests.
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1548

Supplementary legends

Table S1. Diets used in animal studies.

Table S2. The number of host hepatic genes in each metabolic pathway that exhibited a significant increase (positive numbers) or decrease (negative numbers) in expression upon consumption of a 1.5% oxalate diet.

Table S3. The number of microbial metabolites in each metabolic pathway that exhibited a significant increase (positive numbers) or decrease (negative numbers) in expression upon consumption of a 1.5% oxalate diet by the host.

Table S4. The significant positive and negative correlations between microbial metabolites and host hepatic gene expression for those metabolites/genes significantly altered by 1.5% oxalate consumption. Data are listed with the host microbiome, metabollite and gene ID, long with correlation values and false discovery rate corrected p-values.

Table S5. The number of microbial genes in each metabolic pathway that exhibited a significant increase (positive numbers) or decrease (negative numbers) in abundance upon consumption of a 6% oxalate diet by the host.

Table S6. Media recipe used to test the impact of substrates on oxalate metabolism.

Table S7. Media recipe used to test the proportion of the NALB community that can utilize substrates as sole carbon and energy sources.

 Supplementary Figures

A: Bacteroidetes
B: Firmicutes
C: Proteobacteria
D: Synergistetes
E: Tenericutes
F: Actinobacteria
G: Actinobacteria
H: Thermotogae
I: Thermotogae
J: Spirochaetes
K: Spirochaetes
L: Chrysiogenetes
M: Chrysiogenetes
N: Thermi
O: Thermi
P: Thermodesulfobacteria
Q: Thermodesulfobacteria
R: Deferribacteres
S: Deferribacteres
T: Cyanobacteria
U: Caldithrix
V: Caldithrix
W: Chloroflexi
X: Chloroflexi
Y: Fusobacteria
Z: Fusobacteria
a: Aquificae
b: Aquificae
c: Verrucomicrobia
d: Planctomycetes
e: Acidobacteria
f: Acidobacteria
g: Chlamydiae
h: Chlamydiae
i: Deinococcus-Thermus
j: Chlorobi
k: Lentisphaerae
l: Lentisphaerae
m: WWE1
n: Elusimicrobia
o: Elusimicrobia
p: TM7
q: Dictyoglomi
r: Nitrospirae
s: Gemmatimonadetes
t: Gemmatimonadetes
u: Fibrobacteres
v: Fibrobacteres
w: Euryarchaeota
x: Crenarchaeota
y: Nanoarchaeota

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1577   .

Fig. S3

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Fig. S4

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Fig. S5

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Taxonomic cohort

Group 1	No_bact
Group 2	Ox
Group 3	Ox_form
Group 4	All
Group 5	No_ox

Taxonomic cohort

Metabolic cohort

Fig. S8

Metabolic cohort

Fig. S9

Group 1	No_bact
Group 2	Ox
Group 3	Ox_form
Group 4	All
Group 5	No_ox

Metabolic cohort

A

B

C

D

E

1593
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1607

1608 **Supplementary Tables**

Table S1. Composition of the diets used in the diet trials.

Ingredients	0% oxalate (g/Kg)	1.5% oxalate (g/Kg)	3% oxalate (g/Kg)
Casein	200	200	200
L-Cysteine	3	3	3
Corn Starch	285.5	NA	NA
Maltodextrin	120	120	120
Sucrose	100	185.4	185.4
Anhydrous Milkfat	NA	200	200
Soybean Oil	70	70	70
Cellulose	150	150	150
Mineral Mix	42	42	42
Vitamin Mix	12	12	12
Choline Bitartrate	2.5	2.5	2.5
TBHQ, antioxidant	0.014	0.054	0.054
Sodium Oxalate	0	15	30

1609

Table S2. The number of host hepatic genes in each metabolic pathway that exhibited a significant increase or decrease in expression upon consumption of 1.5% oxalate.

Microbiome	tracking_id	gene	locus	Ave No Oxalate	Ave 1.5% Oxalate	log2(fold_change)	test_stat	q_value	FDR	direction	Protein	Gene ontology (Biological process)	Gene ontology (cellular component)	Gene ontology (molecular function)

Table S1. The number of microbial metabolites that exhibited a significant increase or decrease in expression upon consumption of 1.5% oxalate by the host.

1614

Table S7. Minimal media used to quantify the proportion of the microbiota that can use sole carb

Component	Amount/L	Concentration	
KH$_2$PO4	100 mL	100 mM	
NaHCO$_3$	0.4 g	4.8 mM	
NaCl$_2$	0.08 g	1.37 mM	
CaCl2	1 mL	0.80%	0.8g/100mL stock; autoclave
Vitamin K (menadione)	1 mL	5.8 mM	1 mg/mL stock solution; protect from light; autoclave
FeSO$_4$	1 mL	1.44 mM	0.4 mg FeSO$_4$/mL stock solution; filter sterilize
Histidine Hematin Solution	1 mL	0.1%	1.2 mg hematin/mL in 0.2M histidine; filter sterilize after preparation of stock; protect from light; store at 4C
NH4Cl	1 g		
Tween 80	2 mL	0.05%	
MgSO$_4$-7H$_2$0***	1 mL	0.008 mM	
ATCC Vitamin Mix***	10 mL	1%	
ATCC Trace Mineral Mix***	10 mL	1%	
For sole C&E media, add one of the following to Media A			
Aspartic acid	0.02g		
Mannose	0.9g		
Galactose	1.8g		
Sodium acetate	6g	0.60%	
Sodium formate	4g	0.40%	Requires sodium sulfate
D-glucose	0.4 g	2.2 mM	Add to 10ml DI H2O and filter sterilize
Fructose	1 g	2.2 mM	Add to 10ml DI H2O and filter sterilize
Sucrose	1.71g		Add to 10ml DI H2O and filter sterilize
Methylvaleric acid	561ul		Add both methylvaeric and methylbutyric
Methylbutyric acid	517ul		
Oxalate	6.75g	50mM	
pH to 7			
Filter sterilize and bring into anaerobic chamber			
Cysteine***	0.5g		Add to 10ml DI H2O and filter sterilize in anaerobic chamber
sodium sulfate	2g	0.20%	Only add if adding sodium formate

1615 **Let media sit in anaerobic chamber for at least 24hrs to be fully reduced before inoculation

Table S8. Microorganisms used in the taxonomic cohort.

Species	Commercial source	Isolation source
Oxalobacter formgienes	ATCC 35274	human
Desulfovibrio piger	DSMZ749	Sheep rumen
Methanobrevibacter smithii	DSMZ11975	animal feces
Ruminococcus gnavus	ATCC 29149	human
Coprococcus comes	ATCC 27758	human
Bacteroides thetaiotaomicron	ATCC 700349	human
Lactobacillus helveticus	ATCC 55796	Unknown
Lactobacillus plantarum	ATCC 700210	Unknown

Supplemental references

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