Higher-order interactions shape microbial interactions as microbial

community complexity increases

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ABSTRACT

Non-pairwise interactions, or higher-order interactions (HOIs), in microbial communities have

been claimed to explain the emergent features in microbiomes. Yet, the re-organization of

microbial interactions between pairwise cultures and larger communities remains largely

unexplored from a molecular perspective but is central to our understanding and further

manipulation of microbial communities. Here, we used a bottom-up approach to investigate

microbial interaction mechanisms from pairwise cultures up to 4-species communities from a

simple microbiome (*Hafnia alvei*, *Geotrichum candidum*, *Pencillium camemberti* and *Escherichia*

coli). Specifically, we characterized the interaction landscape for each species combination

involving *E. coli* by identifying *E. coli's* interaction-associated genes using an RB-TnSeq-based

interaction assay. We observed a deep reorganization of the interaction-associated genes, with

very few 2-species interactions conserved all the way up to a 4-species community and the

emergence of multiple HOIs. We further used a quantitative genetics strategy to decipher how 2-

species interactions were quantitatively conserved in higher community compositions. Epistasis-

based analysis revealed that, of the interactions that are conserved at all levels of complexity,

82% follow an additive pattern. Altogether, we demonstrate the complex architecture of microbial

interactions even within a simple microbiome, and provide a mechanistic and molecular

explanation of HOIs.

Introduction

Microbiomes are multidimensional systems containing up to thousands of interacting species. In

part due to this complexity, a common strategy to investigate their biology has been to use bottom-

up or reductionist approaches. Using *in vitro* microbial communities or monocultures, the features

of microbial communities are measured in low-dimensional settings, with the underlying objective

to understand whether high-dimension phenotypes can be predicted from lower-level

observations. The lack of predictability of microbial community features from monoculture

observations has demonstrated the critical importance of microbial interactions in shaping

microbial communities. For instance, community assembly[1,2], community function[3], community

resistance to invasion[4] or its effects on its host[5] are highly different from the simple combination

of individual species effects. Some of these studies have also shown that, while 2-species, or

pairwise culture, observations could partially predict what happens in higher communities[1,2,6],

context-specific phenotypes emerge as the microbial community becomes more complex, limiting

the use of pairwise information to obtain a descriptive picture of larger communities. For instance,

the function (amylolytic activity) of a soil-associated microbial community of 6 species has been

shown to differ from the simple linear combination (*i.e.* the addition) of the observed function of

pairwise cultures[3]. Similarly, 13 to 43% of measured *Drosophila melanogaster* traits (lifespan,

reproduction and development) in flies carrying a microbiome of 5 species were not predictable

from the associated traits from flies inoculated with pairwise combinations of the same 5 species[5].

In the zebrafish gut microbiome, while strong negative pairwise interactions were measured, the

assembly of a more complex microbiome of 5 species strikingly diverged from any assembly

prediction based on pairwise interactions, and all 5 species actually co-occur in the final

microbiome[7].

Reorganization of the interaction profile with varying community complexity and the presence of

higher-order interactions (HOIs) are the most likely explanation for the lack of predictability of

complex community phenotypes from pairwise observations. In ecology, HOIs are described as

key to stabilizing communities and promoting biodiversity in biological ecosystems [8–10] They are

commonly described as the modification of pairwise interactions when another species is

introduced, or any interaction that cannot be described by a pairwise model [11,12]. For instance,

while the bacterium *Escherichia coli* can successfully invade cultures of *Chlamydomonas*

reinhardtii as well as cultures of *Tetrahymena thermophila*, it is unable to invade a coculture of

the alga and the ciliate. This is due to *C. reinhardtii* inhibition of *E. coli* aggregation specifically in

the presence of *T. thermophila*, which renders the bacterium vulnerable to predation[13]. Changes

in microbial interactions and HOIs are undoubtedly a significant feature of microbiome ecology

and functioning. Thus, investigating HOIs and deciphering how microbial interactions are

rearranged when microbial systems increase in complexity are essential to our understanding of

microbiomes and our ability to manipulate them.

In this work, we investigate how interactions are reorganized when the complexity of a microbial

community increases from two to four species. We use a simplified cheese rind microbiome

composed of the two gamma-proteobacteria *E. coli* and *Hafnia alvei*, the yeast *Geotrichum*

candidum and the filamentous fungus *Penicillium camemberti*. Our previous work comparing the

pairwise interaction patterns of this model microbiome to the interaction pattern in the full

community highlighted the prevalence of HOIs and the lack of conservation of pairwise

interactions[14]. However, we couldn't precisely resolve the origin of these HOIs or specific rules

underlying the emergence of these HOIs. For instance, we couldn't determine whether 2-species

interactions are alleviated by the introduction of a specific species or by the introduction of all the

other species. Similarly, we couldn't conclude whether community-specific interactions are

actually specific to the community or whether they arise at an intermediate level and

are maintained in the whole community. Relying on the ability to deconstruct and reconstruct this

model system and on the RBTnSeq-based interaction assay we have previously optimized to

compare gene fitness values across multiple conditions[15], we aim to identify quantitative changes

in gene fitness values for *E. coli* in different interactive conditions to identify the genetic basis of

interactions at every level of community complexity.

Comparing interaction-associated genes across conditions, we can identify pairwise interaction-

associated genes that are also observed at higher levels of complexity as well as genes

associated with HOIs. Here, HOIs are defined as interaction-associated genes that emerge in the

3 or 4 species cultures and 2-species interaction-associated genes that are no longer observed

in the 3 or 4 species cultures. Analysis of the genes associated with HOIs and their functions

allowed us to further characterize the deep reorganization of the interaction landscape and

highlights that it is mostly associated with the reprogramming of metabolic interactions and the

introduction of a fungal partner. We further focus on the genetic basis of 2-species interactions

that are conserved in higher levels of complexity to elucidate principles behind interaction

conservation. We use an epistasis and quantitative genomics approach[16,17] to understand

whether interactions that are conserved follow a linear, or additive, pattern. The evaluation of

interaction effects as quantitative traits allows us to define another form of HOIs as cases in which

there is a lack of additivity in interactions that are conserved from simpler to more complex

community composition. This form of HOIs is consistent with a more quantitative definition of

HOIs, highly similar to the definition of epistasis in population genetics[18], that identify HOIs (or

epistasis) as any deviation, for a given quantitative trait, from the prediction of a linear model

where only pairwise interactions are included. Carrying out this analysis, we observe that 82% of

the conserved interactions follow an additive pattern of conservation from 2-species to 4-species,

and that 18% of the conserved 2-species interaction is associated with non-linear models of

conservation.

Overall, our work provides a unique illustration of the highly complex reorganization of interaction

mechanisms when microbial community complexity changes. This provides a mechanistic

explanation of HOIs in microbial communities that is essential for the further global understanding

of microbial communities.

Results

Sets of interaction-associated genes change across interactive conditions

To investigate how microbial interactions are reorganized in a microbial community with

increasing complexity, we reconstructed *in vitro* a modified bloomy rind cheese-associated

microbiome on Cheese Curd Agar plates (CCA plates) as described in our previous work[14]. The

original community is composed of the gamma-proteobacterium *H. alvei*, the yeast *G. candidum*

and the mold *P. camemberti.* Using a barcoded transposon library of the model bacterium *E. coli*

as a probe to identify interactions, we investigated microbial interactions in 2-species cultures (*E.*

coli + 1 community member), in 3-species cultures (*E. coli* + 2 community members) and in 4-

species cultures (or whole community: *E. coli* + 3 community members) (Figure 1A).

Quantification of species' final CFUs after 3 days of growth highlighted consistent growth for *H.*

alvei and *G. candidum* independent of the culture condition and slightly reduced growth for *E. coli*

in interactive conditions compared to growth alone except for following growth with *P. camemberti*

(Supplementary Figure 1). Although we were unable to quantify spores of *P. camemberti* after

three days, growth of *P. camemberti* was visually evident in all of the expected samples.

Previously, we developed an assay and a pipeline to identify microbial genes associated with

interactions by adapting the original RB-TnSeq approach[19] to allow for consistent implementation

of biological replicates as well as for direct quantitative comparison of fitness values between

different culture conditions[15]. More specifically, the original RBTnSeq assay relies on the use of

a pooled library of randomly barcoded transposon mutants of a given microorganism (RBTnSeq

library)[19]. Measuring the variation of the abundance of each transposon mutant before and after

growth, the pipeline allows the calculation of a fitness value for each mutant. A negative fitness

indicates decreased growth of the mutant relative to a wild type strain, whereas a positive fitness

value indicates increased growth in the studied condition. Then, to identify genes associated with

interactions, we measure and compare gene fitness across the different studied conditions, for

example, comparing growth alone to growth in the presence of another species. Then, any gene

whose fitness values significantly change between such conditions is identified as an interaction-

associated gene.

In this work, we used the *E. coli* RBTnSeq Keio_ML9 library[19] and grew it for 3 days alone or in

the seven different interactive conditions studied here (Figure 1A). For each interactive condition,

we calculated the Interaction Fitness Effect (IFE) for 3699 *E. coli* genes as the difference between

the gene fitness in the studied interactive condition and the gene fitness in growth alone

(Supplementary Data 1). To identify genes associated with interactions, we then tested for all the

IFEs that are significantly different from 0 (adjusted p-value ≤ 0.1; two-sided t-test and Benjamini-

Hochberg correction for multiple comparison[20]). Negative IFE occurs when gene fitness

decreases in the interactive condition, and positive IFE occurs when gene fitness improves in the

interactive condition. Here, we identified between 6 (with *P. camemberti*) and 71 (with *H. alvei* +

P. camemberti) significant IFEs per condition (Figure 1B). Both negative IFEs and positive IFEs

were found in each interactive condition except for the 2-species culture with *P. camemberti*,

where only negative interactions were identified. A total of 330 significant IFEs associated with

218 unique genes were identified (as the same gene can have a significant IFE in multiple

conditions) including 125 genes associated with negative IFE and 120 genes associated with

positive IFE (Supplementary Figures 2 and 3).

To gain insight into the interaction mechanisms among microbes, we next analyzed the functions

associated with IFEs. Here, the vast majority of genes associated with significant IFEs are part of

an interaction network, highlighting the presence of genes with connected functions and from

similar pathways (Figure 1C). A significant fraction of the genes associated with a negative IFE

are part of amino acid biosynthesis and transport (17% - Figure 1C and Supplementary Figures

2 and 4), and more specifically with histidine, tryptophan and arginine biosynthesis. This points to

competition for these nutrients between *E. coli* and the other species. Another large set of genes

is related to nucleotide metabolism and transport (14% - Figure 1C and Supplementary Figures

2 and 5), highlighting competitive interactions for nucleotides and/or their precursors. The majority

of these genes relate to purine nucleotides and more specifically to the initial steps of their *de*

novo biosynthesis associated with the biosynthesis of 5-aminoimidazole monophosphate (IMP)

ribonucleotide. Of the genes with a positive IFE, 15% are related to amino acid biosynthesis and

transport (Figure 1C and Supplementary Figures 3 and 4), suggesting cross feeding of amino

acids between *E. coli* and the other species. More specifically, this includes phosphoserine,

serine, homoserine, threonine, proline and arginine. The presence of amino acid biosynthetic

genes among both negative and positive IFEs indicate that trophic interactions (competition

versus cross-feeding) depend on the type of amino-acid and/or the species interacting with *E.*

coli. For both negative and positive IFEs, numerous genes were annotated as transcriptional

regulators (Figure 1C and Supplementary Figures 2 and 3) emphasizing the importance of

transcriptional reprogramming in response to interactions. These transcriptional regulators

include metabolism regulators as well as regulators of growth, cell cycle and response to stress.

Finally, these interaction-associated genes and these interaction mechanisms are consistent with

previous findings in this microbiome[14] as well as in a study of bacterial-fungal interactions

involving *E. coli* and cheese rind isolated fungal species[15].

Introduction of a third-interacting species deeply reshapes microbial interactions

The differences in the number and sign of significant IFEs observed among the different

interactive conditions, with different numbers of interaction species, suggest that the number and

type of interacting partners influence interaction mechanisms. To characterize how the

interactions are reorganized with community complexity, we then investigated if and how the

genetic basis of interactions changes when the number of interacting partners increases by

comparing the genes associated with significant IFE in 2-species cultures, in 3-species cultures

and then in 4-species cultures.

First, we have identified 104 IFEs associated with 98 genes in 2-species cultures as well as 168

IFEs associated with 136 unique genes in 3-species conditions (Supplementary Figure 6 and

Supplementary Data 2). Comparing these gene sets, we can identify how the interaction-

associated genes change when a third-species is added to a 2-species culture. We identified 45

2-species interaction-associated genes maintained in at least one 3-species condition

(maintained interaction-genes), 55 2-species interaction-associated genes no longer associated

with interaction in any 3-species condition (dropped interaction-genes) and 100 3-species

interaction-associated that aren't associated with any 2-species interaction-associated genes

(emergent interaction-genes) (Figure 2A, Supplementary Figure 6 and Supplementary Data 3).

Both dropped and emerging interaction-associated genes represent 3-species HOIs; the third

species either removes an existing interaction or brings about a new one.

We further carried out functional analysis of maintained, dropped and emerging interaction-genes

to elucidate whether maintained and HOIs interaction-genes would be associated with specific

functions and thus interaction mechanisms (Figure 2B). For each set of genes, we calculated the

fraction of genes of that set associated with a given COG ontology category. Metabolism and

transport is the most observed COG group (Figure 2B - teal dots). For maintained interaction-

genes, this indicates that some trophic interactions can be maintained from 2-species to 3-species

conditions. For instance, serine biosynthetic genes *serA*, *serB* and *serC* as well as threonine

biosynthetic genes *thrA*, *thrB* and *thrC* are associated with positive IFEs in the 2-species condition

with *G. candidum* as well as in the 3-species conditions involving *G. candidum* (Supplementary

Figure 4). This suggests that, (i) *G. candidum* facilitates serine and threonine cross feeding and

(ii) this cross-feeding is still observed when another species is introduced. However, metabolism-

related genes identified among the dropped and emerging interaction-agenes indicate that many

trophic interactions are also rearranged through HOIs. Genes associated with lactate catabolism

(*lldP* and *lldD*) and lactate metabolism regulation (*lldR*) have a negative IFE in the 2-species

culture with *H. alvei*, suggesting competition for lactate between *E. coli* and *H. alvei*. Yet, these

genes are no longer associated with a significant IFE when at least another partner is introduced

(Supplementary Figure 7). Histidine biosynthesis genes *hisA*, *hisB*, *hisD*, *hisH* and *hisI* have a

negative IFE in the 2-species culture *with H. alvei* and sometimes in the 3 species culture with *H.*

alvei + *P. camemberti*. However, the negative IFE is alleviated whenever *G. candidum* is present,

suggesting that potential competition for histidine between *E. coli* and *H. alvei* is alleviated by this

fungal species (Supplementary Figure 4). Also, genes related to the COG section "Information

storage and processing" are mostly found among HOIs genes, suggesting a fine-tuning of specific

cellular activity depending on the interacting condition. For instance, we identified many

transcriptional regulators of central metabolism among the dropped genes (*rbsR* and *lldR*) and

the emerging genes (*purR*, *puuR*, *gcvR* and *mngR*), highlighting again the reorganization of

trophic interactions associated with HOIs. Also, many transcriptional regulators broadly

associated with growth control, cell cycle and response to stress were found among the emerging

interaction-genes with 3-species (*hyfR*, *chpS*, *sdiA*, *slyA* and *rssB*), underlining a noticeable

modification of *E. coli's* growth environment with 3-species compare to with 2-species.

Finally, we further aimed to understand whether HOIs are associated with the introduction of any

specific species (Figure 2C and Supplementary Figure 8). We observe that interaction-associated

genes with *H. alvei* are more likely to be dropped, as 65% of them are alleviated by the

introduction of a fungal species (Figure 2C). This can be seen, for instance, with the

reorganization of *E. coli* and *H. alvei* trophic interactions following the introduction of *G. candidum*

(alleviation of lactate and histine competition for instance). Also, we observe that 76% of the

interactions in the 3-species cultures with *H. alvei* + *P. camemberti* and 65% in the 3-species

culture with *H. alvei* + *G. candidum* are emerging genes (compared to 38% of emerging

interaction-associated genes in the 3-species condition with *G. candidum* + *P. camemberti*)

(Figure 2C). For the 3-species with *H. alvei* + *P. camemberti*, they include for instance the genes

associated with purine *de novo* biosynthesis (*purR*, *purF*, *purN*, *purE*, *purC*) and the genes

associated with pyrimidine *de novo* biosynthesis (*pyrD*, *pyrF*, *pyrC*, *carA* and *ulaD*), suggesting

important trophic HOIs. For the 3-species with *H. alvei* + *G. candidum*, emerging interaction genes

include for example the transcriptional regulators *chpS*, *sdiA* and *slyA*, indicating the presence of

a stress inducing environment. Together, these observations suggest that the introduction of a

fungal partner may introduce multiple 3-species HOIs by both canceling existing interactions and

introducing new ones.

HOIs are prevalent in a 4-species community

To further decipher whether microbial interactions continue to change with increasing community

complexity, we investigated the changes in the genetic basis of interactions going from 3-species

to 4-species experiments. We identified 58 interaction-genes in the 4-species condition (*E. coli*

with *H. alvei* + *G. candidum* + *P. camemberti*), compared with 145 genes associated with

interactions in any 3-species conditions. Comparing these two sets of genes we identify: 26 3-

species interaction-genes that are maintained in the 4-species condition (including 16 directly

from 2-species interactions), 115 3-species interaction-genes that are no longer associated with

interactions in the 4-species condition (dropped interaction-genes) and 32 interaction-genes that

are observed solely in the 4-species condition (emerging interaction-genes) (Figure 3A,

Supplementary Figure 6 and Supplementary Data 3). Both dropped and emerging interaction-

genes represent 4-species HOIs. Here, HOIs are remarkably abundant when introducing a single

new species and moving up from 3-species interactions to 4-species interactions. Functional

analysis of maintained and HOI genes reveals the presence of many metabolism related genes

in every gene set (Figure 3), suggesting that some trophic interactions can be maintained from 3-

species to 4-species interactions while some other trophic interactions are rearranged with HOIs.

For instance, most of the genes of the initial steps of *de novo* purine biosynthesis have been

found to have a negative IFE in the 3 species condition with *H. alvei* + *P. camemberti* (*purC*, *purE*,

purF, *purL* and *purN*) as well as in the pairwise condition with *H. alvei* for *purH* and *purK*

(Supplementary Figure 5), suggesting competition for purine initial precursor IMP in these

conditions. Yet, the introduction of the yeast *G. candidum* as a fourth species cancels the negative

IFE value, suggesting that the competition is no longer happening in its presence. Altogether, the

observation of noticeable trophic HOIs moving up from 2 to 3 species and then from 3 to 4-species

interaction highlights a consistent reorganization of trophic interactions along with community

complexity. Also, genes related to Cell wall/membrane/envelope biogenesis are found abundantly

among the 4-species emerging genes (Figure 3B) and they represent the largest functional

fraction of this gene set. These genes have a negative IFE and are related to Enterobacterial

Common Antigen (ECA) biosynthetic processes (*wecG*, *wecB* and *wecA*) (Supplementary Figure

9). While the roles of ECA can be multiple but are not well defined[21], they have been shown to be

important for response to different toxic stress, suggesting the development of a specific stress in

the presence of the four species.

As for the 2 to 3 species comparison, we investigated whether the introduction of a specific fourth

species would be most likely associated with HOIs. The 3-species culture that appears to be the

least affected by the introduction of a fourth member is with *G. candidum* + *P. camemberti* where

34% of the observed interactions are still conserved in the 4-species condition after the

introduction of *H. alvei* (versus 22% for with *H. alvei* + *G. candidum* when *P. camemberti* is added

and 21% for with *H. alvei* + *P. camemberti* when *G. candidum* is added) (Figure 3C and

Supplementary Figure 10). Together, these observations suggest that, again, the introduction of

a fungal partner may introduce multiple 4-species HOIs.

Finally, by increasing the number of interacting species in our system and investigating interaction

gene maintenance and modification with every increment of community complexity, we are able

to build our understanding of the architecture of interactions in a microbial community. Altogether,

we have observed a total of 218 individual genes associated with interactions in any experiment.

Only 16 of them (7%) were conserved across all levels of community complexity (Figure 3D).

Starting from 2-species interaction genes, 48% of them were maintained with 3-species and only

15% (16 out of 104) were still maintained with 4-species. Thus, we demonstrate here a

progressive loss and replacement of 2-species interactions as community complexity increases

and the prevalent apparition of HOIs. Tracking back the origins of the genetic basis of interactions

in the 4-species experiment that represents the full community of our model, we identify that 28%

of the full community interactions can be traced back to 2-species interactions, 18% are from 3-

species interaction and 54% are specific to the 4-species interaction (Figure 3D and 3E). Most of

the maintained interaction-genes from 2-species as well as from 3-species are associated with

metabolism (Figure 3D and Supplementary Figure 11) while Signal transduction and cell

membrane biosynthesis genes are most abundant among the 4-species interaction-genes as

previously mentioned. To conclude, this shows that the genetic basis of interactions and thus the

sets of microbial interaction are deeply reprogrammed at every level of community complexity

and illustrates the prevalence of higher order interactions (HOIs) even in simple communities.

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The majority of maintained 2-species interaction-genes in the 4-species culture follows an

additive conservation behavior

While HOIs are abundant in the 4-species condition, our data yet suggest that up to 28% of the

interactions are maintained from 2-species interactions. However, we don't know whether and

how 2-species interactions are quantitatively affected by the introduction of other species and

whether they would follow specific quantitative models of conservation. For instance, we can

wonder how the strength of a given 2-species interaction is modified by the introduction of one or

two other species, or how two 2-species interactions associated with the same gene will combine

when all the species are present. In other words, can we treat species interactions as additive

when we add multiple species? Such information would generate a deeper mechanistic

understanding of the architecture of microbial interactions while allowing us to potentially predict

some whole community interactions from 2-species interactions. Here, two main hypothetical

scenarios can be anticipated. First, the conservation of 2-species interactions follows a linear or

additive behavior, where the introduction of other species either doesn't affect the strength of the

conserved 2-species interaction or two similar 2-species interactions combine additively. The

second scenario identifies non-linear or non-additive conservation of 2-species interactions,

where the strength of the conserved 2-species interaction is modified by the introduction of other

species or two similar 2-species interactions are not additive. The second scenario would

encompass for instance synergistic effects or inhibitory effects following the introduction of more

species. We next use an epistasis and quantitative genomics approach to understand whether

interactions that are conserved follow a linear, or additive, pattern. For the 16 genes that are

associated with interaction in 2-species cultures, in associated 3-species cultures and in the 4-

species condition, we use epistasis analysis to test the linear behavior of IFE when the number

of interacting species increases, as IFEs are quantitative traits related to the interaction strength.

In multi-dimensional systems, an epistasis analysis quantifies the additive (or linear) behavior of

conserved quantitative traits. In quantitative genetics, for instance, epistasis measures the

quantitative difference in the effects of mutations introduced individually versus together[18,22,23].

Using a similar rationale, we can use IFEs as a quantitative proxy for interaction strength and test

whether the IFEs of the maintained interaction genes in 3-species and in 4-species conditions

result from the linear combination of associated 2-species IFEs (Figure 4A). Nonlinear

combination, or non-additivity of 2-species IFEs in higher community level also highlights higher-

order interactions.

We adapted the pipeline Epistasis[17], originally designed for quantitative genetics investigation.

We implemented the linear model with the gene fitness values for growth alone, for each of the

2-species conditions, for each of the 3-species cultures and for the 4-species condition. For each

gene, the software finds the simplest mathematical model that reproduces the observed IFEs

across all levels of community complexity. In the simplest case, the model will have a term

describing the effects for adding each species individually to the *E. coli* alone culture; that term

corresponds to the 2-species IFE. Then, if the IFE for two *E. coli*'s partners combined (3-species

IFE) differs from the sum of their individual effects (corresponding 2-species IFE), the software

adds a term capturing this epistasis (Figure 4A). Here, we call that term 3-species epistatic

coefficient or $\varepsilon_{i,j}$. Finally, if the IFE for the combined community (*E. coli* plus all three species; 4-

species condition) differs from the prediction based on the 2-species and 3-species terms, the

software will add a high-order interaction term to the model (Figure 4B). Here, we name that term

4-species epistatic coefficient or ε_{ijk}.

We performed this analysis on the 16 genes that are associated with interactions at every level

of community complexity. To identify real additive behavior of IFE from non-additivity, we screen

for 3-species epistatic coefficients and 4-species epistatic coefficients that are significantly

different from 0 (adjusted p-value ≤ 0.01, correction for multiple testing Benjamin-Hochberg). We

found that 13 genes behaved additively from 2-species to 4-species culture, with no epistatic

contributions in the 3-species conditions nor in the 4-species condition (Figure 4C, *(i)*). One gene

(*gadW*) exhibited nonlinear conservation of IFE only in the 4-species condition, but additive IFE

conservation from 2-species to 3-species (Figure 4C, *(ii)*). Another gene (*lsrG*) showed epistasis

in one 3-species condition but no epistasis in the 4-species condition (Figure 4C, *(iii)*) Finally, one

gene (*gltB*) displayed both non-additivity in 3-species and 4-species conditions (Figure 4C, *(iv)*).

If we look more closely at the additive genes, we find genes (*betA*, *betT*, *purD* and *purH*) are

associated with the conservation of negative IFEs (Supplementary Figure 12). While *betA* and

betT are associated with choline transport (*betT*) and glycine betaine biosynthesis from choline

(*betA*)[24], *purD* and *purH* are associated with *de novo* purine biosynthesis[25]. This suggests that

requirements for glycine betaine biosynthesis from choline and for purine biosynthesis caused by

microbial interactions, possibly due to competition for the nutrients used as precursors, are

additively conserved from individual 2-species interactions requirements. Also, 5 genes

associated with amino acid biosynthesis (*serA*, *thrC, cysG, argG* and *proA*) are associated with

the additive conservation of positive IFE (Supplementary Figure 12), suggesting that cross

feeding can be additive when the community complexity increases. Altogether, this highlights the

existence of 2-species interactions, including trophic ones, conserved in an additive fashion in the

highest-level of complexity.

This leaves 3 genes (18%) of the maintained 2-species interaction-associated genes that are

associated with non-additive behavior, and thus HOIs, at at least one higher level of community

complexity (Figure 4C - *(ii)*, *(iii)* and *(iv)*). The gene *gadW* is associated with non-additivity at the

4-species level, suggesting that while IFEs are additive in 3-species cultures, the introduction of

a fourth species introduces HOI. Moreover, the observed 4-species IFE is greater than the IFE

predicted by a linear model (Figure 4D), highlighting a potential synergistic effect when the 4

species are together. The gene *lsrg* is associated with non-additivity only at the 3-species culture

w *G.c + P.c*. More specifically, this indicates that HOI arise when these 2 fungal species are

interacting together with *E. coli,* but that no more HOI emerge when *H. alvei* is introduced (ie, the

4-species IFE can be predicted by the linear combination of the lower levels IFEs). As the

observed IFE for the 3-species condition w *G.c + P.c* is greater than the predicted IFE (Figure

4C), this suggests a synergistic effect between the 2 fungal species. Finally, the gene *gltB* is

associated with non-additivity at both the 3-species and 4-species levels. For this gene, the

conservation of IFE is never associated with an additive model. Here, the observed 4-species IFE

is not as negative as it would be as the result of the linear combination of the associated lower

IFE (Figure 4D), suggesting the existence of a possible IFE threshold, or plateau effect.

Altogether, this indicates that maintained 2-species-interactions can follow nonlinear behaviors

that could involve synergistic effects, inhibitory effects or constraints.

Discussion

Interactions between microbes are responsible for the specific and multiple phenotypes observed

in microbial communities compared to monocultures. Knowledge of microbial interactions could

be the key to controlling microbial communities, but deciphering these interactions is challenging

in complex microbiomes. Moreover, pairwise culture interactions are often insufficient to predict

what happens in more complex microbiomes, suggesting an important reprogramming of

interactions as community complexity increases in terms of the number of species present[3,5,7,13,14].

Understanding the restructuring of these interactions in complex communities is thus essential to

comprehending the biology of microbial communities. Using an *in vitro* multi-kingdom community,

we performed a molecular investigation of the reorganization of interaction profiles as community

complexity changed. Relying on the tractability of our model system and an RBTnSeq-based

interaction assay, we tracked interactions in 2-species, 3-species and 4-species cultures. In this

work, the combination of a qualitative and quantitative comparison of interaction profiles at the

molecular level underlines the complex dynamics of interaction reorganization with community

complexity and the existence of multiple forms of higher-order interactions.

This work offers an example of the different forms that HOIs can take in biological systems. We

report multiple mechanistic HOIs as defined in ecological studies and represented here by any

pairwise interaction-associated genes that are not observed in 3 and more species conditions as

well as any interaction-associated genes observed in higher-levels than pairwise cultures[12]. We

also report another form of HOIs, as defined in quantitative genetics, which are associated with

the non-additive behavior of conserved 2-species interactions in 3 or 4 species communities[22].

Here, each HOI level refers to different biological phenomena occurring in the same biological

system. Yet, they are essential and complementary to decipher the extremely convoluted

architecture and dynamics of microbial interactions and microbiome biology.

As the number of interaction-associated genes strongly decreased in the 4-species culture

compared to 2 or 3 species setups, our work points out a strong reduction of the interaction

landscape with 4 species that is associated with the loss of many lower-level interactions and the

emergence of context-specific interactions. While 43% of the 2-species interaction-associated

genes are still found with 3 species, only 15% are still found with 4 species, representing less

than a third (28%) of the total of 4-species interactions. This highlights the increasing dilution and

replacement of original 2-species interactions. To summarize, the more complex a community

gets, the more mechanistic HOIs emerge. While our work was limited to 4 species, it remains

necessary to verify whether this statement will be true for more complex communities: whether

more 2-species interactions will be lost and more HOIs will keep emerging at each level or whether

the interaction landscape will stabilize. Indeed, Friedman *et al.*, have highlighted that growth

observation for 2- and 3-species combination could predict the assembly of 7- to 8-species[2]; this

would suggest that interactions, or at least key interactions driving community assembly, could

change less dramatically in higher complexity microbiomes.

Our molecular approach enabled us to identify that most of the reorganization of the

interaction profile is associated with the reprogramming of metabolic or trophic interactions

including both competition for nutrients and cross-feeding. As more species are introduced it

appears that the dynamics of nutrient consumption is rearranged. For instance, we observed that

some 2-species competition for amino acids and for lactate between *E. coli* and *H. alvei* can be

alleviated by the introduction of *G. candidum*. While the competition for amino acids is likely

alleviated by amino acid cross-feeding from *G. candidum*, as this species is known to release

amino acids into the environment through digestion of proteins and peptides[26–28], the mechanism

relieving competition for lactate is unclear. Possibly, *G. candidum* provides other nutrients sources

like amino acids that alleviate the need for *E. coli* to rely on lactate. Trophic interactions are

described as core determinants in community assembly[29,30] and simple rules of metabolic

interdependencies and metabolic specialization can be sufficient to predict the assembly of rather

complex communities[31–33]. Yet in complex systems, such as the gut, with complex nutrient

composition, the important reorganization of metabolic interactions as community complexity

changes could likely explain the difficulty in predicting community assembly and composition in
some studies[7]. As previously suggested[34], ecological and metabolic factors associated with the
present species such as niche overlap, degree of metabolic specialization and species similarities
are likely to be drivers of these metabolic HOIs. Indeed, microorganisms display incredible
metabolic abilities, from nutrient usage to rapid metabolic switching, and in the presence of
multiple nutrient sources and/or other microorganisms they are likely to readjust the sequence of
nutrient uptake. Niche occupation and nutrient access are also two crucial aspects in the success
or failure of microbial invasion[4,35]. The reorganization of metabolic interactions in different
community composition could likely explain the poor predictability of invasion resistance from
simple species-combinations and the emergence resistance-specific phenotype.

To some extent, our work also highlights the importance of fungal species as major actors in
reshaping interaction networks. Here, more 3-species HOIs and 4-species HOIs were observed
when one fungal species was added either as a third species with two bacteria or as a fourth
species with another fungus and two bacteria. In microbial communities, fungi are known to
impact community structure and access to nutrients through the formation of hyphal highways[36,37],
to impact community assembly through environmental modification[38–40] as well as to impact
community protection through the production of multiple secondary metabolites with antibiotic or
antimicrobial properties[15,39,41]. In this specific context, fungi-associated HOIs seem to be related
to their metabolic characteristics, whether through cross-feeding or competition for nutrients. Yet,
the emergence of specific requirements for ECA biosynthetic genes in *E. coli* when all species
are present, suggesting a potential toxic stress, may reveal other fungal context-specific
properties, while it could also inform about a more precise role of the ECA in *E. coli*. We believe
this work contributes, along with other recent studies, to advocate for the need to include fungal
species more frequently into microbiome work studies.

Finally, to understand principles behind the conservation of pairwise interactions, we used

epistasis analysis to quantify the additive or non-additive behavior of conserved 2-species

interactions in 3 and 4 species conditions. Epistasis analysis offers an adaptable approach to test

the linear behavior of quantitative traits in systems with increasing complexity, whether it is the

effects of accumulation of mutations in a genome[18,42], the effect of drug combinations[43] or the

dynamics of predators-prey ecosystems[44]. Recent studies in the field of microbiome research

have also relied on epistasis analysis to elucidate fundamentals of microbial communities such

as how the nutrient composition of the environment determines the assembly and the diversity of

a microbial community[34,45], how the functional landscape of microbial community is built[3] or how

the commensal microbiome determines the development, lifespan and reproduction of its host[5].

In this work, using the quantitative metric IFE for the strength of interactions, we used an epistatic

model to characterize the additivity or non-linearity of IFE of conserved 2-species interactions

when *E. coli* is growing with 2 and 3 other species (3-species and 4-species conditions

respectively). We observed that most of the conserved 2-species interaction genes followed an

additive model of conservation, including trophic-interaction related genes. While our study was

limited to a small number of interacting species, it remains to be investigated if this linear behavior

is propagated if the community complexity increases again. While we have observed both

synergistic effects and limitations effects for nonlinear conservation of interaction strength, we

believe that such behavior are likely to arise in more complex contexts and that additivity will

eventually stop. For instance, additivity of pairwise interactions is likely to saturate and to stop at

higher-levels of complexity due to environmental constraints (nutrient supply for instance) and/or

the metabolic capacities of the different species as highlighted in [34]. While this theory can apply

to conserved trophic interactions, like the ones highlighted in our work, other scenarios could

include molecule-driven or environment-mediated interactions such as exchange of metabolites,

quorum sensing, antibiosis and modification of the physiochemical properties of the environment.

While trait additivity is fairly easy to quantify in high-dimensional systems, our study, along with

other work using epistasis to study microbial communities[3,5,34,45] suggest that additivity of

quantitative microbial features is not the only scenario in nature, and strongly emphasizes the

need to develop mathematical approaches to accurately understand the dynamics and

functionalities of microbiomes.

Overall, our work identifies the reorganization of microbial interactions along with community

complexity at the molecular level. While more advanced modeling is still required, this knowledge

of the mechanistic reorganization of interactions and patterns of HOIs is essential for bottom-up

approaches to be able predict, from minimal information, the biology of complex microbiomes and

will offer novel opportunities to design synthetic microbial communities or control natural ones.

Methods

Strains and media

Strains

The bloomy rind cheese community was reconstructed with the same strains from [14]: *H. alvei*

JB232 isolated from cheese[46] and two industrial cheese strains: *G. candidum* (Geotrichum

candidum GEO13 LYO 2D, Danisco – CHOOZITTM, Copenhagen, Denmark) and *P. camemberti*

(PC SAM 3 LYO 10D, Danisco - CHOOZITTM).

Medium

All assays have been carried out on 10% cheese curd agar, pH7 (CCA) (10% freeze-dried Bayley

Hazen Blue cheese curd (Jasper Hill Farm, VT), 3% NaCl, 0.5% xanthan gum and 1.7% agar).

The pH of the CCA was buffered from 5.5 to 7 using 10M NaOH.

Competition assay – RBTnSeq Assays

The *E. coli* barcoded transposon library Keio_ML9[19] was used for all RBTnSeq assays on CCA

during a 3-day growth in eight different culture conditions: alone, 2-species conditions (with *H.*

alvei; with *G. candidum;* and with *P.camemberti*), 3-species conditions (with *H. alvei* + *G.*

candidum; with *H. alvei* + *P. camemberti*; and with *G. candidum* + *P. camemberti*), and in the

single 4-species condition (with *H. alvei* + *G. candidum* + *P. camemberti*) (Figure 1).

From the species and library inoculation to cell harvest after 3 days of growth, we followed the

same procedure as described in[14]. We amplified the *E. coli* barcoded transposon library Keio_ML9

into 25 mL of liquid LB-kanamycin (50 mg/mL) up to an OD of 0.6-0.8. A 5mL sample of this

preculture was spun down and kept at -80C as the T0 sample required for fitness calculation. The

remaining cells were then washed in PBS1x-Tween0.05% and used to inoculate the competition

assays with $7*10^6$ cells of the library on each 100 mm petri dish plate. When necessary, the other

community members were then inoculated at the following densities: for *H. alvei*: $7*10^6$ cells; for

G. candidum: $7*10^6$ cells; for *P. camemberti*: $7*10^5$ cells.

After 3 days, cells were harvested by flooding the plates with 1.5mL of PBS1X-Tween0.05%,

gentle scraping and then transferring the resuspended cells into 1.5mL tubes. Cells were

centrifuged for 3 min at RT at 10 KRPM and stored at -80C until gDNA extraction.

All assays have been performed in triplicate.

gDNA extraction, library preparation and sequencing

gDNA from the samples of the competition assays was extracted by phenol-chloroform extraction

(pH 8) as described in [14]. For each sample, we resuspended the cells into 500 mL of buffer B (200

mM NaCl, 20 mM EDTA) and then transferred them into a 2mL screw-capped tube previously

filled with 125 mL of 425-600 mm acid-washed beads and 125 mL of 150-212 mm acid-washed

beads. Then, 210mL of SDS 20% and 500mL of Phenol:Chloroform (pH 8) were added to each

sample before mechanical lysis by vortexing the tubes for 2 minutes at maximum speed. Tubes

were then centrifuged for 3 min at 8 KRPM at 4C and 450mL of aqueous phase were recovered

for each sample. 45 mL of sodium acetate 3M and 450 mL of ice-cold isopropanol were added

and tubes were incubated for 10 min at -80C. Tubes were then centrifuged for 5 min at 4C at 13

KRPM, supernatant was removed and the pellet was washed in 750 mL of 70% ice-cold ethanol

before being resuspended in 50mL of DNAse/RNAse free water.

For library preparation, the 98C BarSeq PCR described in [19] was used to amplify the barcoded

region of the transposons and PCR was performed in a final volume of 50 mL: 25 mL of Q5

polymerase master mix (New England Biolab), 10 mL of GC enhancer buffer (New England

Biolab), 2.5 mL of the common reverse primer (BarSeq_P1[19]) at 10 mM, 2.5 mL of a forward

primer from the 96 forward primers (BarSeq_P2_ITXXX[19]) at 10 mM and 50 ng to 2 mg of gDNA.

The following PCR program was used: (i) 98℃ - 4 min, (ii) 30 cycles of: 98℃ – 30 s; 55℃ – 30 s;

72℃ – 30 s, (iii) 72℃ – 5 min. After the PCR, 10 mL of each of the PCR products were pooled

together to create the BarSeq library. 200 mL of the pooled library were purified using the MinElute

purification kit (Qiagen) and final elution of the BarSeq library was performed in 30 mL in DNAse

and RNAse free water.

The BarSeq library was quantified using Qubit dsDNA HS assay kit (Invitrogen) and then

sequenced on HiSeq4000 (50 bp, single-end reads), by the IGM Genomics Center at the

University of California San Diego.

Data processing and interaction fitness effects (IFE) analysis

For each library, BarSeq reads were first processed using the Perl script BarSeqTest.pl from[19] to

obtain the count file (all.poolcount) containing the number of reads per barcode for each

sample. This pipeline requires a table where each barcode is mapped to a location in the genome.

The Arkin lab (Physical Biosciences Division, Lawrence Berkeley National Laboratory, Berkeley,

California, USA) kindly provided the TnSeq table for the *E. coli* library. The original script used for

this analysis originates from [19] is publicly available on https://bitbucket.org/berkeleylab/feba.

The generated all.poolcount information was then implemented into custom R scripts from[15] to

determine the average fitness scores for each gene across three RBTnSeq assay replicates for

each of the eight cultures (https://github.com/DuttonLab/RB-TnSeq-Microbial-interactions).

Insertion mutants that did not have a sufficient T0 count in each condition or that were not centrally

inserted (10–90% of gene) were removed from the analysis and counts were then normalized

using a set of five reference genes (*glgP*, *acnA*, *modE*, *leuA* - average of 52 strains

each). Detailed explanation of the fitness calculation strategy can be found in the Readme

document as well as in[15]. In each condition, to assess the possible variability between replicates,

we measured the correlation between the three replicates (Supplementary Figure 13). In this set

of experiments, Pearson coefficient between replicates varied from 0.79 to 0.86 suggesting low

technical noise.

Gene fitness values were then compared between interactive conditions and *E. coli* growth alone

conditions using two-sided *t*-tests (when the equality of variance was verified by Fisher test) and

correction for multiple comparison (Benjamini–Hochberg method[20]). Comparisons associated

with an adjusted *P* value lower than 10% were considered a significant interaction fitness effect.

Epistasis model analysis

We used the Python package Epistasis[17] to run the epistasis analysis on *E. coli*'s genes. We

implemented the model with the average fitness values across the three biological replicates

along with the corresponding variance, for each gene and for each of the culture conditions

(Alone, w *H.a*, w. *G.c* , w *P.c*, w *H.a* + *G.c*, w *H.a* + *P.c*, w *G.c* + *P.c*, w *H.a* + *G.c* + *P.c*). The

model is run for each gene individually. The 'genotypes' expected in the model correspond to the

culture conditions and are binary coded based on the presence or not of *E. coli*'s partners *G.*

candidum, *H. alvei* and *P. camemberti*. For instance, the Alone condition corresponds to

phenotype 000, the w *G.c* condition is coded 100, the w *H.a* + *P.c* condition is coded 011, the w

H.a + *G.c* + *P.c* is coded 111 and so on. The 'phenotype' implemented in the model corresponds

to the average fitness value across three biological replicates. After generating the genotype-

phenotype map for each gene, the model was run a first time using the 'local' parameter to set-

up the center of the map, and returns the set of epistatic coefficients for each gene calculated as

follows:

$IFE_{obs,Ha,Gc} = IFE_{Ha} + IFE_{Gc} + \varepsilon_{Ha,Gc}$

$IFE_{obs,Ha,Pc} = IFE_{Ha} + IFE_{Pc} + \varepsilon_{Ha,Pc}$

$IFE_{obs,Gc,Pc} = IFE_{Gc} + IFE_{Pc} + \varepsilon_{Gc,Pc}$

$IFE_{obs,Ha,Gc,Pc} = IFE_{Ha} + IFE_{Gc} + IFE_{Pc} + \varepsilon_{Ha,Gc} + \varepsilon_{Ha,Pc} + \varepsilon_{Gc,Pc} + \varepsilon_{Ha,Pc,Gc}$

To determine whether each coefficient was different from zero, we generated 7,000

pseudoreplicates from our experimental variance from each gene and then calculated the

probability each coefficient was above or below zero from this distribution. P-values were then

adjusted for multiple comparison testing using Benjamini Hochberg Correction[20]. As it has been

shown previously that epistatic analyses can fail if the effects of mutations combine non-linearly

instead of linearly (e.g. mutational effects multiply rather than add), we used the epistasis package

to look for such nonlinearity. However, no nonlinearity was observed (Supplementary Figure 14).

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Author Contributions

724 R.J.D., M.J.H. and M.A.M. conceptualized the study. M.A.M. performed the experiments. The Epistasis

725 pipeline was written and adapted by M.J.H. and A.J.M. Data analyses were performed by M.A.M. and A.J.M.

726 The article was written by M.A.M. and revised with input from all authors. The figures were made by M.A.M

727 with input from all authors. The study was supervised by R.J.D. and M.J.H.

Additional information / Competing Interest Statement

The authors declare that no financial and non-financial competing interests exist in relation to the work

described.

Figure legends

Figure 1: Changes of *E. coli*'s interaction-associated genes in 2-species, 3-species and 4-
species cultures. A. Experimental design for the identification of interaction-associated genes in 7
interactive conditions from the Brie community. The *E. coli* RBTnSeq Keio_ML9 (Wetmore *et al.*, 2015) is
either grown alone or in 2, 3 or 4 species cultures to calculate *E. coli* gene fitness in each condition (in
triplicate). Interaction fitness effect (IFE) is calculated for each gene in each interactive culture as the
difference of the gene fitness in the interactive condition and in growth alone. IFE that are significantly
different from 0 (two-sided t-test, Benjamini-Hochberg correction for multiple comparisons) highlight the
genes associated with interaction in an interactive condition. **B.** Volcanoplots of IFEs calculated for each
interactive condition. Adjusted p-values lower than 0.1 highlight significant IFEs. Negative IFEs (blue)
identify negative interactions and positive IFE (red) identify positive interactions. Numbers on each plot
indicate the number of negative (blue) or positive (red) IFEs. **C**. Functional analysis of the interaction-
associated genes (significant IFEs). Interaction-associated genes have been separated into two groups:
negative IFE and positive IFE. For each group, we represent the STRING network of the genes (Nodes).
Edges connecting the genes represent both functional and physical protein association and the thickness
of the edges indicates the strength of data support (minimum required interaction score: 0.4 – medium
confidence). Nodes are colored based on their COG annotation and the size of each node is proportional
to the number of interactive conditions in which that given gene has been found associated with a significant
IFE. Higher resolution of the networks with apparent gene names are found in Supplementary Figures 2
and 3.

Figure 2: Comparison of the genetic basis of interaction for 2-species and 3-species
conditions. A. Venn Diagram of 2-species and 3-species interaction-gene sets. This Venn Diagram
identifies 2-species interaction-genes that are dropped when a third species is introduced (Left side;
Dropped interaction-genes = any 2-species gene that are not found in any 3-species condition), 2-species
interaction-genes that are maintained in at least one associated 3-species condition (Intersection;
Maintained interaction-genes) and interaction-genes that are specific to 3-species condition (Right side;
Emerging interaction-genes). **B.** Functional analysis of the dropped, maintained and emerging interaction-
genes from 2-species to 3-species. Each dot represents the fraction of genes of the studied gene set
associated with a given COG category (Number of genes found in the category / Total number of genes in
the gene set). The color of the dots indicates the general COG group of the COG category: Teal:
Metabolism; Blue: Information storage and processing; Orange: Cellular Processes and Signaling ; Grey:
Unknown or no COG category. **C.** Species-level analysis of 3-species HOIs: for each 2-species condition,
we measure the fraction of interaction-genes that are dropped in associated 3-species cultures (Dropped
in 3-species) or maintained in at least one of the 3-species cultures (Maintained in 3-species); for each 3-
species condition, we measure the fraction of interaction-genes that have been conserved from at least one
associated 2-species condition (Maintained from 2-species) or that are emerging with 3-species (Emerging
in 3-species).

Figure 3: Organization of the interactions in the 4-species community. A. Venn Diagram of 3-
species and 4-species interaction-gene sets. This Venn Diagram identifies 3-species interaction-genes that
are dropped when a fourth species is introduced (Left side; Dropped interaction-genes = any 3-species
gene that are not found in the 4-species condition), 3-species interaction-genes that are maintained in the
4-species condition (Intersection; Maintained interaction-genes) and interaction-genes that are specific to
4-species condition (Right side; Emerging interaction-genes). **B.** Functional analysis of the dropped,
maintained and emerging interaction-genes from 3-species to 3-species. Each dot represents the fraction

of genes of the studied gene set associated with a given COG category (Number of genes found in the
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of the COG category: Teal: Metabolism; Blue: Information storage and processing; Orange: Cellular
Processes and Signaling; Grey: Unknown or no COG category. **C.** Species-level analysis of 4-species
HOIs: for each 3-species cultures we measure the fraction of interaction-genes that is conserved in the 4-
species culture (Maintained in 4-species) and the fraction of interaction-genes that has been dropped
(Dropped in 4-species). **D.** Alluvial plots of the interaction genes across community complexity levels. **E**.
STRING network of the 4-species interaction genes (Nodes). Edges connecting the genes represent both
functional and physical protein association and the thickness of the edges indicates the strength of data
support (minimum required interaction score: 0.4 – medium confidence). Nodes are colored based on the
level of community complexity the genes are conserved from.
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Figure 4: Quantitative analysis of IFE conservation for the interaction associated genes
conserved from 2-species to 4-species conditions. A. Schematized quantitative epistasis/non-
linearity measured in 3-species conditions (with partner i and j). Epistasis (ε_{ij}) is the difference between the
individual IFE of partner i and partner j (red and orange bars) versus placing them together (green).
Mathematically, we need three terms (IFE_i, IFE_j, and ε_{ij}) to reproduce the observed IFE for the 3-species
condition. **B.** This analysis can be extended to higher levels of community complexity: 4-species (*E. coli*
with 3-partners i, j, and k). The model first accounts for epistasis between i/j, i/k, and j/k. In this example, i
and j exhibit epistasis; i/k and j/k are additive (dark blue and purple). The predicted IFE for the 4-species
community is the sum of the individual 2-species effects (red, orange, light blue) and the 3-species epistatic
terms (green). The 4-species epistatic coefficient is the difference between this low-order prediction and
the observed IFE for the i,j,k community (pink). **C.** Conservation profiles of the 16 2-species interaction-
associated genes conserved up to 4-species. 2-species conditions: a colored square indicatea the 2-
species condition(s) in which the interaction-associated gene was identified; a grey square indicates non-
significant 2-species IFEs. 3-species conditions: a teal square indicates that the associated IFE is
associated with additive behavior from associated 2-species IFE (no ε_{ij} epistatic coefficient), a red square
indicates that the associated IFE display non-additivity from 2-species IFE and thus epistasis, a grey square
corresponds to a 3-species condition that is not associated with significant 2-species IFE (no epistasis
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with non-additivity from lower-order IFE. **D.** Comparison of the observed and predicted IFE for the genes
and condition associated with 3-species and 4-species non-additive IFE.
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Supplementary material list

Supplementary Figures:

<u>Supplementary Figure 1</u>: Growth of the community species in the studied conditions

<u>Supplementary figure 2</u>: Functional analysis of interaction-associated genes with negative IFEs

<u>Supplementary figure 3</u>: Functional analysis of interaction-associated genes with positive IFEs

<u>Supplementary figure 4</u>: IFE profiles of Amino acid biosynthesis genes identified in this study

<u>Supplementary figure 5</u>: IFE profiles of Purine biosynthesis associated genes identified in this

study

<u>Supplementary Figure 6</u>: Comparison of interaction-associated genes across the different levels

of community complexity

Supplementary figure 7: IFE profiles of lactate metabolism genes

Supplementary figure 8: Condition specific comparison of interaction-associated genes for 2 and

3-species conditions

Supplementary figure 9: IFE profiles of Enterobacterial Common Antigen (EAC) genes

Supplementary figure 10: Condition specific comparison of interaction-associated genes for 3 and

4-species condition

Supplementary figure 11: Functional network of the 4-species interaction-genes and their origin

Supplementary figure 12: IFE profiles of the 16 2-species interaction genes maintained up to 4-

species

Supplementary figure 13: Pearson correlation of gene fitness across replicates

Supplementary figure 14: Non-linearity analysis of IFE in the Epistatis model

Supplementary Datasets:

Supplementary Data 1: RB-TnSeq based interaction analysis (Fitness values, Interaction Fitness

Effects and associated statistics)

Supplementary Data 2: Interaction-associated genes at each level of community complexity

Supplementary Data 3: Comparison of interaction-associated genes across the different levels of

community complexity

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842   **Figures**

A.

E. coli RBTnSeq library

H. alvei (H.a)

G. candidum (G.c)

P. camemberti (P.c)

Alone

Pairwise (PW or 2S)

3-species (3S)

4-species (4S)

GeneFit$_{Al}$

GeneFit$_{Int}$

Identification of genetic basis of interactions

IFE$_{Gene}$= GeneFit$_{Int}$ - GeneFit$_{Al}$ → IFE$_{Gene}$ ≠ 0

Interaction-associated gene

B.

PW

E. coli w *H.a*
32:22

E. coli w *G.c*
15:29

E. coli w *P.c*
6:0

3S

E. coli w *H.a + G.c*
29:36

E. coli w *H.a + P.c*
11:21

E. coli w *G.c + P.c*
50:21

4S

E. coli w *H.a + G.c + P.c*
27:31

- Negative IFE
- Positive IFE
- Non significant IFE

Adj-pvalue

IFE

C.

Positive IFE

Negative IFE

COG Categories

- Energy production and conversion
- Amino acid metabolism and transport
- Nucleotide metabolism and transport
- Carbohydrate metabolism and transport
- Coenzyme metabolism
- Inorganic ion transport and metabolism
- Secondary structure
- Cell wall/membrane/envelop biogenesis
- Cell motility
- Post-translational modification, protein turnover, chaperone
- Function unknown
- Cell cycle control and mitosis
- Translation
- Transcription
- Replication and repair
- Signal transduction
- Intracellular trafficking and secretion

Figure 1: Changes of *E. coli*'s interaction-associated genes in 2-species, 3-species and 4-species
cultures. A. Experimental design for the identification of interaction-associated genes in 7 interactive
conditions from the Brie community. The *E. coli* RBTnSeq Keio_ML9 (Wetmore *et al*., 2015) is either grown
alone or in 2, 3 or 4 species cultures to calculate *E. coli* gene fitness in each condition (in triplicate).
Interaction fitness effect (IFE) is calculated for each gene in each interactive culture as the difference of the
gene fitness in the interactive condition and in growth alone. IFE that are significantly different from 0 (two-
sided t-test, Benjamini-Hochberg correction for multiple comparisons) highlight the genes associated with
interaction in an interactive condition. **B.** Volcanoplots of IFEs calculated for each interactive condition.
Adjusted p-values lower than 0.1 highlight significant IFEs. Negative IFEs (blue) identify negative
interactions and positive IFE (red) identify positive interactions. Numbers on each plot indicate the number
of negative (blue) or positive (red) IFEs. **C**. Functional analysis of the interaction-associated genes
(significant IFEs). Interaction-associated genes have been separated into two groups: negative IFE and
positive IFE. For each group, we represent the STRING network of the genes (Nodes). Edges connecting
the genes represent both functional and physical protein association and the thickness of the edges
indicates the strength of data support (minimum required interaction score: 0.4 – medium confidence).
Nodes are colored based on their COG annotation and the size of each node is proportional to the number
of interactive conditions in which that given gene has been found associated with a significant IFE. Higher
resolution of the networks with apparent gene names are found in Supplementary Figures 2 and 3.
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Figure 2: Comparison of the genetic basis of interaction for 2-species and 3-species conditions. A.
Venn Diagram of 2-species and 3-species interaction-gene sets. This Venn Diagram identifies 2-species
interaction-genes that are dropped when a third species is introduced (Left side; Dropped interaction-genes
= any 2-species gene that are not found in any 3-species condition), 2-species interaction-genes that are
maintained in at least one associated 3-species condition (Intersection; Maintained interaction-genes) and
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Functional analysis of the dropped, maintained and emerging interaction-genes from 2-species to 3-
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Species-level analysis of 3-species HOIs: for each 2-species condition, we measure the fraction of
interaction-genes that are dropped in associated 3-species cultures (Dropped in 3-species) or maintained
in at least one of the 3-species cultures (Maintained in 3-species); for each 3-species condition, we measure
the fraction of interaction-genes that have been conserved from at least one associated 2-species condition
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