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Synthea™ Novel coronavirus (COVID-19) model and synthetic data set

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ABSTRACT

March through May 2020, a model of novel coronavirus (COVID-19) disease progression and treatment was constructed for the open-source Synthea patient simulation. The model was constructed using three peer-reviewed publications published in the early stages of the global pandemic, when less was known, along with emerging resources, data, publications, and clinical knowledge. The simulation outputs synthetic Electronic Health Records (EHR), including the daily consumption of Personal Protective Equipment (PPE) and other medical devices and supplies.

For this simulation, we generated 124,150 synthetic patients, with 88,166 infections and 18,177 hospitalized patients. Patient symptoms, disease severity, and morbidity outcomes were calibrated using clinical data from the peer-reviewed publications. 4.1% of all simulated infected patients died and 20.6% were hospitalized. At peak observation, 548 dialysis machines and 209 mechanical ventilators were needed. This simulation and the resulting data have been used for the development of algorithms and prototypes designed to address the current or future pandemics, and the model can continue to be refined to incorporate emerging COVID-19 knowledge, variations in patterns of care, and improvement in clinical outcomes. The resulting model, data, and analysis are available as open-source code on GitHub and an open-access data set is available for download.

Introduction

Synthetic data generation is a proven approach to sharing realistic-but-not-real data without the privacy and security risks associated with real health data.

Synthetic data is not deidentified data. Synthetic data is generated either from models based on aggregated statistics (e.g., modeling and simulation without direct access to any individual data points) or models abstracted from sensitive data (e.g., machine learning models that were trained from, but do not preserve, individual data records). Deidentified data are often modified from real data points using methodologies such as masking or deleting fields and introducing noise.

The assumption that deidentification guarantees privacy or eliminates risk is false [1]. Synthetic data has been widely used as a safe alternative to deidentification. Synthetic data is considered ethically superior to deidentified data, because there is no individual sensitive record underneath any synthetic record that can ever be reidentified [1]. Synthetic clinical data sets can be openly shared to enable innovation, such as from the open-source Synthea (“Synthetic Health”) project which publicly provides millions of longitudinal synthetic health records [2]. Synthetic data is being used for software testing and validation (including privacy and security testing), education, academic research, feasibility assessments and algorithm validation, but not yet for clinical discovery and scientific inference [3]. Criticisms of Synthea are that it does not fully account for variations in health care delivery by providers, has limited heterogenous health outcomes after major interventions, but it can be improved and validated [4], and that it does not yet contain sufficient clinical notes [5].

Other synthetic generation techniques, such as Generative Adversarial Networks (GANs) used in medical imaging are experiencing rapid growth (150 articles in the last three years) and the results are filling an important niche in data science [6].

Synthetic data aligns with the Open Science movement which includes open access, open source, and open data among its principles to address the scientific reproducibility problem.

The scientific reproducibility problem is especially severe in health
research (especially health machine learning) where data sets and code are more likely to be unavailable. Synthetic data has been identified as a way for researchers to meaningfully release data, code, and results [7].

When properly constructed and validated, synthetic data used in data analytics and machine learning tasks has been shown to have the same results as real data in several domains without compromising privacy [8]. However, these domains are generally not as complex or as high-stakes as health care responses to a pandemic such as COVID-19, so synthetic health data should always be validated for a researcher’s specific use-case prior to utilization. Without access to the unpublished raw data, only peer-reviewed research results with summary statistics, we have attempted to calibrate the synthetic data to those reference statistics (as presented in Methods and Materials and Results). We outline limitations and suggested uses in the Discussion section.

Materials and methods

March through May 2020, a model of novel coronavirus (COVID-19) disease progression and treatment was constructed for the open-source Synthea patient simulation. The model was constructed during the

### Table 1
**Study characteristics.**

| Source              | Location        | Timing                        | Total Patients | Admitted Patients | Survivors | Non-Survivors | Outcomes Not Determined at Publication |
|---------------------|-----------------|-------------------------------|----------------|-------------------|-----------|---------------|-----------------------------------------|
| Zhou et al. [9]     | Wuhan           | Jan 11, 2020 – Jan 31, 2020   | 191            | 191               | 137 (71.73%) | 54 (28.27%)  | 0                                       |
| Guan et al. [10]    | Wuhan           | Dec 11, 2019 – Jan 31, 2020   | 1099           | 1099              | 64 (5.82%)  | 15 (1.36%)   | 1029 (93.63%)                           |
| Richardson et al.   | New York City   | Mar 1, 2020 – Apr 4, 2020 (34 days) | 5700          | 5700              | 2081 (36.51%) | 553 (9.70%) | 3066 (53.79%)                           |
| Synthetic Data      | Massachusetts   | Jan 20, 2020 – May 26, 2020 (127 days) | 124,150 (88,166 infected) | 18,177            | 14,654 (80.61%) | 3548 | 0                                       |

### Table 2
**Modules and their Descriptions.**

| Module                          | Description                                                                 |
|---------------------------------|-----------------------------------------------------------------------------|
| covid19/admission               | Determines exposure and infection rates.                                   |
| covid19/admission               | Contains the daily loop during hospitalization and ICU treatment.           |
| covid19/determine_risk          | Determines risk based on comorbidities, severity of disease, and whether or not the patient will survive. |
| covid19/infection               | Determines whether or not patients will be testing, the testing results, and whether or not they are admitted to the hospital. |
| covid19/measurements_daily      | Records daily lab values.                                                   |
| covid19/measurements_frequent   | Records frequent lab values.                                                |
| covid19/measurements_vitals     | Records vital signs.                                                        |
| covid19/medications             | Potentially enrolls a critical or severe patient in one of eighteen clinical trials. |
| covid19/nonsurvivor_lab_values  | Sets lab values for patients who will not survive.                          |
| covid19/survivor_lab_values     | Sets lab values for patients who will survive.                              |
| covid19/outcomes                | Determines outcomes and complications based on risk and disease severity.   |
| covid19/end_outcomes            | Ends complications after recovery (if applicable).                          |
| covid19/supplies_hospitalization| Contains the daily supplies used within the hospital for 1 patient, 1 physician, and 1 nurse. |
| covid19/supplies_icu            | Contains the daily supplies used within ICU for 1 patient, 1 physician, and 1 nurse. |
| covid19/supplies_intubation     | Contains the supplies used for intubation.                                  |
| covid19/symptoms                | Determines the symptoms presenting in each patient.                         |
| covid19/end_symptoms            | Ends symptoms after recovery (if applicable).                               |
| covid19/diagnose_blood_clot     | Patients will likely develop blot clots during inpatient and ICU stay.      |
| covid19/treat_blood_clot        | Blood clots need to be treated once they are developed.                     |
| covid19/diagnose_bacterial_infection | Patients may develop a secondary bacterial infection in the ICU.           |
Table 3
Outcomes.

| Outcome         | All Patients (n = 88,166) | Hospitalized (n = 18,177) | ICU Admitted (n = 3,367) | Required Ventilation (n = 2,914) |
|-----------------|---------------------------|----------------------------|--------------------------|----------------------------------|
| Home            | 0.80                      | 0.02                       | 0.02                     | 0.02                             |
| Isolation       |                           |                            |                          |                                  |
| Hospital        | 0.20                      | 1.00                       | 1.00                     | 1.00                             |
| Admission       |                           |                            |                          |                                  |
| ICU             | 0.04                      | 0.20                       | 1.00                     | 1.00                             |
| Admission       |                           |                            |                          |                                  |
| Ventilated      | 0.03                      | 0.16                       | 0.79                     | 1.00                             |
| Recovered       | 0.95                      | 0.80                       | 0.32                     | 0.14                             |
| Death           | 0.04                      | 0.19                       | 0.67                     | 0.85                             |

Table 4
Supply and device usage.

| DESCRIPTION                         | QUANTITY |
|-------------------------------------|----------|
| Alcohol disinfectant                | 245,937  |
| Antiseptic towelette                | 1,947,098|
| Basic endotracheal tube single-use  | 2914     |
| Carbon dioxide breath analyzer      | 2914     |
| Disposable air-purifying respirator | 446,438  |
| Endotracheal tube holder            | 2914     |
| Endotracheal tube stylet single-use | 2914     |
| Face shield                         | 437,696  |
| Human plasma blood product (product)| 143      |
| Isolation gown reusable             | 48,350   |
| Isolation gown single-use           | 2,583,654|
| Laryngoscope blade single-use       | 2914     |
| Lubricant                           | 2914     |
| Nasogastric tube device             | 2914     |
| Nitrile examination/treatment glove non-powdered sterile | 5,759,164 |
| Operating room gown single-use      | 2914     |
| Protective glasses device           | 8742     |
| Suction system                      | 2914     |
| Surgical cap single-use             | 2914     |
| Syringe device                      | 5828     |
| Viral filter                        | 2914     |

the daily consumption of Personal Protective Equipment (PPE) and other medical supplies.

The COVID-19 models within Synthea were primarily modeled on three peer-reviewed clinical papers, based on findings from Wuhan, China [9,10] and mortality data from New York City, USA [11]. The characteristics of these studies and the final synthetic data are summarized in Table 1. Data from the primary reference Tables and Figures used as input into the modeling process are included within this paper along side our results for comparison purposes. Model clinical definitions, commentary, and assumptions are detailed in Appendix A.

The Synthea simulation is divided into “modules” which are summarized in Table 2. The Synthea models are viewable at:

- https://synthetichealth.github.io/module-builder.

and can be downloaded from:

- https://github.com/synthetichealth/synthea/tree/master/src/main/resources/modules

Results

We generated 124K patients and performed some basic analysis to produce Figures and summarize outcomes corresponding to Figures and Tables from our primary data sources and present these for comparison. It is important to note that the model was developed from the primary source tables, and not the raw data from these sources which was unpublished.

Infection rate and mortality

Of the 88,166 infections in the generated population (not all the simulated patients became infected), 18,177 patients were hospitalized. Based on current knowledge this hospitalization rate is high, but at the early stages of the pandemic, we estimated hospitalization rates based on projected outcomes related to patient comorbidities and risk factors without consideration of disease prevention measures. The simulated infection timeline is illustrated in Fig. 1. The mortality graph illustrated in Fig. 2 shows the mortality disparity between age and gender groups.

Outcomes

Outcomes are enumerated in Table 3. The “Outcome” column describes an outcome (e.g. ventilated, recovered, or death), and the other columns are cross correlated with other groups (e.g. all patients, patients who were hospitalized, patients who were admitted to the ICU, and patients who required ventilation).

Regarding cells marked with “1.00” – that indicates that 100% of the patients in that group had that outcome. For example, the cell corresponding to the “ICU Admitted” column and “Hospital Admission” row is “1.00” – indicates that all patients who were admitted to the ICU were also admitted to the hospital (in this case, a prerequisite event in our model).

Supply and device usage

The amount of supplies consumed for this particular simulation run are enumerated in Table 4. The simulation ran for 88K infected patients, of which 18,177 were admitted to the hospital. A discussion on the assumptions made about supply consumption and device usage are documented in Appendix A. Supply models are documented in Appendix B: Supply and Device Lists.

For this simulation, at peak 548 hemodialysis machines were needed, with 209 mechanical ventilators, as illustrated in Fig. 3.

Major complications among survivors and Non-Survivors

Complications among survivors and non-survivors are listed in Tables 5 and 6 for synthetic patients and the reference data, respectively. There are discrepancies between the these outcomes (compare the “percent” columns in each table) because the outcomes in the model are not fixed by percentages from Table 6, but are based on risk-factors that determine severity and mortality including gender, age, and comorbidities that differ from the reference population.

For comparison, Table 6 reproduces reference data from the “Outcomes” portion of Table 2 from Ref. [9].

![Fig. 3. Device usage over time.](image-url)
Take Field Marshall Moltke to be true, that all models are wrong, then Synthea is wrong. And if we take George Box quote above disease progression and treatment. If we take the George Box quote above reference data is listed in Table 8 and the simulation results are listed in Absense of the Primary Composite End Point of the Study Patients, According to Disease Severity and Presence or Absense of the Primary Composite End Point from Ref. [10], except for Loss of Taste which was based upon the findings from Ref. [12]. The symptoms in Ref. [10] are based on disease severity (severe and non-severe) while our findings are broken down by survivor and non-survivor, which are overlapping but not identical populations. The reference data is listed in Table 8 and the simulation results are listed in Table 9 (all infected synthetic patients) and Table 10 (synthetic patients admitted into the ICU).

### Patient timelines

Patient timelines were modified from the illustration of common patient timelines and statistics from Fig. 1 ("Clinical courses of major symptoms and outcomes and duration of viral shedding from illness onset in patients hospitalized with COVID-19") from Ref. [9] and are paralleled here in Figs. 5 and 6. Fig. 5 shows patients who were hospitalized, some of which are later admitted to the ICU. Fig. 6 shows only the ICU patients.

The average of length of stay for the synthetic patients is detailed in Table 7, with reference ranges from Ref. [9] that are inclusive of both survivors and non-survivors.

### Patient symptoms

Patient symptoms were modeled from Table 1 “Clinical Characteristics of the Study Patients, According to Disease Severity and Presence or Absense of the Primary Composite End Point” from Ref. [10], except for Loss of Taste which was based upon the findings from Ref. [12]. The symptoms in Ref. [10] are based on disease severity (severe and non-severe) while our findings are broken down by survivor and non-survivor, which are overlapping but not identical populations. The reference data is listed in Table 8 and the simulation results are listed in Table 9 (all infected synthetic patients) and Table 10 (synthetic patients admitted into the ICU).

### Discussion

"No plan of operations extends with any certainty beyond the first contact with the main hostile force." – Field Marshall Helmuth Karl Bernhard Graf von Moltke

"All models are wrong, some are useful." – George P.E. Box

Synthea is an open-source modeling and simulation platform for disease progression and treatment. If we take the George Box quote above to be true, that all models are wrong, then Synthea is wrong. And if we take Field Marshall Moltke’s notion of “no plan survives contact with the enemy” as true and expand the scope to modeling and simulation, then we might say that “no model survives contact with reality.” Which is all to say that our model of novel coronavirus is flawed as all models are, and as a model, it cannot not survive contact with reality. Nevertheless, we hope it is useful.

To our knowledge, the Synthea COVID-19 data has been useful in several online challenges, hackathons, and conferences [13–17]. In these venues, the data has spurred innovation and exchange of ideas about software solutions, enabled software development and testing, and has been used as the basis for some prediction modeling.

Those prediction models are likely not suitable for application in the delivery of clinical care, however they do enable a machine-learning team to begin to explore realistic data, develop their ideas and solution, build a processing pipeline – all before they are able to gain secure access to restricted data sets of real COVID-19 patients and outcomes. It also provides learning opportunities to teams that would otherwise be unable to gain access to such data sets and lowers the barrier to entry to participating in AI and ML activities in healthcare.

In the future, when more COVID-19 real-world data sets become available, including EHR data and associated outcomes, it will be possible to tune the model weights and probabilities to match real cohorts and diverse variations in care. For example, using data from one region during a particular month of the pandemic, the model could be calibrated to generate data more representative of that cohort (including infection rates, disease severity, treatments, and outcomes).

Finally, another major weakness of this model is that Synthea does not currently restrict or limit the care or supplies based on capacity, so the resulting data represents an upper bound. The models could be modified to account for this but would require additional pathways to be modeled (for example, what occurs when a required ventilator is unavailable).

### Conclusions

The COVID-19 pandemic has brought unprecedented sharing of data, knowledge, techniques, equipment and supplies across the globe. Nevertheless, there is a role for the distribution of realistic-but-not-real synthetic data sets among the community of health innovation (AI, ML, software, other) both with the academic and the practitioner.

This synthetic data fills in data availability gaps, lowers the innovation barrier to entry, and aligns with the Open Science movement which includes open access, open source, and open data among its principles.

### Table 5

| Complication                  | Total (n = 1,817) | Percent of Inpatient | Survivors (n = 1,4654) | Percent Survivors | Nonsurvivors (n = 3548) | Percent Nonsurvivors |
|-------------------------------|------------------|---------------------|------------------------|-------------------|-------------------------|---------------------|
| Sepsis                        | 6945             | 0.381551            | 3419                   | 0.233315          | 3526                    | 0.993799            |
| Respiratory Failure           | 8710             | 0.478519            | 5237                   | 0.357377          | 3473                    | 0.978861            |
| ARDS                          | 2401             | 0.131909            | 85                     | 0.005800          | 2316                    | 0.652762            |
| Heart Failure                 | 1434             | 0.078783            | 124                    | 0.008462          | 1310                    | 0.369222            |
| Septic Shock                  | 1746             | 0.095924            | 0                      | 0.000000          | 1746                    | 0.492108            |
| Coagulopathy                  | 1389             | 0.076310            | 91                     | 0.006210          | 1288                    | 0.365840            |
| Acute Cardiac Injury          | 1288             | 0.070761            | 20                     | 0.001365          | 1268                    | 0.357384            |
| Acute Kidney Injury           | 1252             | 0.068784            | 8                      | 0.000546          | 1244                    | 0.350620            |

### Table 6

| Complication                  | Total (n = 191) | Percent | Survivors (n = 137) | Percent Survivors | Nonsurvivors (n = 54) | Percent Nonsurvivors |
|-------------------------------|----------------|---------|---------------------|-------------------|-----------------------|---------------------|
| Sepsis                        | 112            | 0.59    | 58                  | 0.42              | 54                    | 1.00                |
| Respiratory Failure           | 103            | 0.54    | 50                  | 0.36              | 53                    | 0.98                |
| ARDS                          | 59             | 0.31    | 9                   | 0.07              | 50                    | 0.93                |
| Heart Failure                 | 44             | 0.23    | 16                  | 0.12              | 28                    | 0.52                |
| Septic Shock                  | 38             | 0.20    | 0                   | 0.00              | 38                    | 0.70                |
| Coagulopathy                  | 37             | 0.19    | 10                  | 0.07              | 27                    | 0.50                |
| Acute Cardiac Injury          | 33             | 0.17    | 1                   | 0.01              | 32                    | 0.59                |
| Acute Kidney Injury           | 28             | 0.15    | 1                   | 0.01              | 27                    | 0.50                |
Fig. 4. Major lab values. Synthetic data (left) and reference data (right).
Fig. 5. Synthetic hospitalized patient times. Survivors (left) and non-survivors (right).

Fig. 6. Synthetic ICU patient timelines. Survivors (left) and non-survivors (right).

Table 7

| Type      | Patients | Average Stay (days) | Reference Range (days, average and range) [9] | Total days |
|-----------|----------|---------------------|-----------------------------------------------|------------|
| Inpatient | 18,177   | 15.03               | 11 (5–15)                                     | 273,224    |
| ICU       | 3677     | 6.08                | 8 (2–12)                                      | 22,379     |

Table 8

| Symptoms                  | All Patients Percentage | All Patients (n = 1099) | Severe Percentage | Severe (n = 173) | Non Severe Percentage | Non Severe (n = 926) |
|---------------------------|------------------------|-------------------------|-------------------|------------------|-----------------------|-----------------------|
| Conjunctival Congestion   | 0.008                  | 9                       | 0.023             | 4                | 0.005                 | 5                     |
| Nasal Congestion          | 0.048                  | 53                      | 0.035             | 6                | 0.051                 | 47                    |
| Headache                  | 0.136                  | 150                     | 0.150             | 26               | 0.134                 | 124                   |
| Cough                     | 0.678                  | 745                     | 0.705             | 122              | 0.673                 | 623                   |
| Sore Throat               | 0.139                  | 153                     | 0.133             | 23               | 0.140                 | 130                   |
| Sputum Production         | 0.337                  | 370                     | 0.353             | 61               | 0.334                 | 309                   |
| Fatigue                   | 0.381                  | 419                     | 0.399             | 69               | 0.378                 | 350                   |
| Hemoptysis                | 0.009                  | 10                      | 0.023             | 4                | 0.006                 | 6                     |
| Shortness of Breath      | 0.187                  | 205                     | 0.376             | 65               | 0.151                 | 140                   |
| Nausea                    | 0.050                  | 55                      | 0.023             | 12               | 0.046                 | 43                    |
| Diarrhea                  | 0.038                  | 42                      | 0.058             | 10               | 0.035                 | 32                    |
| Muscle Pain               | 0.149                  | 164                     | 0.173             | 30               | 0.145                 | 134                   |
| Joint Pain                | 0.149                  | 164                     | 0.173             | 30               | 0.145                 | 134                   |
| Chills                    | 0.115                  | 126                     | 0.150             | 26               | 0.108                 | 100                   |
| Loss of Taste             | 0.64                   | 130 (n = 374)           | n/a               | n/a              | n/a                   | n/a                   |
The Synthea COVID-19 data has been used in many online challenges, hackathons, and conferences, and we hope it will be useful to academics, students, and practitioners.

The synthetic data is available here: https://synthea.mitre.org/downloads.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.jbmed.2020.100007.

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