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Generating Synthetic CDISC Clinical Trial Data.

José C. Lacal; NIHPO, Inc.

ABSTRACT

This paper presents a Python-based platform that generates Synthetic CDISC Clinical Trial Data at scale. The platform programmatically generates realistic synthetic persons (SynthPerson™) that have a complete synthetic Personal Health Record (SynthPHR™). Each SynthPerson™ lives in a series of geographically-accurate synthetic cities (SynthCity™). Groups of SynthPerson™ are then randomly enrolled in a synthetic Clinical Trial (SynthTrial™). Platform users define the parameters of each synthetic clinical trial and the platform generates all CDISC SDTM domains for the desired number of subjects.

INTRODUCTION

This paper describes the structure and functionality of a Python-based platform that generates synthetic health data at scale. One of the output types the platform generates are standard-compliant CDISC SDTM files in SAS Transport File Format (XPORT).

First, the platform allows users to generate very realistic yet fake synthetic individuals ("SynthPerson™"). Each SynthPerson™ receives a complete individual demographic profile including date of birth, gender, and places of birth and residence (SynthCity™), among other user-defined variables.

Second, the platform generates a full Personal Health Record (SynthPHR™) for each SynthPerson™. Each SynthPHR™ includes both Real-World Data from government agencies (EMA, FDA) as well as random values assigned from controlled terminologies (LOINC, SNOMED-CT). The goal of each SynthPHR™ is to provide a life-long, realistic, comprehensive medical history for each SynthPerson™.

Third, user can define the parameters for a synthetic clinical trial (SynthTrial™), virtually enrolling the synthetic subjects defined previously. The platform generates synthetic results for the clinical trial, based on the number of epochs, visits, arms, etc. defined by user. User can play with the clinical trial parameters and can quickly generate output files for different scenarios of the same trial.

Finally, the platform generates different types of output files: CSV, JSON, SAS (xport), and SQLite.

The data generated by this platform is not intended to replace "real" healthcare data. Rather, this platform wants to encourage and facilitate the use of synthetic health data as a temporary placeholder for real data. We believe synthetic health data can be useful to accelerate and shorten all test, QA, and end-to-end system validation in life science applications. The platform's initial focus is to provide synthetic health data across the lifecycle of a clinical trial.

It is worth mentioning that the platform explicitly, purposefully generates fully random data where, for example, a SynthPerson™ with gender equal to "Male" may be assigned a condition of "pregnancy". This synthetic data is designed to test assumptions and rules built into software used with clinical trial data.

The paper is divided in the following sections:

- Market Need
- Creating a Synthetic Person (SynthPerson™)
- Building a Synthetic Personal Health Record (SynthPHR™)
- Building a Synthetic Clinical Trial (SynthTrial™)
- · Future Work and Extensions
- Tools
- References

We close the paper with Conclusions and Acknowledgements.

By the end of the paper the reader will gain an understanding of the structure of the platform's architecture, written in Python3. And reader will be able to create synthetic subjects, synthetic cohorts, and synthetic clinical trials, for free, using the platform's source code available in GitHub.

MARKET NEED

The author identified the need for a tool that generates synthetic health data at scale through his work with the PHUSE Test Data Factory working group.

The motivation behind this platform is to allow all staff levels at an organization participating in clinical trials to easily create and use synthetic data with no restrictions. It is our hope that this platform will accelerate the development and approval of both new medical devices and pharmaceutical products.

THE PROBLEM WE SOLVE

We became aware that many players in the life sciences industry are unable to easily access realistic, unencumbered health data at scale before the real clinical trial data becomes available.

This non-real (yet realistic) synthetic health data can be of assistance during software development and testing. And to evaluate corner cases.

Early adopters report that synthetic health data can potentially shorten Quality Assurance cycles, and also provide a crucial tool for end-to-end System Validation.

Finally, and very importantly, this synthetic health data is available with no copyright, legal, privacy, or regulatory blocks.

OTHER APPROACHES

There are several mechanisms life science organizations rely on to obtain synthetic health data:

- Anonymized real health data. There are multiple tools that anonymize health data.
- Models extracted from real health data. Companies such as Replica Analytics take real health data and through proprietary mechanism the company generates a "model" based on the real data. Such model is then used to generate synthetic data.

In terms of synthetic data, Table 1. Synthetic Health Data generators summarizes a few available synthetic health data generators.

Name	URL	Comments
EMRBOTS.ORG	http://www.emrbots.org	Pre-generated EMR records.
JamesMarcogliese/ Patient-Generator	https://github.com/JamesMarcogliese/ Patient-Generator	Archived by owner.
Synthea	https://synthetichealth.github.io/synthea/	Gold standard.
The Random Patient Generator	https://randompatientgenerator.netlify.app	Single record at a time.

Table 1. Synthetic Health Data generators

We believe our approach is more flexible, scalable, and easier to implement than existing synthetic data generators. Secondly, the synthetic health data this platform generates has absolutely no risk of ever becoming "de-anonymized" as there are no "real" people behind the data. Each anonymization or model-generation tool has an implied de-anonymization risk factor. And the platform is free, under the Affero GPL (AGPL) Open Source license.

CREATING A SYNTHETIC PERSON (SYNTHPERSON™)

The first stage in the platform allows users to generate synthetic persons (SynthPerson™) with a complete demographic profile for each SynthPerson™. The platform can generate large numbers of records with user-defined parameters such as:

- age range (minimum and maximum ages)
- gender distribution (percentages of Female / Male records)
- race distribution (Black, Hispanic, White, other)
- geographical distribution by country and province / state (including place of birth, place of residence) defined using real locations that includes Latitude and Longitude for GIS uses (SynthCity™). We use US Locations and World Locations data from the US government.
- · realistic, yet synthetic full name

Think of the platform as a tool that helps users to generate "synthetic cohorts" on demand.

At the end of this stage the user will have files with hundreds (or hundreds of thousands) of synthetic individuals. The synthetic person output is available in different file formats: CSV, JSON, and/or SQLite.

BUILDING A SYNTHETIC PERSONAL HEALTH RECORD (SYNTHPHR™)

Once a user has built a cohort of synthetic subjects (SynthPerson™), the second stage in the platform builds a full (synthetic) Personal Health Record (SynthPHR™) for each subject.

When generating the PHR records, the platform utilizes scientifically-valid Controlled Terminologies (including SNOMED-CT CORE, LOINC, and CDISC's own Controlled Terminology) as well as Real-World Data sources (including from the FDA, the European Medicines Agency, and the Center for Medicare and Medicaid Services' ("CMS") National Provider Identifier.

There are versions of many controlled terminologies for languages other than English that can be easily plugged into the platform. The platform is then able to generate PHRs in multiple languages.

Finally, the platform outputs the PHR records in multiple formats, including: CSV, JSON, and SQLite. Additional output formats (FHIR, HL7, OMOP) can be easily added to the platform.

Figure 1: Synthetic Personal Record (SynthPHR™) overview below illustrates the core capabilities of the synthetic PHR generation stage.

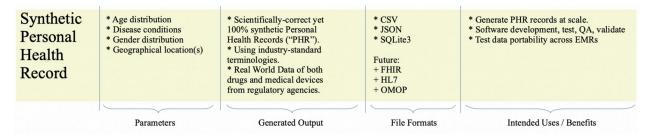


Figure 1: Synthetic Personal Record (SynthPHR™) overview

The software platform is divided into "Functional Blocks" for ease of development and re-use.

We'll now analyze each functional block's capabilities.

Table 2 below summarizes the functional blocks used to generate Synthetic Personal Health Records.

Functional Block	Purpose: Randomly assigns to each subject	
Demographics	Generates records of each Synthetic Person	
Conditions	SNOMED-CT CORE-defined medical conditions	
Devices	FDA-approved medical devices	
Drugs	EMA- or FDA-approved pharmaceutical products	
Lab Results	LOINC-defined lab results	
Procedures	SNOMED-CT CORE-defined procedures	
Providers	Current Medicare-registered healthcare providers	
Vitals	Vital signs	

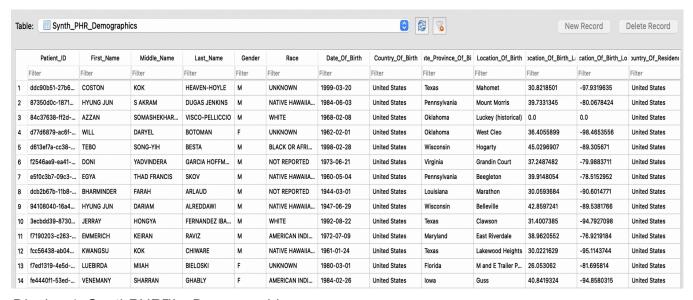
Table 2. Functional Blocks used to generate Personal Health Records

It is important to note that each functional block listed above is available through an API endpoint. This software architecture allows each functional block to be independently re-used for multiple purposes, as we'll cover in 03. Re-use Functional Blocks below.

DEMOGRAPHICS

This functional block generates the synthetic person record. The Patient_ID field is used as the Foreign Key across the synthetic PHR tables.

Display 1: SynthPHR™ - Demographics below shows the Demographics section of a SynthPHR™ SQLite file.



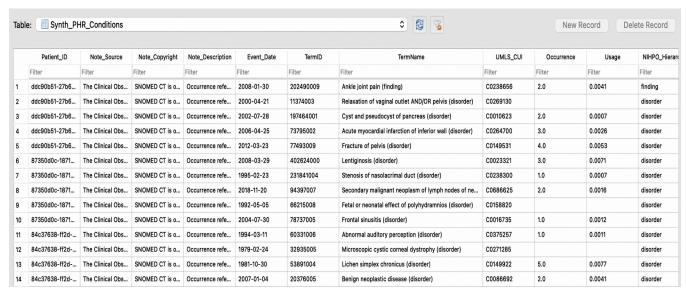
Display 1: SynthPHR™ - Demographics

CONDITIONS

This functional block uses SNOMED-CT CORE, and its 5,316 Findings, to assign random medical conditions to each synthetic subject. Each record has a random event date assigned to the condition.

SNOMED-CT CORE includes fields for "Occurrence" (number of institutions having this concept on their problem list) and "Usage" (the average usage percentage among institutions). The platform uses both Occurrence and Usage to generate random records with the proper statistical frequency.

Display 2: SynthPHR™ - Conditions below shows the Conditions section of a SynthPHR™ SQLite file.



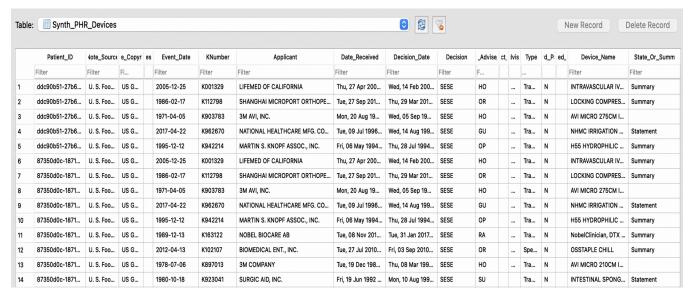
Display 2: SynthPHR™ - Conditions

DEVICES

This functional block takes Real-World Data from the Food and Drug Administration's ("FDA") list of Approved Devices and randomly assigns one or multiple medical devices to each synthetic person's record.

Each device record also receives a random event date when the subject had contact with the assigned medical device.

Display 3: SynthPHR™ - Devices below shows the Devices section of a SynthPHR™ SQLite file.

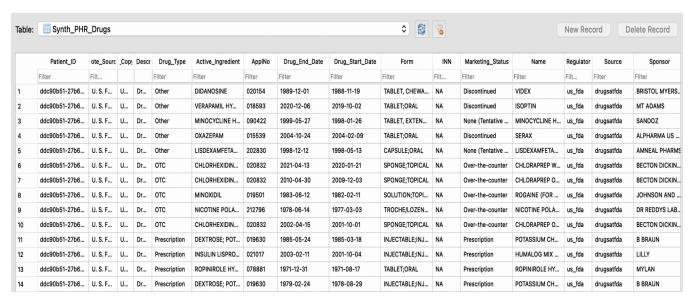


Display 3: SynthPHR™ - Devices

DRUGS

This functional block takes Real-World Data from either the European Medicines Agency ("EMA") or the FDA's Drugs@FDA and randomly assigns pharmaceutical products to each synthetic subject's record.

Display 4: SynthPHR™ - Drugs below shows the Drugs section of a SynthPHR™ SQLite file.

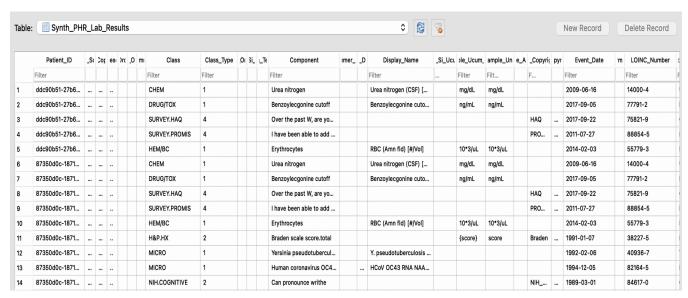


Display 4: SynthPHR™ - Drugs

LAB RESULTS

This functional block randomly assigns LOINC-defined lab results (including descriptions, measurements, and values) to each subject's record.

Display 5: SynthPHR™ - Lab Results below shows the Lab Results section of a SynthPHR™ SQLite file.



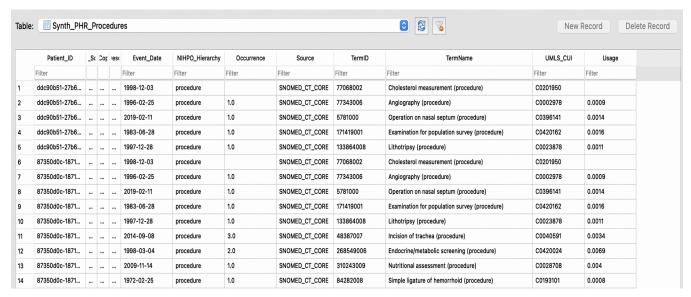
Display 5: SynthPHR™ - Lab Results

PROCEDURES

This functional block randomly assigns SNOMED-CT CORE-defined procedures to synthetic subjects.

The platform uses SNOMED-CT CORE's Occurrence and Usage to generate random procedure records with the proper statistical frequency.

Display 6: SynthPHR™ - Procedures below shows the Procedures section of a SynthPHR™ SQLite file.

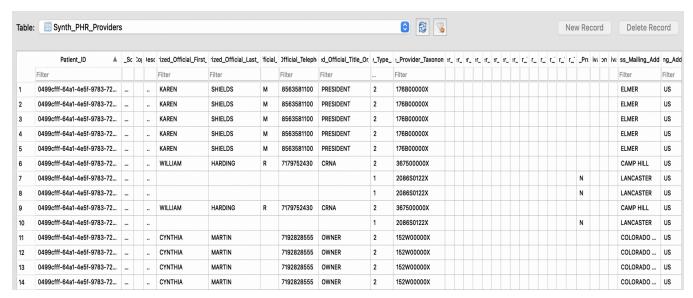


Display 6: SynthPHR™ - Procedures

PROVIDERS

This functional block uses Real-World Data from Medicare's NPI Registry (06.6 Million registered Medicare providers) to randomly assign healthcare providers to each synthetic subject's record.

Display 7: SynthPHR™ - Providers below shows the Providers section of a SynthPHR™ SQLite file.

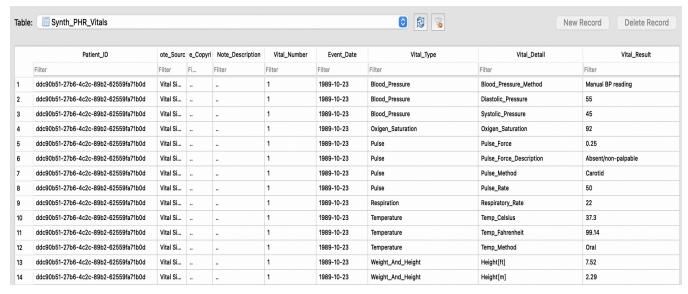


Display 7: SynthPHR™ - Providers

VITALS:

This functional block randomly assigns realistic vital sign readings to the synthetic person's record.

Display 8: SynthPHR™ - Vitals below shows the Vitals section of a SynthPHR™ SQLite file.



Display 8: SynthPHR™ - Vitals

Please note that in all functional blocks listed above, every date in every event (procedures, taking drugs, inserted devices, etc.) falls within the assigned lifetime of the synthetic subject.

BUILDING A SYNTHETIC CLINICAL TRIAL (SYNTHTRIAL™)

The third stage in the platform is to create a synthetic clinical trial using the synthetic cohort defined above. Figure 2: Synthetic Clinical Trial (SynthTrial™) overview below summarizes the goals and objectives of a synthetic trial.

Synthetic Clinical Trial	Re-use SynthPHR below: * Create full Trial Design * Unlimited number of Epochs, Arms, Visits.	* Scientifically-correct yet 100% synthetic clinical trial result data. * Using industry-standard terminologies.	* CDISC: AdAM SDTM * CSV * SAS * SQLite3	* Reduce time to packaged submission after trial closes. * Software development, test, QA, validate * Test systems that use (real) clinical trial data before actual data is available
Synthetic Personal Health Record	* Age distribution * Disease conditions * Gender distribution * Geographical location(s)	* Scientifically-correct yet 100% synthetic Personal Health Records ("PHR"). * Using industry-standard terminologies. * Real World Data of both drugs and medical devices from regulatory agencies.	* CSV * JSON * SQLite3 Future: + FHIR + HL7 + OMOP	* Generate PHR records at scale. * Software development, test, QA, validate * Test data portability across EMRs
	Doman store	Compared Output	File Formate	Intended Uses / Denefits
	Parameters	Generated Output	File Formats	Intended Uses / Benefits

Figure 2: Synthetic Clinical Trial (SynthTrial™) overview

We'll now describe the process the platform follows to generate a full synthetic trial. First, the software takes the synthetic cohort defined above. Then the user defines all the parameters specified in a Trial Design form.

Figure 3: Trial Design form below is a sample representation of how a user defines the parameters of a synthetic clinical trial. There is also a user-friendly GUI available to enter the Trial Design parameters.

```
"variables synth_trial":{
    "comment": These are variables to set the format of the Synthetic Trial design creation. These variables will be removed when the option to  
    "CT_DAYS_TRIAL_DURATION": 100,
    "CT_NUMBER_VISITS": 5,
    "CT_NUMBER_VISITS": 5,
    "CT_NUMBER_FINDINGS": 2,
    "CT_NUMBER_FINDINGS": 2,
    "CT_NUMBER_FINDINGS": 3,
    "CT_NUMBER_FINDINGS": 3,
    "CT_ARMS_NUMBES: ["Placebo", "A", "B"], "Rest", ["Placebo", "A", "B"], "Rest", ["Placebo", "A", "B"], "Follow-Up"],
    "CT_ELEMENTS_DESS: ["Screen", ["Placebo", "A", "B"], "Rest", ["Placebo", "A", "B"], "Fu"],
    "CT_ARMS_NUMES": ["Screen", ["Placebo", "A", "B"], "Rest", ["Placebo", "Rest", ["Placebo", "A", "B"], "Fu"],
    "CT_ARM_CONDITION": ["Randonized B", "Randomized Placebo", "Randomized A"],
    "CT_ARM_SITION_CONDITION": ["Informed consent", "First dose of study drug, where drug is ", "48 hrs after last dose of preceding treat
    "CT_BEGINING_ELEMENT_CONDITION": ["Informed consent", "First dose of study drug, where drug is ", "48 hrs after last dose of preceding treat
    "CT_NUMBER_VISITS_PER_ARM": [5, 5, 5],
    "CT_NUMBER_VISITS_PER_ARM": [5, 5, 5],
    "CT_NUMBER_VISITS_PER_ARM": [5, 5, 5],
    "CT_NUMBER_VISITS_PER_ARM": [10, 25, 40, 65, 90],
    "CT_NUMBER_VISIT_PULE_ENDY: ["In hour after start of Visit", "30 minutes after start of Screen Epoch", "1 hour after start of Visit", "1 hour a
    "CT_VISIT_PLANED_DAY": [10, 25, 40, 65, 90],
    "CT_NUMBER_PLANED_ASSESSMENT SHEEDOWES': 3,
    "CT_DISEASE_MILESTONES_TYPE": ["DIAGNOSIS", "HYPOGLYCEMIC EVENT"],
    "CT_DISEASE_MILESTONES_TYPE": ["DIAGNOSIS", "HYPOGLYCEMIC EVENT", "HYPERGLYCEMIC EVENT"],
    "CT_DISEASE_MILESTONES_TYPE": ["DIAGNOSIS", "HYPOGLYCEMIC EVENT", "HYPERGLYCEMIC EVENT"],
    "CT_NUMBER_RILOUNG_CRITERIA": 1,
    "CT_NUMBER_SUMMARY_PARAMETERS": 10
}
```

Figure 3: Trial Design form

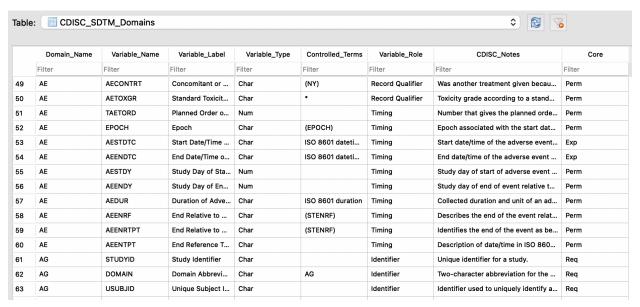
Once the user defines the desired parameters, the platform then proceeds to generate the trial data following these steps.

01. TABLE-DRIVEN RECORD CREATION

NIHPO has codified the CDISC SDTM structure into a series of tables in a SQLite database file. Think of this as the "Computable CDISC Standards."

The platform uses these tables to programmatically create a record for each SDTM Domain, where the Domain record structure (name, description, and type of field) is defined in these tables.

Display 9: CDISC SDTM structure definition below shows how the platform represents the CDISC SDTM Domains in a customized table.



Display 9: CDISC SDTM structure definition

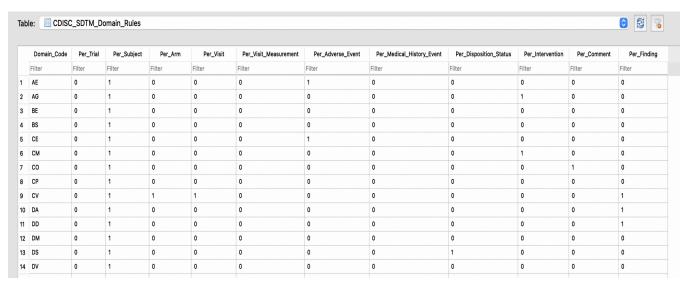
This approach of representing the Domains in a database table allows developers to quickly and easily extend the platform's functionality to other CDISC standards (AdAM is next on our list). And developer can also quickly adapt to changes in the standards: developer will simply update this table to reflect any changes to Domain-specific fields.

02. PROCESSING RULES DEFINED IN TABLES

Before the platform generates a record for a Domain the software needs to know the "creation rules" for each Domain.

For example: for the "AE" Domain, the platform needs to create one record per Subject, per Adverse Event. These "rules" are codified in a database table in the SQLite file as well.

Display 10: CDISC SDTM Domain Rules below displays part of the rules defining what records to create for each Domain.



Display 10: CDISC SDTM Domain Rules

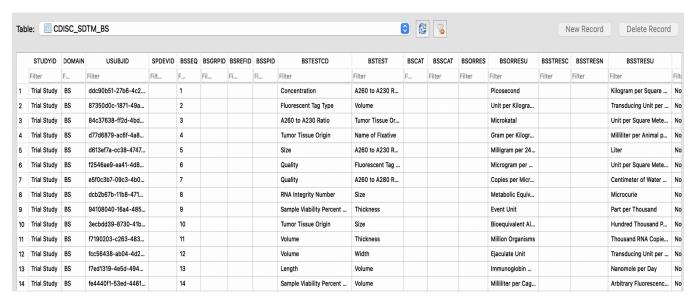
This table can be easily updated as the standards evolve.

03. RE-USE FUNCTIONAL BLOCKS

The platform now knows what fields to create for each Domain record. And the rules for when creating each record. Next, the platform has to "fill-in" each Domain-specific record. For example, the "LB" Domain has the fields "LBLOINC" ("LOINC Code") and "LBSPEC" ("Specimen Type").

As seen in Table 2. Functional Blocks used to generate Personal Health Records above, the platform generates data of different types on demand. To populate the LB Domain, the platform calls the Lab Results functional block and receives appropriate values to insert into the LBLOINC and LBSPEC fields.

And in the BS Domain, the fields BSTESTCD, BSTEST, BSORRESCU, and BSSTRESU are populated with values from the CDISC Controlled Terminology. See Display 11: CDISC SDTM BS Domain below.



Display 11: CDISC SDTM BS Domain

The USUBJID field in each SDTM record corresponds to the Subject ID in the synthetic PHR. User can trace a single synthetic subject throughout the clinical trial and all the way back to the subject's personal health history.

Please notice that this modular approach to generating and re-using synthetic health data is highly scalable: developer can add new functional blocks (e.g, generate synthetic medical images) and the platform will call those new functional blocks as needed (e.g. populate an EDC with synthetic images).

04. PANDAS-BASED INTERNAL STRUCTURE REPRESENTATION

The entire platform runs as a series of Pandas DataFrames for high performance and ease of use.

The use of Pandas also gives the platform enormous flexibility and scalability. The internal representation of the Domains is easily changeable on the fly, and the Pandas DataFrames can be exported to a large variety of output formats.

05. FLEXIBLE OUTPUT

The platform currently exports all CDISC SDTM domains in CSV, SAS, and SQLite formats. Developers can add the ability to generate new output format types (FHIR, HL7, OMOP) based on customer needs.

NIHPO already demonstrated how the platform can easily load the synthetic data (both PHR as well as trial data) directly into an Electronic Data Capture ("EDC") system like Medidata Rave.

06. CONFORMANCE LEVELS

The platform's output files are designed to meet several conformance levels. In order of increasing complexity:

- Structural conformance: All the generated output files have a structure that matches the expected structure of the SAS XPORT format.
- Standard (CDISC) conformance: The format of each generated record in each SDTM Domain matches the CDISC definitions. The output SAS files generated by the platform are validated with the Pinnacle 21 Community edition.
- Scientific conformance: The platform uses both Controlled Terminologies as well as Real-World Data to ensure the content of each record, while randomly-generated, is scientifically accurate.
- Semantic conformance: The output files are not intended to replace "real" healthcare data. Rather, the goal of this synthetic data is to act as a temporary placeholder for real data. Therefore, the generated synthetic data files are not intended to be semantically correct.

Synthea's output, on the other hand, has a high degree of both scientific and semantic compliance due to Synthea's use of their fantastic Generic Module Framework (GMF) that "enables the modeling of various diseases and conditions that contribute to the medical history of synthetic patients."

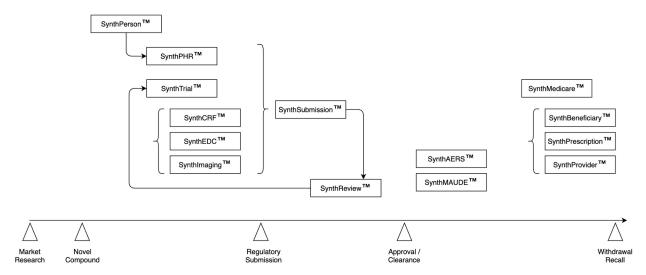
FUTURE WORK AND EXTENSIONS

NIHPO's long-term goal is to build a "Clinical Trial Composer." This will be a desktop application where users will be able to "compose" a Clinical Trial just like a musician composes a song, or a movie director edits raw video footage, on their desktops.

Musicians use sophisticated GUIs to lay tracks, edit sequences and audio samples, and then to generate the finished product. We wonder why not using the same mental model for "composing" (adding, editing, aligning, testing, outputting) all the elements of a (synthetic) clinical trial?

The Clinical Trial Composer will enable any staff role (from a market-focused analyst to a data-focused statistician) to quickly and easily define, create, and use synthetic health data. Either instead of or as a placeholder until real data is available. From the user's desktop, without IT involvement.

Drawing 1: Synthetic Health Data roadmap below shows NIHPO's roadmap for synthetic health data.



Drawing 1: Synthetic Health Data roadmap

Synthetic Case Report Forms (SynthCRF™)

The platform already generates valid records for Adverse Events, for example. It is then easy to extend the platform to fill out the corresponding forms for Adverse Events. The same method applies to all forms.

The platform will populate each trial-related form based on a user-defined mapping of what fields go where in each form.

Synthetic Electronic Data Capture (SynthEDC™)

A logical output for the platform is to populate an EDC (Electronic Data Capture) system with all the synthetic data generated for both subjects as well as the trial events, visits, measurements.

At this time the platform can already programmatically populate Medidata Rave through Rave's API.

Synthetic Medical Imaging (SynthImaging™)

The platform will be extended to generate on-demand synthetic medical images at scale. The platform will use publicly-available medical imaging datasets as a reference for all imaging modalities and disease conditions. The platform will then randomly insert markers into the reference images to create synthetic images. For example: the platform will generate breast cancer images with randomly-placed lesions.

These medical images will be customizable to fit a user's specific needs. The synthetic image files will be unencumbered, scientifically valid, and available in multiple formats (DICOM, JPG, PNG).

CONCLUSION

This paper described a database-driven software platform that generates realistic, yet synthetic health data. The use of both Real-World Data and controlled terminologies ensures that the generated data is scientifically valid. The software is structured as functional blocks that are easily re-used and extensible.

We presented additional functionality and a road map of future capabilities under development.

The platform's source code is available in GitHub at https://github.com/nihpo/SynthHealthData under an Open Source license (AGPL 3.0).

TOOLS

These are the Python libraries used in this work:

Pandas [https://pandas.pydata.org/]

Xport [https://github.com/selik/xport]

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CONTACT INFORMATION

Your comments and questions are valued and encouraged. Contact the author at:

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