Supplementary Materials

Supplementary Table 1. Description of the components for reporting a highly multiplexed tissue imaging experiment

An example of a structured data base for these components is available at [https://htan-portal](https://htan-portal-nextjs.now.sh/explore)nextis.now.sh/explore. In addition, documentation for automated data ingress, as implemented in the HTAN consortium, is available at [https://ncihtan.github.io/HTAN-Data-Ingress-Docs/.](https://ncihtan.github.io/HTAN-Data-Ingress-Docs/)

Supplementary Table 2. Overview of relevant other initiatives / standards which guided MITI reporting guidelines

Initiative / Standard

"Standardized" validation of antibodies for research applications. Human Protein Atlas¹

The Resource Identification Initiative²

A Global View of Standards for Open Image Data Formats and Repositories³

QUAREP-LiMi: A community-driven initiative to establish guidelines for quality assessment and reproducibility for instruments and images in light microscopy⁴

Minimum Information guidelines for fluorescence microscopy: increasing the value, quality, and fidelity of image data⁵

Minimum Information About a Microarray Experiment (MIAME)⁶

Minimum Information about a Genome Sequence⁷

Guidelines for reporting single-cell RNA-seq experiments - minSCe⁸

Minimum Information for Biological and Biomedical Investigations^{904/04/2022 07:36:00}

Minimum Information Specification For In Situ Hybridization and Immunohistochemistry Experiments (MISFISHIE)**¹⁰**

MIRO: guidelines for minimum information for the reporting of an ontology**¹¹**

BINA: 4D Bioimaging North America (BINA)**¹²**

MethodsJ2**¹³**

Sharing biological data: why, when, and how**¹⁴**

PDX-MI: Minimal Information for Patient-Derived Tumor Xenograft Models**¹⁵**

REMBI: Recommended Metadata for Biological Images—enabling reuse of microscopy data in biology**¹⁶**

Supplementary Table 3. Open source visualization and analysis tools tailored for highly multiplexed imaging methods

Supplementary Table 4. Highly multiplexed imaging methods

Supplementary Table 4: An overview of the most commonly used antibody-based highly multiplexed tissue imaging methods. Low-plex imaging methods, such as Hematoxylin and Eosin (H&E), Immunohistochemistry (IHC), Vectra and others are supported but not included in the table.

Supplementary Note

1. The components needed to describe a highly multiplexed tissue imaging experiment

The proposed metadata schema is currently designed to record information from tumor atlas samples and includes clinical data elements to provide information about biospecimens from human subjects with either cancer or precancer lesions. However, the data elements presented here can be adapted for experiments utilizing samples from patients with a range of disease types and the framework can be modified to accommodate non-human samples as well as non-tumor samples. A minimum set of clinical data elements is provided here (**Supplementary Table 1**) that covers participant demographics, diagnosis, exposures, molecular testing, treatments and follow-up. In the HTAN initiative [\(https://humantumoratlas.org\)](https://humantumoratlas.org/), attributes are available for reporting additional characteristics such as prior patient history, family history, and molecular testing. The complete HTAN data standards are browsable at [https://htan-portal-nextjs.now.sh/standards.](https://htan-portal-nextjs.now.sh/standards)

Following the example of guidelines for reporting genomic data, we have indicated the level of significance for these attributes as either "required" or "recommended." A value (specified below) must be added for attributes marked as required. The values will be represented by strings, dates, numeric or boolean variables, as appropriate. Whenever possible, valid values will be limited to either a predefined set of keywords (e.g., "Alive" or "Dead") or a numeric interval (e.g., positive integer). Values of 'Unknown', 'Not Reported' and 'Not Applicable' can be used if information is missing for certain samples. 'Unknown' indicates that it is unclear whether data was or was not reported, 'Not Reported' indicates that the information was never collected and cannot be updated, and 'Not Applicable' indicates that the attribute does not apply to the participant or the study. When "required" attributes are conditional (e.g., only available for a specific method/technology or only relevant to a specific disease type) 'Not Applicable' should be used. 'Unknown' or 'Not Reported' should be used whenever possible. The number '0' represents the numerical value.

Submitters of image data must remove Protected Health Information (PHI) and must de-identify the data prior to submission. Participant PHI that must be removed according to the safe harbor method for de-identification includes names, medical record numbers, geographical identifiers smaller than a state, contact information, all dates (other than year) related to the participant (including birthdate, encounter dates such as procedure and follow up dates, date of death). One example of an automated deidentification procedure is provided by DICOM, and some repositories may require stringent removal of all absolute dates even if they are not directly related to PHI such as the date of image acquisition.

To obfuscate PHI, dates are reported as calculated fields (in days) using reference or anchor dates ("index date") as described by the GDC. Recommended index dates are included in the attribute descriptions (**Supplementary Tables 5, 6**). As an example, the HTAN initiative utilizes the date of birth of the participant as the index date. TCGA used the date of pathologic diagnosis as the index date.

To enable effective processing by computational tools, all metadata files must follow tidy data practices⁴⁰. Specifically, metadata tables should have rectangular shape with rows corresponding to observation instances (e.g., patients, channels, markers, etc.) and columns corresponding to attributes **(Supplementary Tables 5-12**) measured in each instance. Adherence to tidy data standards is straightforward when metadata tables are stored using standard formats like comma-separated value (CSV) or H5AD⁴¹. When composing metadata tables manually, users are cautioned that Microsoft Excel is known to corrupt data upon entry⁴²; the issue can be avoided by using alternative spreadsheet software, e.g., Google Sheets.

Implementation and maintenance of the MITI standard in YAML

The metadata definitions in this manuscript (Supplementary Table 1) represent a conceptual design for a standard in human-readable form. General definitions are accompanied by detailed specifications, also in the form of human readable tables, for metadata fields and their allowed values (Supplementary Tables 5-12). To enable implementation of MITI in a real-world setting, the specification is available in a machine-readable YAML format through a publicly accessible GitHub repository [\(https://github.com/labsyspharm/MITI\)](https://github.com/labsyspharm/MITI). It is the intention of MITI developers to build software tools to implement MITI based on these YAML files.

The choice of YAML as a markup language was motivated by its simple declarative structure making it both machine and human readable. Individual YAML files capture attributes, their description and significance (Supplementary Tables 5-12), but also additional information that is essential for validating specific files; this includes ensuring that data in each field has the correct attribute (e.g., boolean, integer, string, etc.) and that it meets constraints on valid values (e.g., a predefined set of keywords). MITIv1.0 YAML files are an exact match to the content presented here, but MITI is expected to undergo regular updates as it is deployed on a large scale by the imaging community; collaborative revision will be facilitated by the version control and source code management functionality provided by Git (and GitHub).

2. Data Levels for antibody-based multiplexed tissue Imaging

As of August 2021, the Minimal Information and Tissue Imaging standard (MITI) is still in an "request for comment" period, but we expect the final data levels for multiplexed tissue images generated using antibody reagents to be close to what is described below.

The concept of "data levels" (or tiers) was first developed by the Cancer Genome Atlas [\(TCGA\)](https://isb-cancer-genomics-cloud.readthedocs.io/en/latest/sections/data/TCGA_top.html), Genomic Data Commons [\(GDC\)](https://gdc.cancer.gov/) and the database of Genotypes and Phenotypes [\(dbGAP\)](https://www.ncbi.nlm.nih.gov/gap/) to standardize the transformation of raw data (as generated by a measurement apparatus) into processed and interpreted data as used in research publications. Use of data levels promotes uniform and reproducible data analysis and interpretation 33 . Data levels for genomic data also distinguish between restricted access data that carries a de-identification risk (Level 1 and 2 data such as primary sequence) and open access data (Level 3 data such as RNA-seq gene counts). In the case of tissue images de-identification is not considered a risk and only the extent of data processing is considered in establishing a data level.

Level 1 MITI data comprise the raw numerical output of acquisition instruments (microscopes, slide scanner, mass cytometers etc.). These data may be in a variety of vendor-specific formats, although all microscope vendors and investigators are strongly encouraged to conform to universally recognized *Bioformats* standards. For a whole slide image, Level 1 will contain many individual image tiles (images recorded from different x, y positions in the specimen).

FASTq files are a common type of Level 1 data in genomics.

Level 2 MITI data comprise full-resolution primary images in the universal OME-TIFF format that have undergone stitching, registration, illumination correction, background subtraction, intensity normalization etc. to generate high quality mosaic images. The processing of Level 1 data to generate Level 2 data must be performed using automated software routines (not human intervention), ideally using open-source algorithms whose operation is transparent. The generation of an image mosaic from multiple image tiles using e.g., ASHLAR⁴³ is a prototypical Level 1 to Level 2 transformation.

BAM files are a common type of Level 2 data in genomics.

Level 3 MITI data are the results of image processing and include segmentation masks, images labelled by humans (e.g., to identify nuclei or annotated histology) or by software algorithms. The generation of Level 3 data may involve human interpretation, which should be recorded as part of the image metadata. To provide conformity with GDC data access concepts, full-resolution primary OME-TIFF images that have been subjected to human, or human-assisted software-based quality control are considered Level 3 data. A typical transformation from Level 2 to 3 images involves removing channels

in which staining failed (a bad reagent batch) or cyclic data acquisition was interrupted (e.g., a dropped slide).

We anticipate that Level 3 images will be the primary types of images made available via public-facing data repositories. A key feature of microscopy in general, and tissue imaging in particular, is that virtually all types of human and computational analysis require access to full resolution data files, which can be very large. In contrast, in genomics, many types of analysis are possible using highly processed and compressed files; sustaining access to Level 3 images therefore imposes a substantial burden.

For tissue imaging, level 3 data types include:

- Level 3 Image mosaics that have been subjected to quality control, typically to remove staining and channel specific issues, and for cyclic methods, channels in which tissue damage has reached unacceptable levels.
- Segmentation masks, which are typically generated using software, such as UnMICST 44 but subjected to some level of human oversight or, in the case of machine learning, to supervised training. The models used to generate masks should be recorded.
- "Data Overviews" involving browser-based tools such as MINERVA 21 (or OME Viewers if an $OMERO^{25}$ database is available) that make it possible to browse images without having to download them. Viewing in these cases should involve as little additional interpretation as possible.

mRNA expression levels (RNA-seq gene count tables) are a common type of Level 3 genomic data.

Level 4 data are numerical data generated from processing Level 3 data, most commonly to create "spatial feature tables" describing marker intensities, cell coordinates and other single-cell features (the analogy is with count tables in RNA sequencing).

Level 5 data are results (e.g., cell type annotation) derived from Levels 4 spatial feature tables and level 3 images. Typical level 5 data include:

- MINERVA "Data Explorations" that use digital docents and human-generated annotation to guide users through the features of a complex set of images. The analogy is with a traditional figure.
- Dimensionality-reduced version of Level 4 data including all model parameters
- Machine learned models (other than segmentation models) from images or other numerical data
- Models that integrate image data with other data modalities
- Cell type and state annotations
- Tissue architecture information such as ducts in normal tissue and tumor nests in malignant tissue

3. Clinical and Patient-Derived Metadata

Clinical Data Elements are used to report patient related metadata including demographics, diagnosis, exposures, treatment and follow-up and are based on the Genomic Data Commons (GDC) Data Model. 'NOS' ('Not otherwise specified') indicates that a general diagnosis was possible but sufficient information was not available to provide a specific diagnosis. Complete data standards, including valid values, for HTAN are available on the HTAN Data Portal at [https://htan-portal-nextjs.now.sh/standards.](https://htan-portal-nextjs.now.sh/standards) Note that metadata describing patient-derived material used to create a model may also be reported using these data elements where applicable.

Supplementary Table 5. Clinical and Patient-Derived Data Elements for Highly Multiplexed Tissue Imaging Experiments

4. Non-Human Metadata Elements for Highly Multiplexed Tissue Imaging Experiments

Separate data elements report on the creation, quality assurance, and study of tissues from non-human model organisms for imaging experiments. With mouse tissues being a prominent example, Supplementary Table 6 aggregates the existing standards defined for mouse models by the Mouse Tumor Biology (MTB) Database^{45,46} and the Patient-Derived Xenograft Minimum Information (PDX-MI) Standards¹⁵, in accordance with guidelines set forth by the Alliance for Genome Resources⁴⁷.

Supplementary Table 6. Mouse Metadata Elements for Multiplexed Tissue Imaging Experiments

5. Biospecimen Metadata

For each participant in a study, one or several biospecimen samples may be analyzed. Each biospecimen should be assigned a unique label (Biospecimen ID). Relationships between participants and biospecimens can be indicated using the Parent ID; Parent IDs may be used to indicate the source of the biospecimen and when multiple biospecimens are derived from the same source. For tissue imaging, samples are either frozen or fixed and then sectioned and mounted onto slides. In this case each slide is a unique biospecimen from the same parent tissue block. An implementation example is included in Section 11 below.

These biospecimen metadata attributes include information about the method of tissue acquisition, sample processing and handling, and histologic assessment.

Supplementary Table 7. Biospecimen Attributes for Highly Multiplexed Tissue Imaging Experiments

6. File-level Metadata (data level 1)

Raw files without any preprocessing steps are considered Level 1 and the following attributes are needed to sufficiently describe the individual files. These files are sometimes in proprietary formats. For some imaging assays such as whole slide scanning of H&E and IHC stained sections where the output of the machine is immediately usable and doesn't require any pre-processing (e.g., in Leica/Aperiogenerated .svs-format files), a format translation may be the only step required to create the "Level 2" OME-TIFF file.

Supplementary Table 8: File-level Metadata for Highly Multiplexed Tissue Imaging Experiments

7. Channel-level Metadata Attributes (data levels 1 and 2)

Channel-level metadata can be provided in a companion CSV file with each OME-TIFF file associated with one such table. This companion CSV, referenced by filename in the corresponding level 1 and 2 file level metadata table **(Supplementary Table 7),** should have as many rows as necessary to describe each channel in the image data file -- with at least one row of data for each channel within the image data file. Each column in the CSV will represent a single attribute defined below, for all channels. Antibodies must be identified with their RRID identifiers² and validation should follow previously described practices1,48 although validation results are currently external to the MITI standard.

The first two attributes listed below are required in order to align other information in this CSV to the metadata in the OME-TIFF header and in the file-level metadata. Beyond these two, the submitting center has flexibility to choose what information to provide -- *but ideally the list of attributes should be finite and agreed-upon*. If there are channels which represent more than one target, or more than one antibody or fluorophore, then that information should be provided on multiple rows (and the corresponding Channel ID and Channel Name repeated) to follow tidy data standards⁴⁰.

8. OME-TIFF Header Metadata Attributes (data level 2)

OME-TIFF is an open file format that combines the TIFF format for storing binary pixel data with an OME-based XML metadata header. Using the Bio-Formats software plug-in proprietary file formats are converted into OME-based files that can be opened using any Bio-Formats compatible software.

Supplementary Table 10. OME-TIFF Header Metadata for Highly Multiplexed Tissue Experiments

9. Processing- and Segmentation level Metadata Attributes (data level 3)

Processing-level attributes describe steps taken to address issues at the pixel level that compromise downstream analyses. This may include novel steps to identify and correct for image artefacts and reject channels that do not meet data standards. Thus, the output file will be an OME-TIFF image of similar bit depth, lateral size and resolution to the level 2 OME-TIFF but may have fewer channels.

Segmentation-level attributes primarily include information on the generation of the individual masks (e.g., segmentation method, individual thresholds, cellular expansion etc.) and the represented object classes (e.g., Nuclei, Cytoplasm, Cell, Tumor, Stroma etc.). Thus, segmentation masks can represent either cellular compartments or larger cellular communities / tissue structures as well as the same classes segmented with different parameters / methods. This allows dozens of masks to be associated with individual images and image-derived features. Individual pixels in segmentation masks should be labelled with unique object IDs within the scope of each image mask. Background pixels are set to zero. All masks should be saved as TIFF files containing integer values (8/16/32bit). The size and resolution should correspond to the level 2 OME-TIFF image.

Intermediate steps during segmentation (probability maps, e.g., UNET) / overlapping mask from instance segmentation (e.g., MASK-R-CNN) should be converted to a single channel labeled mask as described above. Those files can be stored alongside level 3 metadata.

Supplementary Table 11. Processed-data level Metadata for Highly Multiplexed Tissue Imaging Experiments

10. Object-level Metadata Attributes (data level 4)

Segmentation-level attributes are associated with a CSV, FCS, or H5AD, etc file containing single cell level measurements across all channels (see channel-level; **Supplementary Table 8**) that have successfully passed QC. Therefore, masks for single cells (see segmentation-level; **Supplementary Table 10**) that have also successfully passed QC are combined with the individual channels for quantification. Non-cellular level information can be added as a separate column into the CSV, FCS, or H5AD file and recorded in the cell-level attributes of the files. A Python package ANNData, used for handling similar information for single-cell omics⁴¹, is particularly well-suited here.

Supplementary Table 12. Cell-level Attributes for Highly Multiplexed Tissue Imaging Experiments

11. Cell-state Level Metadata Attributes (data level 5)

Attributes associated with cell types and cell states can be specified as a separate Level 5 table or in additional columns that augment Level 4 information (**Supplementary Table 11**) to reduce storage size. Each cell can be associated with multiple types/states, but each association must be specified on a separate row in the corresponding level 5 data file. The cell type/state annotations are encoded by a set of keywords from a predefined dictionary cataloguing all possible states and allowing for "Other/Unknown". The dictionary itself is typically derived from known marker-cell type associations (e.g., databases, literature, etc.) or in a data-driven fashion via clustering and cluster annotations. In the metadata table, the dictionary is stored a semicolon-delimited list of keywords (**Supplementary Table 12**). We envision that future versions of the MITI standard will define cell type ontologies to capture hierarchical relationships between the various cell types and states (e.g., "T-cell" is a child node of "Lymphocyte", which is itself a child node of "Immune"), much like GO ontologies currently catalogue hierarchical associations between protein function terms⁴⁹. When implemented, the dictionary field in the metadata table will be replaced by a reference to the cell type ontology resource and its specific version.

Supplementary Table 13. Cell-state Attributes for Highly Multiplexed Tissue Imaging Experiments

12. Implementations

Example metadata is provided below for two different types of samples. First, a colorectal cancer specimen acquired from the Cooperative Human Tissue Network (CHTN) and used as part of an HTAN trans-network project (HTAN TNP CRC1). Second, a COVID-19 patient specimen. Clinical, Biospecimen and Imaging metadata (e.g., for t-CyCIF) are provided.

Full example implementation can be found here:

[https://docs.google.com/spreadsheets/d/1ZSSAxLJ1ci8XQqZch93VmTgZNY6zlt3lgvNiN4e_n-](https://docs.google.com/spreadsheets/d/1ZSSAxLJ1ci8XQqZch93VmTgZNY6zlt3lgvNiN4e_n-Y/edit?usp=sharing)[Y/edit?usp=sharing](https://docs.google.com/spreadsheets/d/1ZSSAxLJ1ci8XQqZch93VmTgZNY6zlt3lgvNiN4e_n-Y/edit?usp=sharing)

Example 1: Overview colorectal cancer example (CRC1)

Example 2: COVID-19 example

13. Reporting Guidelines Discussion

These guidelines for reporting highly multiplexed tissue imaging experiments have been developed as part of discussions in the Human Tumor Atlas Network (HTAN) working groups (Clinical/Biospecimen Working Group, Molecular Characterization Working Group, Data Analysis Working Group, Policy Working Group), and have been modified through a series of HTAN-wide request for comments led by the HTAN Data Coordinating Center (DCC) and through discussions with members of the Image Analysis Working Group of the Cancer Systems Biology Consortium and Physical Sciences-Oncology Network (CSBC/PS-ON) communities, the National Cancer Institute Imaging Data Commons (IDC),

Human Cell Atlas (HCA), the Human BioMolecular Atlas Program (HuBMAP), cBioPORTAL for Cancer Genomics, and the Open Microscopy Environment (OMERO).

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