# Benchmarking of shotgun sequencing depth highlights limitations of strain-level analysis and shallow metagenomics

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## Abstract

Shallow metagenomics promises taxonomic and functional insights into samples at an affordable price. To determine the depth of sequencing required for specific analysis, benchmarking is required using defined microbial communities. We used complex mixtures of DNA from cultured gut bacteria and analysed taxonomic composition, strain-level resolution, and functional profiles at up to eleven sequencing depths (0.1-50.0 Gb). Reference-based analysis provided accurate taxonomic, and strain-level insights at 0.5-1.0 Gb. In contrast, *de-novo* metagenome-assembled genome (MAG) reconstruction required deep sequencing (>10 Gb), and even high-quality MAGs were chimeric, with

54.5 to 81.8 % accurately representing the original strains, depending on the bioinformatic approach

used.  However, the issue of chimeric MAGs can be reduced by using strain-aware assembly methods

or long-read sequencing. Functionally, 2 Gb provided reliable insights at the pathway level, but

sufficient proteome coverage was only achieved at or above 10 Gb. Library preparation and host DNA

contamination were identified as confounders in shallow metagenomic analysis. This comprehensive

analysis using complex mock communities provides guidance to an increasing community of scientists

interested in using shallow metagenomics, and highlights the limitations of MAGs in accurately

capturing strain-level diversity.

## Introduction

Next-generation sequencing is essential for microbiome research, enabling comprehensive analysis of

complex microbial communities at an ever-increasing sample size. However, the widespread use of

this technology contrasts with the low number of studies that have tested the robustness and accuracy

of conclusions derived from widely used analysis workflows.

The most frequent used method for microbiota analysis is 16S rRNA gene amplicon sequencing due to

its ease of implementation, both experimentally and bioinformatically, and low cost compared to

metagenomics. However, it is limited to structural analysis of the microbiota (diversity and

composition) and taxonomic resolution is generally limited to the genus level (strain analysis may be

possible for certain taxonomic groups when using amplicon sequence variants). Experimentally it is

also prone to amplification bias[1]. Whilst deep metagenomics offers a solution to these shortcomings,

it is challenging to perform with low biomass samples or those with a high fraction of non-microbial

DNA (e.g., human tissue samples) and is also more cost intensive.

Shallow metagenomics, commonly referred to as shotgun sequencing at a depth ≤1 Gb (ca. 3 million

reads), has been proposed to overcome the limitations of both high-throughput 16S rRNA gene

amplicon and deep metagenomic sequencing[2–4]. Few studies have attempted to benchmark shallow

metagenomics and thereby define which information is accessible at what sequencing depth, and how

reliably it can be obtained. A common approach used by most benchmarking studies is to compare

sequencing techniques and depths using native samples, such as human stool[3–7]. The main

disadvantage of this is that the exact composition of the input is unknown, preventing accurate

benchmarking. Even fewer studies investigated the impact of sequencing depth using samples with

defined microbial composition, hereon referred to as mock communities[2,8]. Cattonaro et al. used a

commercially available mock community, containing 20 strains, of which the abundance of 5 was

below their detection threshold[8]. Xu et al. used mock communities with two different distributions,

including up to 69 human gut bacterial species[2]. However, their analysis relied on a limited set of

sequencing depths and focused on comparing shallow metagenomics with 16S rRNA gene amplicon

sequencing. Other common practices are to bioinformatically subsample deeply sequenced datasets

to mimic different sequencing depths or to generate artificial mock communities in-silico[3,6,9]. However,

these approaches do not include the impact of real sample processing and sequencing in the

laboratory.

Given the need to better define the strengths and limitations of shallow metagenomics, we

systematically evaluated the effects of shotgun sequencing depth on composition, strain-level

diversity, and functional readouts (**Supplementary Fig. S1**). For this, we used 13 complex mixtures of

bacterial DNA: an even distribution with 70 bacterial strains (Mock-even-70), a staggered distribution

with 24 strains (Mock-stag-24), including 10 additional versions with different compositions (Mock-

stag-24 v1-10), or a staggered distribution with 70 strains (Mock-stag-70) (**Supplementary Table S1**,

**Supplementary Fig. S2**). As wet-lab factors can cofound results, DNA libraries were prepared in two

laboratories and in the presence/absence of background DNA isolated from the gut of germfree mice.

**Methods**

**DNA extraction and preparation of the Mock communities**

For the creation of the mock communities (Mock-even-70, Mock-stag-24, Mock-stag-24 v1-10 for

multi-coverage binning, and Mock-stag-70), DNA was obtained from isolates in our collections of

mouse and human gut bacteria [10,11] (**Supplementary Fig. S2)**. DNA was extracted from freshly grown

strains revived from frozen glycerol stocks based on the method of Godon et al. 1997 [12] modified as

described in Afrizal et al [10]. DNA concentration was measured using a Qubit fluorometer (Thermo

Fisher Scientist). The DNA of all 70 isolates was pooled in either equimolar amounts (Mock-even-70),

or in a staggered distribution (Mock-stag-70). For 24 selected isolates, the DNA was pooled in a

staggered distribution (Mock-stag-24). For testing multi-coverage binning to generate MAGs, ten

additional mock communities with 24 DNA extracts in 10 different distribution patterns were created

(Mock-stag-24 v1-10). The distribution of DNA from the different isolates in each Mock community is

provided in **Supplementary Table S1**.

Non-bacterial background DNA was isolated, as described above, using gut content collected from

germfree mice (LAVE ethical approval 81-02.04.2023.A253) in accordance with the German Animal

Protection Law (TierSchG). All mice were fed a standard chow *ad libitum* (γ-irradiated ssniff

Spezialdiäten ref. V1124-927). The germfree status of the mice was confirmed by microscopic

observation after Gram-staining and by cultivation on both anaerobic and aerobic agar plates. Mice

were culled and caecal content was collected and stored immediately at -80°C. After DNA extraction,

the background DNA was mixed 1:1 (v/v) with Mock-even-70 and Mock-stag-24.

**Library preparation and short-read sequencing**

In sequencing facility 1 (UKA), DNA libraries of the mock communities were prepared using the

NEBNext Ultra II FS DNA Library Prep Kit for Illumina (NEB, USA) according to the manufacturer's

instructions, using 100 ng (Mock-even-70 and Mock-stag-24), 200ng (Mock-stag-70) or 40 ng (Mock-

stag-24 v1-10 for multi coverage binning) of input DNA and an automated platform (Beckman Coulter,

USA). Enzymatic shearing to approximate 250 bp was performed for 30 minutes. Adaptor-ligated DNA

was enriched using PCR (Mock-even-70, Mock-stag-24, Mock-stag-70: 5 cycles; Mock-stag-24- v1-10

multi-coverage binning: 7 cycles) and NEBNext Multiplex Oligos for Illumina (NEB, USA) for unique dual

barcoding. AMPure beads (Beckman Coulter, USA) were used for size selection and clean-up of adaptor

ligated DNA.

Sequencing facility 2 (UMC) used the Nextera XT DNA Library preparation kit (Illumina, USA) with

Nextera XT indexes (Illumina, USA) and 1 ng template DNA according to manufacturer's protocol.

Twelve cycles of PCR were used for indexing. AMPure beads (Beckman Coulter, USA) were used for

double-sided selection and clean-up of adaptor ligated DNA.

For cleaned DNA library from both facilities fragment size (~320 bp library fragment size ≙ ~200 bp

genomic DNA insert size) was determined on an Agilent D1000 Tapestation (Bioanalyzer System,

Agilent Technologies, USA) using High Sensitivity D1000 screentapes.

Quality check (Bioanalyzer System, Agilent Technologies, USA), DNA quantification (Quantus, Promega,

USA), and sequencing of the resulting libraries were conducted at the IZKF Core Facility Genomics (UKA,

RWTH Aachen University). The libraries for Mock-even-70, Mock-stag-70 and Mock-stag-24 were

pooled to reflect the nine or eleven different sequencing depths targeted, and sequenced on a

NovaSeq6000 (Illumina, USA) with NovaSeq 6000 Reagents v1.5 (2x150 cycles). Mock-stag-24 v1-10

for multi-coverage binning were sequenced at 10 Gb with the same chemistry at the NGS Competence

Center Tübingen (NCCT).

**Long-read sequencing**

The Mock-stag-70 DNA (200 fmol) was prepared for long read sequencing with the SQK-LSK114 kit

(Oxford Nanopore Technologies), following the manufacturer's protocol and the NEBNext Companion

module v2 (New England Biomedicals). About 80 fmol of a >20Kb library was loaded on a R10.4.1

flowcell (FLO-PRO114, Oxford Nanopore Technologies) and sequenced for 72h on a Promethion P2

solo (Oxford Nanopore Technologies) using Minknow v. 25.05.12. The flowcell was washed using the

EXP-WSH004 kit and leftover library was re-loaded and left to sequence until the flowcell end of life.

Reads were base called using Dorado (v. 1.0.0) using super accuracy mode (model:

r1041_e82_400bps_sup_v5.2.0). Long read sequencing was performed at the Joint Microbiome

Facility of the Medical University of Vienna and the University of Vienna under project ID JMF-2507-

23.

**Bioinformatic analysis**

An overview of the bioinformatic workflow is provided in **Supplementary Fig. S3**. All steps are

described in detail in the following sections.

**Reference genomes**

The genomes of all strains used in the Mock communities are hereon referred to as "reference

genomes". They have been deposited in a public repository and published previously[10,11]. A

phylogenetic tree was constructed from the genomes of the 70 isolates using PhyloPhlAn[13] v3.0.67

(options: *--diversity medium –f supermatrix_aa.cfg*) (**Supplementary Fig. S2**). Genome characteristics,

including size and GC content, were analysed using Biopython[14] v.1.79 and bioawk[15] v1.0

(**Supplementary Table S2**).

**Pre-processing of shotgun metagenomic data**

Raw reads of samples with the different empiric sequencing depths (**Supplementary Table S3**) were

further subsampled bioinformatically to the exact targeted sequencing depth (below). The raw FASTQ

files were subsampled using seqtk[16] v1.2 with default settings. The targeted number of paired-end

reads (2 x 150 bp) per sequencing depth was as follows: 333,333 read pairs (0.10 Gb), 833,333 (0.25

Gb), 1,666,667 (0.5 Gb), 2,500,000 (0.75 Gb), 3,333,333 (1.0 Gb), 5,000,000 (1.5 Gb), 6,666,667 (2.0

Gb), 16,666,667 (5.0 Gb), 33,333,333 (10.0 Gb). Adapters were removed and subsampled raw reads

were quality-filtered with Trimmomatic[17] v.0.39 (options: *TRAILING:3 LEADING:3*

*SLIDINGWINDOW:5:20 MINLEN:50 ILLUMINACLIP:{adapters.fa}:2:30:10*). The bbduk command

(options: *hdist=1 k=31*) in BBMap[18] v.38.84 was used for removal of phiX sequences. Quality-filtered

reads of all Mock communities were assembled into contigs using MEGAHIT[19] v1.2.9. Additionally, the

quality-filtered reads of Mock-stag-70 were assembled into contigs with metaSPAdes v.4.2.0[20]. Contigs

of metagenomes sequenced at 10 Gb, 20 Gb and 50 Gb assembled with either of the two assemblers

were aligned to the reference genomes with blastn (perc_identity, 97%; evalue, 1e-10; alignment

length, >150 bp). In addition to the 3 mock communities sequenced separately at all sequencing

depths, and to the 10 Mock-stag-24 communities with different compositions (v1-10) sequenced at 10

GB, a further validation step included in-silico subsampling of the 50 Gb Mock-stag-70 to 10 sequencing

depth (0.1 Gb – 20 Gb), each ten times, using seqtk[16] v1.2 (default settings with 10 different seeds).

**Taxonomic coverage**

Coverage of the reference genomes by the quality-filtered metagenomic reads was determined using

coverM[21] v0.6.1 (options: *coverm genome --mapper bwa-mem --methods covered_fraction --min-*

*covered-fraction 0 --coupled*). The relative abundance profiles were calculated using the read count

option of coverM (options: *coverm genome --methods count --min-covered-fraction 0 --coupled*), which

were converted to relative abundance for each sample.

Non-supervised taxonomic profiles were generated using MetaPhlAn v4.0.1[22] with the

mpa_vJun23_CHOCOPhlAnSGB_202403 database.

Average nucleotide identity (ANI) values between the reference genomes of four *Escherichia coli*

strains and four *Phocaeicola vulgatus* strains were calculated using FastANI[23] v1.34.

**Functional analysis**

Protein-coding genes were predicted in the pooled reference genomes and the assembled contigs of

the Mock samples (individually) using prodigal [24] v2.6.3.

Gene functions were annotated using KEGG Orthology and KofamScan[25] v1.3.0. Pathway completeness

was assessed by KEGG-Decoder[26] v1.3, as percentage of KOs covered, which are included in the

manually curated canonical pathways used by KEGG-Decoder.

To determine the ability of each sequencing depth to capture the protein-encoding potential in the

Mock communities, the genes predicted in the reference genomes were used to create a Diamond[27]

(v2.0.15) protein sequence database, with which the protein sequences predicted in the assemblies

(one assembly for each of the sequencing depths) were compared (options: *diamond blastp –sensitive*

*–query-cover 80 –id 90*).

**Metagenome-assembled genomes (MAGs)**

Contigs <1,000 bp were removed prior to reconstructing MAGs. An index table was built from the size-
filtered contigs using bowtie2[28] v2.5.1 (*bowtie2-build*) with default options. The decontaminated
paired-end reads were aligned to the bowtie index of size-filtered contigs (*bowtie2 –S - --very-sensitive-*
*local –no-unal –p 30*). Bam files were sorted with samtools[29] v1.17 (*samtools view –bS).* Contigs were
binned using Metabat2[30] v2.12.1 and its algorithm for calculating coverage of each sequence in the
assembly (*jgi_summarize_bam_contig_depths*) before creating the bins (*metabat2 -m 1500 --maxP 95*
*--minS 60 --maxEdges 200 --unbinned --seed 0*).

The quality of the resulting bins was evaluated with checkM[31] v1.1.3 using the lineage workflow.
Accordingly, the MAGs were categorised as being of high quality (>90% completeness, <5%
contamination), medium quality (>70% completeness, <10% contamination), or low quality (all that
did not fulfil the previous criteria). They were then taxonomically classified using GTDB-Tk[32] v2.3.2
(*gtdbtk classify_wf*) with the Genome Taxonomy Database r207. The coverage of the reference
genomes by the different MAGs was determined using coverM[21] v0.6.1 (*coverm genome --mapper*
*bwa-mem --methods covered_fraction --min-covered-fraction 0 –single; no multiple read mapping*).
Reference genomes were aligned to MAGs by blastn v2.13.0 *(-evalue 1e-10 -perc_identity 90.0*) and
circular alignments plotted using shinyCircos[33].

For comparing sample-specific (approach above) to multi-coverage binning for the ability to
reconstruct high-quality, non-chimeric MAGs (i.e. one genome match only), the workflow of Mattock
and Watson[34] was used on Mock-stag-24 v1-10, sequenced at a depth of 10 Gb each.

**Long-read sequence analysis**

The raw reads were filtered to a minimum average read quality of Q20 and a minimum length of
1,000 bp using chopper (v0.10.0)[35]. The filtered reads were used to randomly subset 11 additional
datasets corresponding 0.1, 0.25, 0.5, 0.75, 1, 1.5,2, 5, 10, 20, and 50 Gb using rasusa (v2.1.1)[36]. Each
subset was subsequently assembled using flye (v2.9.5)[37] with "–nano-hq" and polished once with
medaka (v2.1.0, github.com/nanoporetech/medaka) using the –bacteria flag. Contigs <1,000bp were
removed. Assemblies were quality checked using QUAST[38] v5.3.0 and metagenomic binning was
performed using metabat2[30]. Bin coverage was estimated using the
*jgi_summarize_bam_contig_depths* function with a minimum percent identity of 90. Quality and
chimeric nature of MAGs was assessed as described above for the short-read data.

**Statistics and Plotting**

All statistical tests were performed in R[39] v4.4.1. using RStudio v2023.03.0+386 and the packages vegan[40] , reshape[41], tidyverse[42] and dplyr[43]. For creation of the graphs, the R package ggplot2[44] v3.5.1, ggpubr[45] v0.6.0, ggbreak[46] and ggfortify[47] v0.4.17 were used. The specific statistical tests used in each analysis are stated in the results.

**Results**

**Shallow metagenomics enables reliable reference-based taxonomic composition**

We first investigated the impact of sequencing depth on taxonomic composition. For the three main Mock communities (Mock-even-70, Mock-stag-24, Mock-stag-70), reads were detected for all reference genomes already at 0.1 Gb. To obtain an overview of genome coverage, completeness categories were compared between the sequencing depths. At 0.1 Gb, most of the genomes (63 to 91 %) had a low coverage (0-25 %) (**Fig. 1A**). Genome coverage increased substantially until 5 Gb of sequencing, with a clear effect of mock community complexity. Most genomes reached >90 % coverage at 5 Gb in Mock-even-70 and Mock-stag-24. However, in Mock-stag-70, coverage continued to increase gradually from 5 Gb (36 % genomes at >90 % coverage) to 50 Gb (64 %), but 11 genomes (16 %) added with 0.001 ng (0.00046‰) to 0.1 ng (0.0046 %) had still low coverage (0-25 %) at the highest sequencing depth (50 Gb).

We then looked at the individual strains across the sequencing depths (**Supplementary Fig. S4**). In Mock-even-70, the lowest coverage at 0.1 Gb was 3.34 % for *Phocaeicola sartorii* CLA-AV-12 and the highest 58.7 % for *Bacteroides uniformis* CLA-AV-11, which reached 99 % coverage already at 0.75 Gb. Full genome coverage (100 %) was only achieved at 10 Gb for V*eillonella intestinalis* CLA-AV-13. In Mock-stag-24 and Mock-stag-70, higher coverage was associated with increasing DNA concentration. The reference genomes with lowest concentration in Mock-stag-24 (0.01 %, 0.04 ng) had a minimum coverage of 0.53 % at 0.1 Gb and a maximum coverage of 34.21 % at 10 Gb. In Mock-stag-70, the lowly abundant genomes - 0.1ng (0.0046%) to 0.001 ng (0.00046‰) - reached a coverage of 0.8 % to 21.8 % at highest sequencing depth (50 Gb), whilst the genomes of the five strains with highest DNA amounts (>4.6 %) reached between 40.50 % and 98.25 % coverage already at 0.1 Gb.

Next, we assessed the relative abundance of strains and compared them to their theoretical values. For Mock-even-70, relative abundances oscillated around the expected value of 1.43 % for most species, without any significant effects of the sequencing depth on the overall relative abundance

profile (p-value = 0.78; Kruskall-Wallis test) (**Supplementary Fig. S5A**). Six species showed values >2.5

% for several sequencing depths, with highest values of 10-15 % for *B. uniformis* CLA-AV-11. In addition,

marked differences due to sequencing depth were detected in the case of *Collinsella* sp. CLA-ER-H5.

Sequencing depth had also no influence on the overall relative abundance profile in the case of Mock-

stag-24 and Mock-stag-70 (p-value = 1 in both cases; Kruskall-Wallis) (**Supplementary Fig. S5B**). In

addition to sequencing the mock communities separately, Mock-stag-70 sequenced at 50 Gb was

subsampled multiple times (10 replicates) bioinformatically for each sequencing depth ≤20 Gb to test

variability. Variations in the relative abundance of individual species was low in general (average

coefficients of variation <5 %), with increasing variability at lower sequencing depths (**Fig. 1B**; statistics

in **Supplementary Table S5**).

As reference genomes are not available for metagenomic analysis in most studies, the mock

communities were also taxonomically analysed using the commonly used profiler MetaPhlAn[22], hereon

referred to as non-supervised approach. Overall, the taxonomic assignment in this approach was less

sensitive, *i.e.*, fewer species were detected. In Mock-stag-24, one strain with low concentration (0.1 %,

0.4 ng, *Hominilimicola fabiformis* CLA-AA-H232) was not detected (**Supplementary Fig. S6**). In Mock-

even-70, 59 species could be assigned with MetaPhlAn4, including 47 matching a reference genome at

species level. In Mock-stag-70, 53 taxa were detected, 44 with a species-level match (**Supplementary

Fig. S6**). The non-supervised taxonomic assignment showed also higher variance from the targeted

relative abundances, especially at lower sequencing depths and with increased complexity of the mock

communities (**Fig. 1 C**; statistics in **Supplementary Table S5**).

In summary, reference-based detection of strains is possible with sequencing as little as 0.5 Gb, but

high coverage of reference genomes needs more data (>5 Gb) under the conditions tested. Relative

abundance profiles were not substantially affected by sequencing depths for most of the strains. In

contrast, non-supervised taxonomic assignment was less sensitive, with fewer species detected.

**Strain-level analysis: *De-novo* MAG reconstruction requires deep sequencing and generates**

**chimeras**

The ability of shallow metagenomics to resolve strain-level variation was investigated using four strains

of *E. coli* and *P. vulgatus* within the Mock-even-70 dataset (Supplementary **Fig. S2**). Coverage of their

reference genomes per sequencing depth, as determined during assignment of all reference genomes,

revealed that all strains were detected already at 0.1 Gb (Supplementary **Fig. S7A**). All four reference

genomes of both species reached >75 % coverage at 5 Gb and >98 % at 10 Gb. All *P. vulgatus* strains

showed a similar increase in coverage with increasing sequencing depth, mirroring ANI values between

the strains that were all close to one another (Supplementary **Fig. S7B**). In contrast, for the *E. coli*

strains, the reference genomes sharing the highest ANI value (*E. coli* Ec8850 and CR B11; ANI = 99.97 %)

showed a congruent coverage increase (Supplementary **Fig. S7B**; their coverage increase curves

overlaid), whilst *E. coli* CLA-AD-1, characterized by an ANI value more distant to the other strains (<

97 %), reached >99 % reference genome coverage already at the 2 Gb sequencing depth

(Supplementary **Fig. S7B**). Only one strain of *E. coli* and *P. vulgatus* was detected in Mock-even-70 and

Mock-stag-70 using MetaPhlAn4 at any of the sequencing depths (Supplementary **Figure S6**).

Reference datasets are rarely available during metagenomic analysis, hence *de-novo* reconstruction of

genomes is widely used to facilitate strain-level analysis. MAGs were thus assembled separately for

each metagenomic sample. Overall, the number of MAGs recovered increased with higher sequencing

depth for all mock communities (**Fig. 2A,** Supplementary **Fig. S8, left panels**). More MAGs than the

actual number of reference genomes (dashed line) were formed at the highest sequencing depths,

whilst not all reference genomes were represented by MAGs (**Fig. 2A,** Supplementary **Fig. S8, right**

**panels)**. The number of MAGs formed per reference genome increased with the amount of data

sequenced, with ≥2 MAGs observed for 22, 12 and 29 of the reference genomes across all sequencing

depths in Mock-even-70, Mock-stag-24, and Mock-stag-70, respectively (**Supplementary Fig. S9**). This

suggests that multiple MAGs are created per reference genome with greater sequencing depth, rather

than coalescing into a single high-quality MAG.

Given the unexpected number of MAGs and their multiplicity per genome, we next determined their

origin. MAGs were grouped by quality and their contigs were assigned to the reference genomes to

determine which isolates they were reconstructed from, with a threshold of >0.25 % coverage of a

reference genome. In Mock-even-70 at the highest sequencing depth (10 Gb), 10 of the 23 high-quality

MAGs (hqMAGs; completeness >90 %, contamination <5 %) were assigned to multiple genomes (red

bars) (**Fig. 2B, top**). The proportion of MAGs assigned to only one (blue) vs. multiple (red) genomes

decreased further with decreasing quality of the MAGs. Taxonomic assignment of hqMAGs to GTDB

showed a result congruent with the assignment to our own reference genomes (**Supplementary Table**

**S4**). Although four *E. coli* strains were included in Mock-even-70, only one MAG assigned to *E. coli* CLA-

AD-1 was reconstructed from each sequencing dataset > 1Gb, except 2 Gb (a second *E. coli* MAG of

low completeness and quality was obtained). In the case of *P. vulgatus* (also represented by four

strains), one MAG was found at 5 Gb and one at 10 Gb, both primarily assigned to *P. vulgatus* HDF,

indicating strain delineation was not possible with the method used (**Supplementary Table S4**).

In Mock-stag-24, a single hqMAG was assembled at 0.75 and 1 Gb (**Fig. 2B, bottom**). Most sequences

of this MAG were assigned to a genome with highest DNA concentration (40 ng, *T. ramosa* CLA-JM-

H52, ≥95 % genome coverage). With increasing sequencing depth, some hqMAGs assigned to genomes

with lower concentrations started to be reconstructed (**Supplementary Table S4**). Surprisingly, a higher proportion of single-origin MAGs occurred with decreasing quality, while at 10 Gb half of the hqMAGs in Mock-stag-24 were chimeric.

To illustrate the chimeric nature of MAGs, three exemplary hqMAGs (Mock-even-70, 10 Gb) were aligned to the reference genomes they covered >0.25 % using blastn (**Fig 2C**). MAG 54 was a best-case scenario with only one reference genome (*V. intestinalis* CLA−AV−13) matched with >98 % coverage. MAG 16 showed fragments of a second reference genome. MAG 40 represented a highly chimeric hqMAG, including 12 reference genomes (of which 10 are shown, ranked by decreasing coverage from outer to inner circle). The mean/maximum number of reference genomes per hqMAG at 10 Gb was 2.3/12, 1.5/2 and 2.1/5 for Mock-even-70, Mock-stag-24 and Mock-stag-70, respectively (**Supplementary Table S3**).

As multi-coverage binning was shown to increase the number and quality of MAGs[34], we sequenced (10 Gb) ten additional Mock-stag-24 communities (v1-10) with varying reference genome distribution (Supplementary **Table S1**). In comparison to single-coverage binning, significantly more hqMAGs per mock community were assigned to only one reference genome using multi-coverage binning (**Fig. 2D,** blue dots). Despite this improvement, chimeric MAGs were still detected in half of the communities (**Fig. 2D,** orange dots).

To further assess ways to enhance MAG reconstruction, the most complex community (Mock-stag-70) was used to test the effects of assemblers (MEGAHIT – as in all analyses above – Vs. metaSPAdes) and the sequencing technology (short-read by Illumina- Vs. long-read by Nanopore-sequencing). MetaSPAdes assemblies generated more hqMAGs assigned to only on reference genome, especially ≥10 Gb (+1 at 10 Gb, +10 at 20 Gb, +5 at 50 Gb) (**Fig. 2E**). This was confirmed statistically by binning MAGs from assemblies generated with either of the two methods (MEGAHIT Vs. MetaSPAdes) using 10 datasets at 10 Gb subsampled in silico from 50 Gb (**Fig. 2F**). Long-read sequencing provided even more hqMAGs with a single reference match (14 of 15 at 10 Gb; 18 of 22 at 50 Gb) (**Fig. 2G**).

To know whether chimeric sequences are generated already during the assembly process, contigs were assembled from the 10 Gb, 20 Gb, and 50 Gb data using either MEGAHIT or metaSPAdes and were aligned to the reference genomes using blastn (Supplementary **Fig. S10**). With both assemblers, the majority of the contigs were assigned to only one reference species (average of three sequencing depths: MEGAHIT, 91.1 ± 1.6 %; metaSPAdes, 93.5 ± 1.0 %), suggesting that 6.5 to 8.9 % misassembled contigs contributed to the reconstruction of chimeric MAGs.

In summary, when high-quality reference datasets are available, read mapping facilitates strain-level analysis of shallow metagenomic data. *De-novo* analysis based on MAG reconstruction leads to

contaminated genomes (chimeras), even at supposed high-quality. Chimerism stems from both the assembly and binning process, and was partially improved by multi-coverage binning for short reads, strain-aware assembly, or long-read sequencing. These findings suggest that strain-level diversity within MAG catalogues is artificially inflated due to chimerism. However, this issue can be reduced by use of strain-aware assembly methods (metaSPAdes) and will be less common once long-read sequencing of metagenomes becomes commonplace.

**Functional coverage is limited by shallow sequencing**

Analysing the functional potential of bacterial communities is a common reason to prefer metagenomics instead of 16S rRNA gene amplicon sequencing. Therefore, we investigated the sequencing depth required for functional analyses at the level of both pathways and genes.

First, we investigated the impact of sequencing depth on pathway completeness, measured as percentage of detected KOs involved in a pathway. Only those pathways occurring in the reference genomes of the respective mock community were considered (Supplementary **Fig. S11**). Of the 178 pathways included in the analysis by KEGG-Decoder[26], predicted proteins for 121 (Mock-even-70, Mock-stag-70) and 118 (Mock-stag-24) pathways were found in the reference genomes. A maximum of 80 pathways were complete at 10 Gb for Mock-even-70, 77 for Mock-stag-24, and 81 for Mock-stag-70 with the two assembly methods tested (Supplementary **Fig. S11**). One pathway was not detected in the mock communities with staggered distributions despite being present in the reference genomes, and 41, 40 and 39 pathways remained incomplete in Mock-even-70, Mock-stag-24 and Mock-stag-70 respectively. The average KEGG pathway completeness increased with sequencing depth (**Fig. 3A**). Pathway completeness reached >80 % already at 2 Gb for Mock-stag-70 and at 5 Gb for the other two mock communities. It then plateaued, with only a slight increase at maximal sequencing depth (Mock-even-70, +7.79 %; Mock-stag-24, +3.69 %; Mock-stag-70, +3.95 %).

To account for functionally unassigned proteins, the protein sequences detected at each sequencing depth were compared to the reference genomes protein repertoire (Mock-70: 227,543 protein sequences; Mock-stag-24: 82,992). The coverage of the predicted protein sequences in the reference genomes within a metagenome continued to increase up to 94.67 % for Mock-even-70 (+ 22.9 % between 5 and 10 Gb), but started to plateau at 5 Gb sequencing depth for the less diverse Mock-stag-24 (+ 12.9 % between 5 and 10 Gb) (**Fig. 3B**). In Mock-stag-70, the protein sequence coverage reached 55.5 % (MEGAHIT) and 58.3 % (metaSPAdes) at 10 Gb and increased only to 71.8 % (MEGAHIT) and 73.8 % (metaSPAdes) at highly deep sequencing (50 Gb). The protein sequence coverage obtained with the three mock communities sequenced separately was confirmed statistically using ten Mock-stag-70 subsampled bioinformatically for each sequencing depth (0.1 – 20 Gb) from the 50 Gb dataset: the

recovered functions increased with sequencing step and variations between the replicates was low
(**Fig. 3C**) (p-values are provided in **Supplementary Table S5**).

In summary, while a moderate sequencing depth of 5 Gb was sufficient for functional analysis at the
pathway level for all mock communities, analysis at the level of single protein sequences requires
greater sequencing depth depending on the diversity and distribution of the microbial community
under investigation.

**Sample processing protocol and background DNA impact shallow sequencing results**
To account for the influence of wet-lab factors on shallow metagenomics results, the DNA libraries
were prepared in two facilities using different protocols (see methods). In addition, the two community
types (Mock-even-70 and Mock-stag-24) were spiked or not with background DNA isolated from the
gut content of germfree mice to simulate host DNA.

PCA plots based on relative abundance profiles showed distinct clustering due to both factors
(background DNA, facility), with more pronounced effects along PC1 linked to differences in library
preparation protocols between facilities (**Fig. 4A**). Within a condition (background DNA /facility pair),
the extreme sequencing depths (0.1 and 10 Gb) tended to be most distant from each other. The
relative abundance profiles of Mock-stag-24 prepared in facility 1, which used more template DNA
(100 vs. 1 ng) and a lower number of PCR cycles (5 vs. 12), were less sensitive to the effects of
sequencing depth when background DNA was present (**Fig. 4A, lower panel**).

The effect of wet-lab factors on reference genome coverage was then assessed by calculating delta-
values between the two facilities or the presence/absence of background DNA. For Mock-even-70,
consistent profiles were observed across nearly all species at the 5 and 10 Gb sequencing depths,
regardless of facility or background DNA (**Fig. 4B**). In contrast, variations in reference genome coverage
of up to 39 % for facilities, and up to 13 % for background DNA were observed at sequencing depths
≤2 Gb. For Mock-stag-24, the variation between samples from the two facilities was additionally
influenced by the initial DNA amount indicated as coloured boxes in **Fig. 4C.** With a reference genome
input >1 ng and a sequencing depth >1 Gb, the total variance in reference genome coverage between
the two facilities dropped below 3.69%. A similar trend was observed for the impact of background
DNA on the coverage of reference genomes in Mock-stag-24, but with a more pronounced influence
of the amount of DNA. The effect of background DNA was negligible (total variance 1.33 %) with ≥10 ng
template DNA and a sequencing depth ≥1.5 Gb. For a DNA amount >1 ng per strain in Mock-stag, a
sequencing depth of 5 Gb or higher was necessary (total variance 3.23 %).

Analysed per strain, the relative abundance profiles in Mock-even-70 were consistent between the

two library preparation strategies, except for marked differences for *Collinsella* sp. CLA-ER-H5 due to

sequencing depth in facility 1 (**Supplementary Fig. S5A**). This indicates that the differences shown in

Figure 4A are due to changes in the relative abundance of a few strains. For Mock-stag-24, deviation

from the theoretical relative abundance values was different between the two facilities

(**Supplementary Fig. S5B**). The relative abundance of *E. clostridioformis*, for example, matched the

expected relative abundance in facility 1, while it had the highest relative abundance in facility 2. The

most abundant species in facility 1 was *T. ramosa*. This indicates that library preparation (specifically

the amount of template DNA and number of PCR cycles) influenced relative abundance profiles.

(**Supplementary Fig. S5B**)

We further analysed the effects of the wet-lab factors on the predicted protein profiles. Overall, facility

1 provided a more complete functional profile for both mock communities (**Supplementary Fig. S12**).

The addition of background DNA was associated with a decrease in coverage, which was attenuated

at high sequencing depths in both mock communities prepared in facility 1. In general, the influence

of background DNA was more pronounced with the protocol used in facility 2.

In summary, library preparation with a higher amount of template DNA and fewer PCR cycles is

recommended for more robust taxonomic and functional profiles. If necessary, a higher sequencing

depth can compensate for the effects of lower DNA amount or the presence of non-target DNA.

**Discussion**

In this work we investigated the potential and limitations of shallow metagenomic sequencing using

complex mock communities and sequencing depths from 0.1 Gb (0.3 million reads) to 50 Gb (166.7

million reads), with a specific focus on strain-level and functional analysis.

Previous studies reported that taxonomic profiles based on shallow shotgun sequencing (0.5-4 million

reads) can reflect those obtained at a higher sequencing depths[2,3,6,8]. Most of those studies relied on

deep sequencing of native samples then subsampled *in-silico*. Using defined input, we have confirmed

these results, showing that shallow metagenomics is suitable for reference-based taxonomic analysis:

reads for all strains were detected already at 0.1 Gb (0.3 million reads), even for lowly abundant taxa

in the staggered communities, enabling prevalence and relative abundance analyses despite overall

low genome coverage. This is in line with the study of Hillmann et al. and Xu et al. who reported that

0.5 million sequences (= 0.15 Gb) and 0.5 Gb, respectively, was sufficient for taxonomic analysis of the

human gut microbiome[2,3]. As most of the metagenomic costs is due to sequencing, being able to pool

more samples on the same run reduces the expenses, making shallow metagenomics at 0.5 Gb/sample

attractive for diversity and composition profiling in studies with large number of samples. However,

accurate analysis necessitates a high-quality, reference database of individual genomes.

Metagenomics is useful for high resolution taxonomic analysis, which is limited with 16S rRNA gene

amplicon sequencing. In a previous study using reference-based analysis, species profiles at 0.5 million

reads (0.15 Gb) showed an average correlation of 0.99 with ultra-deep sequencing (750 Gb)[3]. Using

mock communities, Xu et al. recovered 62 % of the 62 species at 1 Gb/sample using MetaPhlAn2 and

the Refseq database[2]. The analysis of our mock communities with MetaPhlAn4 at 1 Gb showed similar

result (Mock-stag-24: 75%, Mock-even-70: 67%, Mock-stag-70: 43%), without resolution at the strain

level (four strains of each *E. coli* and *P. vulgatus* in Mock-even-70). Using the reference genomes, we

detected reads for all 70 and 24 strains in the mock communities at the lowest sequencing depth of

0.1 Gb. The reference-based detection and discrimination of different strains with an ANI of up to

99.66 % was possible in our study. However, sequencing depths >5 Gb are required to obtain nearly

full genome coverage, which must be adjusted depending on the expected abundance and genome

size of the targeted strains in complex samples.

A sequencing depth ≥5 Gb was required to reconstruct sufficient MAGs, which agrees with previous

findings[3,6]. Importantly, at high sequencing depth (10 to 50 Gb), more MAGs were created than input

strains, yet not all strains were represented by a MAG. Inspecting this further revealed a substantial

number of hqMAGs that were chimeric due to containing fragments assigned to more than one

reference genome. This occurred despite excluding contigs smaller than 1,500 bp during binning to

prevent false inflation of chimerism. These results echo previous reports that ~5 % of genes within

MAGs differ from the dominant reconstructed taxa[48]. A recent study, which evaluated the quality of

short-read assemblies from a natural soil community by mapping them to the respective long-read

data, reported that assembly failures occurred in most genome bins[49], which agrees with our findings.

Our results show that deeper sequencing does not guarantee more complete MAG reconstruction and

does not eliminate chimerism. Data from the staggered Mock communities indicate that having more

reads for a reference genome does not assure its coverage by a MAG and does not prevent the risk of

multiple alignments. Instead, we observed that the creation of several MAGs for the same reference

genome was common. The aforementioned study of a natural soil community also found that

overabundance of reads can lead to high-coverage misassemblies[49]. Bioinformatic approaches that

reduced the occurrence of chimeric hqMAGs in our work were multi-coverage binning and strain aware

assembly, which is in line with previous studies[34,49]. Long-read sequencing also increased the number

of coherent hqMAGs. This highlights the need to consider long-read or hybrid sequencing for projects

where the goal is strain reconstruction, whilst simultaneously recognising the need to also enhance

such approaches further[50]. Nevertheless, none of the approaches tested could resolve the issue

completely and the data presented raises concerns about the prevalence of spurious sequences in
ever-growing MAG catalogues[51], as we used common bioinformatic workflows to create them.

To quantify the functional information lost with decreasing sequencing depth, we calculated the
average KEGG pathway completeness, showing that >2 Gb is required to reach >50 % completeness.
In contrast, one study with a mock community of 62 human gut bacteria reported that the functional
description of shallow metagenomic samples (1 Gb) was "quite similar" to the one obtained from the
reference genomes at KEGG level 1 and 2[2]. Another study based on in-silico subsampling of an ultra-
deep metagenome (2.5 billion reads; 750 Gb) to 0.5 million reads (0.15 Gb) showed a nearly full
recovery of KEGG Orthology groups[3]. This result might be influenced by differences in the complexity
of analysed communities and by the subsampling process being rarefied repeatedly and therefore
creating a higher chance of recovering functions. At the level of predicted protein sequences, our data
suggests that shallow metagenomics is not advisable, as a recovery of <75 % predicted proteins was
reached at sequencing depths ≤5 Gb. This agrees with a previous study of antimicrobial resistance
genes at different sequencing depths, in which at least 80 million reads (24 Gb) was needed to recover
the full richness of AMR gene families[52].

Regarding the influence of wet-lab factors, the performance of library preparation procedures has
previously been compared for traditional metagenomic sequencing of native samples and Mock
communities, revealing that the community diversity, amount of input DNA, and the sequencing
platform alter the results[53–55]. When analysing the effects of library preparation in two facilities and
the addition of background DNA from the gut content of germfree mice, both factors impacted
taxonomic and functional results at the sequencing depths <5 Gb. Strains with a higher relative
abundance were less sensitive to these effects, even at lower sequencing depths. If the use of different
protocols in large studies cannot be avoided (e.g., when handling low biomass samples), or a high
amount of background DNA is to be expected, higher sequencing depth may improve the robustness
of results.

This study has some limitations: (i) Metagenomics can be used to study various environments, which
may require different strategies; due to our own research interests, we focused on wet-lab parameters
related to gut microbiomes. Although we could show their overall effects on metagenomic data, the
study design was not appropriate to disentangle the effect of each parameter separately. Previous
studies have investigated other aspects such as low biomass, contamination, or additional library
preparation protocols (DNA input, PCR cycles, fragment/insert size)[53,56]; (ii) Whilst we used
MetaPhlAn4 for some of the analyses, most results were obtained using the exact strains (*i.e.,* their
genomes) as a reference, which represents an ideal case for taxonomic and functional readouts; (iii)
We have tested multiple approaches, including standard workflows used by many, to study the

chimeric MAGs. We do not exclude that additional strategies not tested in this work may perform better. Future benchmarking of bioinformatic tools, as in Critical Assessment of Metagenome Interpretation (CAMI), will be helpful to move forward with comprehensive testing of new approaches to address chimeric MAGs at scales that go beyond our single study[57]; (iv) the mock communities analysed included only bacteria; whilst bacteria are dominant members in many microbiomes, the work excludes the influence of other types of microbes; (v) We used a higher number and more complex mock communities (up to 70 strains, including different distributions) than in previous studies; they nonetheless are only approximations of native bacterial populations in gut microbiomes, which include ca. 300 species, with 150-200 usually detected by sequencing.

In summary, due to the lack of studies benchmarking shallow metagenomics using complex mock communities, potential users may not be aware of the pitfalls of this approach. The sequencing depth needs to match the main aims of a study. Factors to be considered include the expected microbial diversity in the target samples, the evenness of distribution within the communities, and the amount of DNA available. Shallow metagenomics is a valid choice for a large study aiming at database-guided taxonomic profiles of well-characterised environments. However, it is not appropriate for high-resolution functional analysis and *de-novo* strain resolution. Even at high depths of sequencing, MAG-based approaches require careful planning and execution to minimise the generation and spread of artificial bacterial diversity.

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**Authors contributions**

NT: conceptualization, methods and software, investigation, formal analysis, validation, interpretation, visualization, data curation, writing – original draft; CP: methods and software, validation, interpretation, writing – review and editing; JS and PP: investigation, formal analysis, writing – review and editing;  DB and JP: resources, funding acquisition, writing – review and editing; TCAH: conceptualization, interpretation, writing – original draft; TC: conceptualization, visualization, interpretation, resources, supervision, project administration, funding acquisition, writing – original draft.

**Material and data availability**

The raw metagenomic sequencing data was deposited at the European Nucleotide Archive/NCBI and is accessible under Project no. PRJEB83573.

The code used for bioinformatic analyses is available on GitHub: https://github.com/ClavelLab/Benchmarking-shallow-Metagenomics

All strains (and their DNA) used in this study are available at the Leibniz Institute DSMZ (German Collection of Microorganisms and Cell Cultures): www.dsmz.de/miBC; https://hibc.rwth-aachen.de/.

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**Ethics**

574   All mice experiments were performed under Ethical Approval (LANUV no. 81-02.04.2023.A253) in

575   accordance with the German Animal Protection Law (TierSchG).

**Figure Legends**

**Fig. 1:** Reference-based taxonomic profiles

**A** Number of reference genomes per category of coverage by metagenomic reads (colour gradients) for Mock-even-70, Mock-stag-24, and Mock-stag-70 (top to bottom) at up to eleven sequencing depths (x-axis). **B** Coefficients of variation of relative abundances of the 70 strains in ten *in-silico* datasets for each sequencing depth, subsampled from Mock-stag-70 sequenced at 50Gb. The coefficients of variation between the sequencing depths were tested statistically using a Kruskal-Wallis rank-sum test with Benjamini-Hochberg correction (p-values in **Supplementary Table S5**). **C** Difference (delta-values) between measured relative abundances and theoretical values (x-axis) for the three mock communities after taxonomic assignment using either the reference genomes (blue) or MetaPhlAn4 (red). In the MetaPhlAn analysis, only the taxa that matched reference genomes at the species level were considered.

**Fig. 2:** Strain analysis

**A** Strain analysis based on the MAGs assembled in Mock-even-70 (top) and Mock-stag-24 (bottom) at each sequencing depth individually. The left panels (dark blue) depict the number of bins assembled from the shotgun data; the right panels (lighter blue) show the number of reference genomes matching MAGs (coverM), indicating that multiple MAGs were reconstructed for some Mock species. The reference genome with the highest coverage by MAG reads was chosen as representative of that MAG. **B** Number of high-, medium- and low-quality MAGs assigned to either one (blue) or several (red) reference genomes (with coverM using a cut-off of > 0.25% coverage of reference genomes). **C** Three exemplary high-quality (> 90 % completeness, < 5% contamination) (hq) MAGs (dark grey, outer circle) reconstructed from Mock-even-70 at 10 Gb. They were aligned to the reference genomes they covered by more than 0.25% to illustrate different categories of chimerism. The predominantly covered reference genome is depicted in blue, while chimeric sequences of further reference genomes (inner circles) are shown in red. **D** Number of hqMAGs assigned to one reference genome (blue) or more reference genomes (orange) for the ten different Mock-stag-24 (v1-10) with varying reference genome abundance distribution. MAGs were constructed with either a single- (bright colours) or a multi-coverage (darker colours) binning approach. Statistics: Kruskal-Wallis rank-sum test; *** p-value = 0.0003871. **E** Number of hqMAGs constructed from contigs assembled with either MEGAHIT or metaSPAdes for Mock-stag-70. The MAGs were then assigned to one (green) or more (red) reference genomes as above. **F** High-quality MAGs binned from assemblies generated with either MEGAHIT or metaSPAdes using 10 datasets at 10 Gb subsampled *in-silico* from 50 Gb. Statistics: Wilcoxon rank-sum

test; * p-value = 0,031. **G** Number of hqMAGs binned from assemblies acquired by long-read
sequencing of Mock-stag-70 and categorised as in E.

**Fig. 3**: Functional coverage

**A** Average KEGG pathway completeness of Mock-even-70, Mock-stag-24, and Mock-stag-70 using

contigs assembled with MEGAHIT, and Mock-stag-70 using contigs assembled with metaSPAdes. **B**

Fraction of predicted proteins from the reference genomes covered by the metagenomic assemblies

(MEGAHIT) for three different mock communities at the respective sequencing depths. Reads of Mock-

stag-70 were additionally assembled using metaSPAdes (bottom). **C** Average coverage of functions of

the reference genomes by ten *in-silico* datasets, subsampled to ten different sequencing depths each

from Mock-stag-70 sequenced at 50Gb. Bars are mean values; whiskers are standard deviations.

Statistics:  Kruskal-Wallis  rank-sum  test  with  Benjamini-Hochberg  correction  (p-values  in

**Supplementary Table S5**).

**Fig. 4:** Effects of background DNA (bgDNA) and library preparation in two facilities

**A** PCA plot of relative abundance profiles in Mock-even-70 (top) and Mock-stag-24 (bottom). **B**

Difference in coverage of reference genomes between facility 1 and facility 2 (left) and samples with

or without bgDNA (right) for Mock-even-70. **C** Same as in panel B for Mock-stag. The reference

genomes were ranked (from top to bottom) according to increasing DNA amount in the mixture, as

indicated by the colour gradient (from blue to red; 0.04, 0.4, 1, 2, 4, 10, 20, 40 ng).

**Online Supplementary Files**

**Supplementary Fig. S1:** Schematic overview of the experimental design

The genomic DNA of 70 bacterial isolates (www.dsmz.de/miBC; https://www.hibc.rwth-aachen.de)

was used as input to create 13 different Mock communities. Two Mock communities contained all

members, one each with an even distribution (Mock-even-70) or staggered distribution (Mock-stag-

70). Additionally, mock communities with varying staggered distribution of 24 isolates were created:

Mock-stag 24, sequenced at nine different sequencing depths; Mock-stag 24 v1-10 sequenced at 10

Gb for testing multi-coverage binning for MAG construction. A second version of Mock-even-70 and

one Mock-stag-24 were created by spiking DNA isolated from the gut content of germfree mice.

Libraries for these four mock communities (Mock-even-70 and Mock-stag-24 ± bg) were prepared in

two different sequencing facilities. A library per sequencing depth was then sequenced using the

Illumina technology (short reads) at up to 11 sequencing depths. Mock-stag-70 was also sequenced

using Oxford Nanopore Sequencing (long reads) in a third facility. Bioinformatic analyses included: (i) number and relative abundance of strains; (ii) coverage of reference genomes; (iii) number and diversity of predicted proteins and completeness of functional pathways; (iv) strain-level resolution using both a reference-based and metagenome-assembled genome (MAG) approach.

**Supplementary Fig. S2:** Phylogenetic tree of bacterial strains in the mock communities

A phylogenetic tree of high-quality, draft genomes of the 70 isolates was created using PhyloPhlAn v3.0.67. The phyla to which the strains belong are represented by coloured boxes at the end of the branches. Distribution of the strains in each mock community is provided in **Supplementary Table S1**.

**Supplementary Fig. S3:** Schematics of the bioinformatics workflow

The details of each analysis are described in the methods.

**Supplementary Fig. S4:** Coverage of individual reference genomes

Heatmaps showing the coverage of all reference genomes in Mock-even-70 (**A**), Mock-stag-24 (**B**), and Mock-stag-70 (**C**) by metagenomic reads at up to 11 sequencing depths (x-axis). The grey boxes in panel **A** indicate the multiple *E. coli* and *P. vulgatus* strains. The reference genomes in the mock communities with staggered distribution in panel **B** and **C** were ranked (from top to bottom) according to increasing DNA amount in the mixture, as indicated by the colour gradient in panel B (from blue to red; 0.04, 0.4, 1, 2, 4, 10, 20, 40 ng) or the grey gradient in panel C (concentrations are provided in **Supplementary Table S1**).

**Supplementary Fig. S5:** Relative abundance of reads per reference genome

Relative abundances of each strain in (**A**) Mock-even-70 in facility 1 and 2, (**B**) Mock-stag-24 in facility 1 and 2, and (**C**) Mock-stag-70 in facility 1. Metagenomic reads were assigned to the reference genomes using coverM. Sequencing depths are indicated with the coloured dots. The theoretical relative abundances are indicated by vertical dashed lines. For Mock-stag-24 in panel B and Mock-stag-70 in panel C, the reference genomes are ranked from top to bottom by increasing DNA amount in the mixture either indicated by coloured boxes (from blue to red; 0.04, 0.4, 1, 2, 4, 10, 20, 40 ng) or the grey gradient in panel C (concentrations are provided in **Supplementary Table S1**).

**Supplementary Fig. S6:** Relative abundance after "non-supervised" taxonomic assignment using MetaPhlAn4

Relative abundances of each strain in (**A**) Mock-even-70, (**B**) Mock-stag-24, and (**C**) Mock-stag-70. Metagenomic reads were assigned using MetaPhlAn4. Sequencing depths are indicated with the coloured dots. The theoretical relative abundances are indicated by vertical dashed lines. For Mock-stag-24 in panel B and Mock-stag-70 in panel C, the reference genomes are ranked from top to bottom by increasing DNA amount in the mixture (see concentrations in **Supplementary Table S1**).

**Supplementary Fig. S7:** Strain level resolution based on reference genomes

**A** Reference genome coverage (y-axis) for the four strains of *E. coli* and *P. vulgatus* at the nine different sequencing depths (x-axis). **B** ANI values between the strains within each species.

**Supplementary Fig. S8:** MAGs numbers in Mock-stag-70

Strain analysis based on the MAGs assembled in Mock-stag-70 using MEGAHIT for assembly at each sequencing depth individually. The left panel (dark blue) depict the number of MAGs assembled from the shotgun data; the right panel (lighter blue) show the number of reference genomes matching MAGs (coverM), indicating that multiple MAGs were reconstructed for some Mock species. The reference genome with the highest coverage by MAG reads was chosen as representative of that MAG.

**Supplementary Fig. S9:** Reference genomes per MAG for Mock-stag-24, Mock-even-70, and Mock-stag-70.

Stacked bar charts of the number of MAGs per sequencing depth. Each box represents one reference genome. The size of the box indicates the number of MAGs that were assigned to this reference genome. The colours in the graph for Mock-stag-24 indicate the amount of input DNA for a given strain in the pool. The colour of the graph for Mock-even-70 and Mock-stag-70 indicates the reference genomes.

**Supplementary Fig. S10:** Contigs assigned to reference genomes

Contigs from metagenomes sequenced at 10 Gb, 20 Gb and 50 Gb either assembled with MEGAHIT or metaSPAdes were aligned to the reference genomes with blastn (-perc_identity 97% -evalue 1e-10, alignment length >150 bp). The number of contigs (y-axis) is plotted against the number of reference genomes assigned to a contig (x-axis).

**Supplementary Fig. S11:** Heatmaps of functional coverage.

Completeness of all KEGG pathways present in the reference genomes in Mock-even-70, Mock-stag-

24 and Mock-stag-70 assembled with MEGAHIT, and Mock-stag-70 assembled with metaSPAdes (from

left to right) at the up to 11 sequencing depths (columns).

**Supplementary Fig. S12:** Bar charts of protein sequences recovered.

Protein sequenced predicted in the metagenomic datasets as percentage of the protein sequences

present in the reference genomes (y-axis). The colour gradient indicates the facility where the library

was prepared and the addition of background DNA (bgDNA) from the caecum of germfree mice.

**Supplementary Table S1**: Distribution of the reference genomes DNA in the different mock
communities.

**Supplementary Table S2**: Characteristics of the reference genomes.

**Supplementary Table S3**: Number of reads after sequencing and subsampling.

**Supplementary Table S4:** Assignment of the MAGs to reference genomes and using GTDB.

**Supplementary Table S5:** P-values for Fig. 1B, Fig. 1C and Fig. 3C.

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Tree scale: 0.1 ⊢———⊣

**Phylum**

- ■ Actinomycetota
- ■ Bacillota
- ■ Bacteroidota
- ■ Deferribacterota
- ■ Pseudomonadota

# C

Reference genomes

Mock-stag-70 facility 1

Relative abundance of genomes [%]

Sequencing depth
- 0.1Gb
- 0.5Gb
- 0.25Gb
- 0.75Gb
- 1.0Gb
- 1.5Gb
- 2Gb
- 5Gb
- 10Gb
- 20Gb
- 50Gb

# Mock-even-70 facility 1

# Mock-stag-24 facility 1

Species assigned by Metaphlan

Relative abundance of genomes [%]

Sequencing depth
- 0.1Gb
- 0.25Gb
- 0.5Gb
- 0.75Gb
- 1.0Gb
- 1.5Gb
- 2Gb
- 5Gb
- 10Gb

A

B

Mock-stag-70 facility 1

Mock-stag-24

Mock-even-70

The following is a heatmap figure showing KEGG pathway completeness across sequencing depths.

**KEGG pathway**

Column groups:
- MEGAHIT: Mock-even-70, Mock-stag-24, Mock-stag-70
- metaSPAdes: Mock-stag-70

Row labels (KEGG pathways, top to bottom):
- Adhesion
- alanine
- alpha-amylase
- Anaplerotic genes
- arginine
- Arsenic reduction
- asparagine
- aspartate
- beta-glucosidase
- beta-N-acetylhexosaminidase
- bidirectional polyphosphate
- bifunctional chitinase/lysozyme
- Biofilm PGA Synthesis protein
- Biofilm regulator BssS
- C-P lyase cleavage PhnJ
- carotenoids backbone biosynthesis
- Chemotaxis
- chitinase
- cobalamin biosynthesis
- Cobalt transporter CbiMQ
- Cobalt transporter CbtA
- Cobalt transporter CorA
- Coenzyme B/Coenzyme M regeneration
- Colanic acid and Biofilm protein A
- Colanic acid and Biofilm transcriptional regulator
- Competence factors
- Competence-related core components
- Competence-related related components
- Copper transporter CopA
- CP-lyase complex
- CP-lyase operon
- Curli fimbriae biosynthesis
- cysteine
- Cytochrome aa3-600 menaquinol oxidase
- Cytochrome bd complex
- Cytochrome c oxidase
- Cytochrome o ubiquinol oxidase
- D-galacturonate epimerase
- D-galacturonate isomerase
- diacetylchitobiose deacetylase
- dissim nitrate reduction
- dissimilatory sulfate< >APS
- dissimilatory sulfite< >APS
- DMSO reductase
- DNRA
- end-product myxoxanthophylls
- Entner-Doudoroff Pathway
- F-type ATPase
- Fe-Mn transporter MntH
- Ferric iron ABC-type substrate-binding AfuA
- Ferrous iron transporter FeoB
- Flagellum
- gluconeogenesis
- glutamate
- glutamine
- glycine
- glycolysis
- Glyoxylate shunt
- histidine
- isoleucine
- leucine
- lysine
- MEP-DOXP pathway
- Methanogenesis via acetate
- Methanogenesis via CO2
- methionine
- mevalonate pathway
- Mixed acid: Acetate
- Mixed acid: Ethanol, Acetate to Acetylaldehyde
- Mixed acid: Ethanol: Acetyl CoA to Acetylaldehyde (reversible)
- Mixed acid: Formate
- Mixedacid: Formate to CO2 & H2
- Mixed acid: Lactate
- Mixedacid: PEP to Succinate via OAA, malate & fumarate
- Na-NADH-ubiquinone oxidoreductase
- NADH-quinone oxidoreductase
- NADP-reducing hydrogenase
- Nickel ABC-type substrate-binding NikA
- NiFe hydrogenase Hyd-1
- nitrite oxidation
- nitrogen fixation
- oligogalacturonide lyase
- phenylalanine
- polyhydroxybutyrate synthesis
- proline
- pullulanase
- Retinal biosynthesis
- riboflavin biosynthesis
- Sec.SRP
- serine
- Serine pathway/formaldehyde assimilation
- staphyloaxanthin biosynthesis
- starch/glycogen degradation
- starch/glycogen synthesis
- sulfhydrogenase
- sulfide oxidation
- sulfite dehydrogenase (quinone)
- sulfur assimilation
- TCA Cycle
- thiamin biosynthesis
- thiosulfate/polysulfide reductase
- threonine
- transporter: phosphate
- transporter: phosphonate
- transporter: thiamin
- transporter: urea
- transporter: vitamin B12
- tryptophan
- Twin Arginine Targeting
- Type I Secretion
- Type II Secretion
- Type III Secretion
- Type IV Secretion
- Type Vabc Secretion
- Type VI Secretion
- tyrosine
- V-type ATPase
- valine
- Wood-Ljungdahl
- 3-Hydroxypropionate Bicycle
- 4-Hydroxybutyrate/3-hydroxypropionate

Sequencing depth [Gb] (x-axis): 0.1, 0.25, 0.5, 0.75, 1.0, 1.5, 2.0, 5.0, 10, 20, 50

**Pathway completeness** (legend): 1.00, 0.75, 0.50, 0.25, 0.00