Supplementary Materials: Intestinal Microbiota Composition is Predictive of Radiotherapy-induced Acute Gastrointestinal Toxicity in Prostate Cancer Patients.

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Patient population

Supplementary Table S1 | **MicroLearner PCa: patient population characteristics**

* NCCN risk classification

Acronyms

BMI: Body Mass Index

PCa: Prostate Cancer

NCCN: National Comprehensive Cancer Network

Radiotherapy treatment

All patients received Volumetric Modulated Arc RT (VMAT). One hundred and forty-five patients received conventionally fractionated RT. Fifty-seven were post-prostatectomy patients (adjuvant setting 11 patients, salvage 46 patients) treated with a prescribed dose of 70-72 Gy. Eighty-eight radical patients had a prescribed dose of 74-78 Gy. Seventy radical patients received moderately hypofractionated RT (2.6 Gy/day) with a prescribed dose of 65- 67.6 Gy. One hundred and seventy-two patients received whole pelvis RT (50 Gy) and 142 irradiation of seminal vesicles (66-70 Gy). Treatment details are reported in Supplementary Table S2.

Supplementary Table S2| **MicroLearner PCa: patient treatment characteristics**

Acronyms WPRT: Whole-pelvis radiotherapy PORT: Prostate-only radiotherapy SV: Seminal vesicles HT: Hormone therapy

Diet and lifestyle factors analysis

Patients completed a questionnaire on life style with information on diet habit and physical activity before starting their treatment. A template of the diet and physical activity questionnaire, including the food frequency questionnaire (FFQ) section is reported as Supplementary Table 3. Specific food classes from FFQ were aggregated in the analysis of the diet composition (Supplementary Fig. 1). Supplementary Table 4 reports the statistic of diet and physical activity categories in the patient population, while Supplementary Table S5 reports the criteria used to define the categories.

Supplementary Table S3| **Questionnaire for the evaluation of lifestyle and diet habit**

Supplementary Table S4| Statistic of lifestyle factors in the patient population

* includes pescatarian and vegan

Acronyms PCa: Prostate Cancer FFQ: Food Frequency Questionnaire

Supplementary Table S5| Rules used to define lifestyle-related factors from questionnaires

Supplementary Fig. S1 | **Analysis of diet composition from patient-compiled food frequency questionnaires (FFQs)**

Hierarchical clustering of patients (heatmap columns) based on per week intake of food categories (heatmap rows) using Hamming distance and Ward linkage after defining integervalued intake scores (high-intake=2, medium-intake=1, low-intake=0); food categories "Cereals" and "Meat" include aggregated portions per week (sum) of "Cereals and cerealderived food" and "Cereal-based products", and of "Fresh meat" and "Processed meat", respectively; "Milk-derived products" from FFQs was labelled "Cheese" for simplicity.

Radio-induced gastrointestinal toxicity

Supplementary Table S6| The statistic of GI toxicity grade by symptom assessed in the patient population (n=215) according to the CTCAE

Acronyms

pts: patients

Supplementary Fig. S2 | Analysis of whole-pelvis versus prostate-only radiotherapy

Distribution of mean rectal dose in the toxicity groups stratified in the sub-populations of patients who received prostate only radiotherapy (PORT, n=43) and in whole-pelvis radiotherapy (WPRT, n=172). Despite the whole pelvis can be considered an additional risk factor for toxicity as patients receive more dose to the rectum (Wilcoxon's rank test p <0.001), no association between mean rectal dose and acute GI toxicity was observed in the separate WPRT and PORT sub-populations, respectively.

Supplementary Table S7| Association of potential risk/beneficial factors or drugs with the onset of acute gastrointestinal toxicity during radiotherapy

* treated with oral hypoglycaemic agents; ** treated with ACE inhibitors and/or beta blockers and/or other antihypertensives; *** habitual intake of probiotic: Yogurt, 2 patients; Refluor (*Lactobacillus reuteri*), 2 patients; Enterolactis (*Lacticaseibacillus paracasei*), 1 patient; Serobioma (*Bifidobacterium lactis*, *Bifidumbacterium longum*, *Lactobacillus rhamnosus*), 1 patient; Bifidolactis (*Bifidobacterium lactis*), 1 patient; Codex (*Saccharomyces boulardii*), 1 patient; Lactoflorene (*Lactobacillus acidophilus*, *Bifidobacterium lactis, Bacillus coagulans, Lactobacillus casei*), 1 patient; Dicoflor (*Lactobacillus rhamnosus*), 1 patient.

Cytokine measurement

Ten millilitres of EDTA blood samples (BD Vacutainer™ K2 EDTA-367525) were obtained at baseline. Samples were kept 4 °C for maximum one hour after sampling and then centrifuged for 20 minutes at 2200*g* at 4 °C. Plasma was collected (~4 mL) and centrifugated for 10 minutes at 2200 *g* at 4 °C. Supernatant was immediately stored at ≤−80 °C until analysis (stored in Nalgene CryoBox-50260909).

All analyses were carried out blind to patient and therapy factors. The amount CCL2, PDGF-BB, TGF-β1, TNF- α and TNFR1 was determined using commercially available ELISA kits (Quantikine®ELISA R&D Systems Inc., Minneapolis, MN, USA), according to manufacturer's protocols: Quantikine®ELISA Human TGF-β1 cod. DB100B R&D System, Quantikine®ELISA Human CCL2/MCP-1 cod. DCP00 R&D System, Quantikine®ELISA Human PDGF-BB cod. DBB00 R&D System, Quantikine®ELISA Human TNF-α cod. DTA00C R&D System and Quantikine®ELISA Human TNF RI cod. DRT100 R&D System.

Polycytokinic risk score

We developed a logistic stepwise backward regression model to predict the classes of "Acute GI toxicity" (Positive cases) and "No acute GI toxicity" (Negative cases) using as predictors the log-transformed values of concentration of the plasma cytokines measured. We used the *stepAIC* function from the R package MASS version 7.3-57²³ to identify the best predictors, so selecting CCL2, TNFR1 and TNF-α. The logit model based on the selected predictors was used to obtain a risk probability for each patient and the polycytokinic risk score was defined by standardising the probabilities across the patient population. Model details are reported in Supplementary Table S8.

Supplementary Table S8| **Polycytokinic risk score (PRS) model**

PRS: polycytokinic risk score

Faecal sample collection and processing

Faecal specimens were collected using the OMNIgene•GUT stool devices (DNA Genotek Inc. Ottawa, ON, Canada) consisting of a tube with a preservation buffer to stabilise microbial DNA and a bearing steel bead. Patients were instructed to collect the faeces into the tube avoiding contaminations and to homogenize the sample by shaking. The samples were stored at room temperature and delivered to the centralised laboratory for metagenomics analyses.

Upon arrival, DNA was extracted by QIAsymphony DSP Virus /Pathogen Midi kit (Qiagen) after mechanical lysis with silica beads on an automated QIAsymphony station (Qiagen). Microbial DNA was quantified using a Qubit fluorometer (ThermoFisher) and quality was assessed using a 4200 TapeStation (Agilent). Samples reaching good quality (DNA integrity number >7) both at RT baseline and at RT end were used for metagenomics profiling.

The NGS libraries were performed using 16S Metagenomics kit (ThermoFisher) following manufacturer's instructions. The 16S region was amplified with primer sets recognising V2, V4, V8 and V3, V6-7, V9 hypervariable regions in 2 separate PCR reactions. Fifty nanograms of amplicons were combined and processed for library prep using Ion Plus Fragment Library Kit and Ion Xpress Barcodes Adapters (ThermoFisher). After PCR amplification (1 cycle of 95°C for 5 min; 5 cycles of 95°C for 15sec, 58°C for 15 sec, 70°C for 1 min) and purification using 1.4 volumes of Agencourt AMPure beads (Beckman Coulter), libraries were eluted and their size and quantity were assessed with TapeStation.

Sequencing was performed for 16S libraries by Ion S5 XL whereas base calling and demultiplexing was performed by Torrent Suite (ThermoFisher).

The ThermoFisher Ion Reporter Software metagenomics 16S analysis pipeline was used to generate operational taxonomic unit abundances from the 16S rRNA reads and to assign taxonomy at the genus level by clustering sequences at 97% similarity threshold.

Supplementary Fig. S3 | Abundance-based ranking of intestinal microbiota genera

Binary logarithm of the population-averaged relative abundance of genera in the intestinal microbiota stratified by cohort (discovery and validation) for all the sequenced genera having average relative abundance >=1% in either of the cohorts.

Supplementary Fig. S4 | Occurrence-based ranking of intestinal microbiota genera

The fraction of patient population where genera were profiled, stratified by cohort (discovery and validation) for all the sequenced genera having occurred in at least 10% of patients in either of the cohorts.

Supplementary Table S9 | Differential abundance analysis of genera between toxicity groups

*Occurrence is the percentage of patients in which the genus was detected; p values obtained using Wilcoxon's rank test on the clr-transformed abundances and adjusted with Benjamini-Hochberg procedure.

Supplementary Fig. S5 | Genera showing a trend of association with acute GI toxicity

The distributions of the relative abundance of those genera that showed a trend for association with acute GI toxicity endpoint (p<0.05 in pooled cohort, see Supplementary Table S9) is shown, stratified by toxicity group; only *Flavonifractor* (top-middle) was tested significantly differentially abundant between toxicity groups after adjustment of p values (Benjamini-Hochberg procedure).

Supplementary Fig. S6 | Alpha diversity measures

Shannon's index (a) and Simpson's index (b) show no significant correlation with the total number of taxonomy-assigned read counts at the genus level across the MicroLearner PCa patient population (n=215).

Supplementary Fig. S7 | Association between diversity of baseline microbiota and development of RT-induced early acute GI toxicity

(a) BMI and **(b)** age values across the pooled cohort (n=215) stratified by toxicity group. **(c)** Shannon's index and **(d)** Simpson's index measured in the pooled cohort by restricting to the relative abundance of genera in the core microbiota.

Microbiota-based clusters of patients

Hierarchical clustering using Euclidean distance and Ward linkage method was performed on the core clr abundance profiles standardised across the discovery population (column-wise normalization, heatmap Fig. 3a). The core included all genera having relative abundance ≥2% in ≥10% of the discovery samples and the count data of the core sub-composition were clrtransformed after imputation of zeros via Geometric Bayesian Multiplicative replacement method previous to clustering.

The optimal number of clusters was defined as the one maximising the Jaccard similarity index between the partition of toxicity events obtained by using core bacterial genera and the one obtained by using core bacterial families, defined as the families having relative abundance ≥2% in ≥10% of the discovery patients (Supplementary Fig. S8-S9).

Supplementary Fig. S8 | Patient clustering via core bacterial families

Heatmap showing the normalised abundance profiles (standardised clr-transformed relative abundance values) of the core microbiota bacterial families (rows) from patients in the MicroLearner PCa discovery cohort (columns); core families were defined as those families occurring in at least 10% of the cohort with relative abundance >=2%; hierarchical clustering was performed using Euclidean distance and Ward linkage method; the partition in 8 clusters (black vertical lines) is the one maximising the Jaccard similarity (in terms of toxicity events) with the partition obtained by clustering patients according to their core genera profiles.

Supplementary Fig. S9 | Optimal number of microbiota clusters

The Jaccard similarity index between the microbiota-based partition of toxicity events obtained by clustering patients according to the abundance profiles of core bacterial genera and the microbiota-based partition of toxicity events obtained by clustering patients according to the abundance profiles of core bacterial families, was measured in function of the number of clusters in the partitions. The optimal number of clusters (n=8) was defined as the non-trivial integer that maximised the similarity index in the range [3, 20].

Supplementary Table S10 | Enrichment analysis of microbiota clusters for patient characteristics and lifestyle factors (discovery cohort n=136)

Acronyms

BMI: body mass index; PRS: polycytokinic risk score; FFQ: food frequency questionnaire); w.t.: with; mod.: moderate.

Supplementary Table S11 | Association between microbiota risk classes and variables associated with patient, microbiota and treatment (discovery cohort n=136)

Acronyms

BMI: body mass index; PRS: polycytokinic risk score; mod.: moderate.

Core microbiota unbalance

Supplementary Fig. S10 | Analysis of unbalance of the core microbiota profiles

(a) Statistic of the core microbiota unbalance score, corresponding to the L1-norm of the normalised clr-transformed abundance profiles of the core microbiota genera is shown for the MicroLearner discovery cohort (n=136) stratified by microbiota risk class. **(b)** The withincluster average value of the core microbiota unbalance score is shown in function of the toxicity rate for the 8 microbiota clusters identified in the MicroLearner discovery cohort.

Functional imputation analysis

Functional imputed metagenomics analysis was performed using PICRUSt version 1.1.427. We referenced the core metagenome profiles to the most updated reference collection of OTUs from Greengenes (gg 13 5 otus)²⁸. Because the OTU assignment by the Ion Reporter metagenomic pipeline is based on ThermoFisher-curated Greengenes references, this choice maximised the coherence between inferred functional profiles and taxonomic abundance profiles. The profiles were normalised by the known or predicted 16S copy number abundance and a final metagenome was predicted and mapped to KEGG Orthologs (KOs). The inferred KO IDs annotations based on the Integrated Microbial Genomes and Microbiomes²⁹ were manually verified and curated against the most recent version of KEGG (v.104, 2022/10) and of the Transport Classification database³⁰ and annotated by KEGG modules or Brites.

The quality of the inferred metagenome was checked by calculating the average Nearest Sequenced Taxon Index (NSTI)²⁷ across samples, that quantifies the average over the samples of the average substitutions per site separating each OTU from the reference bacterial genome. We obtained NSTI=0.071+-0.028, consistent with values expected from faecal samples.

Supplementary Fig. S11 | Functional imputation analysis of core microbiota

(a) Heatmap showing the average relative contribution of core genera (columns) to selected KEGG Orthologs (KOs, rows) measured across the MicroLearner discovery cohort (n=136); selected functional terms include 13 KOs that are characteristic of the high-risk microbiota cluster and 29 KOs that are significantly different in terms of relative abundance between the high- and the low-risk core microbiota compositions; KO labels are coloured according to annotation by KEGG modules/Brites related to different aspects of metabolism and transport.

Supplementary Fig. S12 | Comparison of functional partitions of discovery cohort

The partitions of the discovery cohort obtained by clustering patients according to KEGG Ortholog genes (KOs) associated with high-risk microbiota (left) and with KOs differentially abundant in high- versus low-risk microbiota (right) are compared; in the two partitions, the functional clusters that contain most of the high-risk microbiota patents (red) have 100% overlap coefficients; the functional partition on the right can also cluster apart low-risk microbiota patients with more accuracy (cyan cluster, size 28 with 0 toxicity counts).

Supplementary Table S12 | KEGG Orthologs differentially abundant between the high-risk microbiota cluster and the low-risk microbiota cluster

Acronyms

FC: fold change

KO: KEGG Orthologs

Supplementary Fig. S13 | Analysis of microbiota functional traits different in high- versus low- risk microbiota

(a) Heatmap showing the microbiota functional profiles (standardised relative abundance values) of 29 selected KEGG Orthologs (KOs, rows) imputed from 16S core microbiota abundance profiles of the patients in the MicroLearner PCa discovery cohort (n=136, columns) before RT initiation; the KOs selected are significantly differentially abundant between high- and low-risk microbiota classes of patients; hierarchical clustering was used to define 3 functional clusters of patients (yellow vertical lines) and to reveal the functional patterns associated with the composition of the high- and of the low-risk microbiota classes with respect to the onset of acute GI toxicity during RT; KEGG modules containing selected KOs consistently overrepresented/underrepresented in the high-risk microbiota pattern are reported in red/blue on the heatmap right side. **(b)** Network describing the relations between KEGG modules to which the selected KOs are annotated to; nodes describe biological modules and they are linked if they share at least one KO among the selected ones; nodes are coloured according to whether they include functional traits coherently/incoherently over- or underabundant in the high-risk microbiota functional pattern.

Supplementary Fig. S14 | Relative contribution of core microbiota genera to KEGG Ortholog genes of interest.

The distributions across patients of the relative contribution of core microbiota genera to the KEGG Orthologs associated with high-risk microbiota or differentially abundant in high- versus low-risk microbiota are shown, stratified by microbiota risk classes.

Machine-learning for microbiota-based prediction of acute gastrointestinal toxicity

Supplementary Table S13 | Genera differentially abundant between the high-risk microbiota cluster and each of the other microbiota clusters

high-risk cluster versus

cluster specified in column 5

Supplementary Fig. S15 | Analysis of MICLIDE tree predictors across data sets

The distribution of relative abundance of predictors is shown across MicroLearner (ML) discovery and validation cohorts and across MARS early (n=32) and late cohorts (n=87); while the total number of counts is cohort-dependent, the peaks and the shapes of the distributions appears to be similar, suggesting that the MICLIDE tree predictors are detected consistently across data sets and that they are robust with respect to sequencing technology and cohort geography.

Supplementary Table S14 | Confusion matrix of the MICLIDE tree from prediction on the training set

Supplementary Table S15 | Prediction table of the MICLIDE tree from prediction on test sets

Multivariable logistic models of acute gastrointestinal toxicity

We developed different multivariable logistic models (MLMs) to check whether the interplay of potential risk factors could reveal any predictive potential and outperform the microbiotabased prediction.

We considered a first model with cytokines, BMI, age and mean rectal dose as predictors (n=99, patients with cytokines data available). We performed logistic multivariable regression using the lrm function of the 'rms' R package. The model characteristics are summarised in Supplementary Table S16.

Supplementary Table S16 | MLM of acute toxicity including cytokines and clinical risk factors

No coefficient was found to be significantly different from zero (p<0.05).

When we included in the model the Shannon's index for the alpha diversity of the core microbiota as a predictor, we found that the Shannon's index was the only feature with a coefficient significantly different from zero (Supplementary Table 17).

Supplementary Table S17 | MLM of acute toxicity including cytokines, clinical factors, and microbiota diversity

By running a stepwise backward regression starting from the latter set of predictors we found that the best predictors were the set of cytokines already identified for the definition of the polycytokinic risk score together with the Shannon's index (Supplementary Table 18), confirming that the polycytokinic risk defined has predictive potential but lack specificity.

Supplementary Table S18 | MLM of acute toxicity including cytokines and microbiota diversity

Finally, we developed a model enforcing as predictors the clinical risk factors and the microbiota diversity excluding cytokines (n=136, all patients from the discovery cohort). Again, we found that the only coefficient significantly different from zero was the Shannon's index coefficient (Supplementary Table 19).

Supplementary Table S19 | MLM of acute toxicity including clinical risk factors and microbiota diversity

