### An approach for generating realistic Australian synthetic healthcare data

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Australia's National Science Agency

## Why generate synthetic data?











Access to data is essential for research but can be challenging Real-world data can be costly and long to access

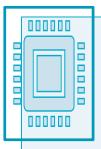
Synthetic data are generated to represent realistic data and/or have the same statistical properties as real data.

Synthetic data has the potential to ease data access

Synthetic data provide a greater protection of patients' sensitive information.



## Different approaches for generating synthetic data



### Synthetic data from real data

• Use real data to build a model that captures the distribution and structure of the real data.

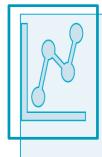
• If the model is good, the synthetic data will have statistical properties similar to those of the real data.

• approach used by Medisyn



### Synthetic data without real data

- Use existing models or background knowledge.
- Accuracy depends on the analyst's background knowledge and the realism of the assumptions made.
- approach used by many studies where analysts want to test scenarios for which real data are not available



## Synthetic data based on real summary statistics of a given population

- use of probability-based logic
- no risk of identification of personal information
- clinical validity may be a challenge

• approach is used by Synthea



## Synthetic data at AEHRC

#### Hamed Hassanzadeh et al\*:

- Historically informed data generation
  - Prospective analysis
  - Simulation of impact of variations in hospital demand and capacity on patient flow metrics

Publication: Kenny et al (2021)

Patient flow simulation using historically informed synthetic data

Digital Health Institute Summit; Brisbane.

<b>Filip Rusak</b> : Synthetic MRI data	John Grimes and students: Started work on Synthea
Publication: Rusak et al (2020) 3D Brain MRI GAN-Based Synthesis Conditioned on Partial Volume Maps.	Added Family history in asthma, Osteoarthritis and cystic fibrosis disease modules.
Simulation and Synthesis in Medical Imaging - MICCAI, Lima, Peru (Online)	Patients' names to Australian names
Publication: Rusak et al (2021) Synthetic brain MRI dataset for testing of cortical thickness estimation methods v1.	Australian time zones
CSIRO: Data Collection	



## The Synthea approach

### Synthea mirrors the reference population:

- demographics
- disease burden
- vaccinations
- medical visits
- socio-economic factors....

Synthetic patients go through clinical journeys per disease module

Synthetic data from Synthea can be exported

• standardised formats such as FHIR

A disease module simulates patients using:

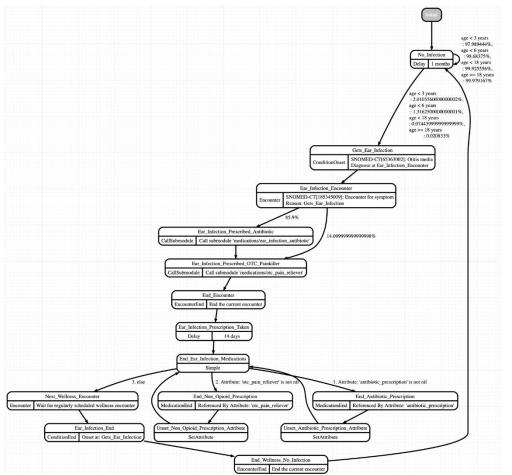
- recommendations from clinical guidelines
- findings from literature
- experts' opinions

### Over 60 modules

• Over >70 submodules



### Example of Synthea disease module



```
"name": "Ear Infections".
"states":
 "Initial": {
   "type": "Initial",
   "direct_transition": "No_Infection",
   "name": "Initial"
  ł,
 "No_Infection": {
   "type": "Delay".
   "exact":
      "quantity": 1,
     "unit": "months"
    "complex_transition": [
        "condition": {
          "condition_type": "Age",
         "operator": "<",
          "quantity": 3,
          "unit": "years"
       "distributions": [
            "distribution": 0.02010556.
            "transition": "Gets_Ear_Infection",
            "remarks": [
              "72.38% of children < 3 get an ear
               infection. This gives an incidence
               of .7238 / (3 * 12) = 0.020105556
                per month",
              "Source: https://www.nidcd.nih.gov
               /health/statistics/ambulatory-care
                -visits-diagnosis-otitis-media"
            "distribution": 0.97989444.
            "transition": "No_Infection"
```



## Data generated with Synthea

 21	lorgioc ocu
 aı	lergies.csv

- 😬 careplans.csv
- claims\_transactions.csv
- 🗈 claims.csv
- conditions.csv
- devices.csv
- encounters.csv
- imaging\_studies.csv
- immunizations.csv
- medications.csv
- observations.csv
- organizations.csv
- patients.csv
- payer\_transitions.csv
- payers.csv
- procedures.csv
- 🖭 providers.csv
- 📄 supplies.csv

	Patients											
Id	BIRTHDATE	DEATHDATE	DRIVERS	FIRST	LAST	MARITAL	GENDER	СІТҮ	LAT		HEALTHCARE EXPENSES	INCOME
0829aa3c	11/10/2021			Kristen940	Wolf938		F	Seisia	-10.86021218	142.3901182	7345.27	13222
b44e0d21	5/2/1977		\$99978024	Valentin929	Cummings51	М	М	Morningside	-27.45419732	153.0762477	55191.9	4588
a4ffdc0	7/11/2006		S99925423	Venus149	Wuckert783		F	Kedron	-27.44963239	153.068354	68195.31	12952
aee03c13	7/9/2018			Alfred550	Graham902		М	Little Mountain	-26.81196347	153.1004452	12637.75	40971
c9068102	11/7/1962		\$99946901	Shanita956	Rippin620	м	F	Elanora	-28.13850819	153.4756598	1018411.71	13670

Observations								
DATE	PATIENT	ENCOUNT ER	CATEGORY	CODE	DESCRIPTION	VALUE	UNITS	
2021-10-10T13:45:53Z	0829aa3c	a2ab0d59	vital-signs	8302-2	Body Height	53.1	cm	
2021-10-10T13:45:53Z	0829aa3c	a2ab0d59	vital-signs	72514-3	Pain severity - 0-10 verbal numeric rating	3.0	{score}	
2021-10-10T13:45:53Z	0829aa3c	a2ab0d59	vital-signs	29463-7	Body Weight	5.3	kg	
2021-10-10T13:45:53Z	0829aa3c	a2ab0d59	vital-signs	77606-2	Weight-for-length Per age and sex	99.0	%	

	Medications							
START	STOP	PATIENT	PAYER	ENCOUNTER	CODE	DESCRIPTION	BASE_COST	REASONDESCRIPTION
2022-09-05T13:45:53Z	2022-09-19T13:45:53Z	0829aa3f	b1c428d6	eb1bea60	198405	lbuprofen 100 MG Oral Tablet	332.58	
2018-02-28T09:20:05Z	2018-03-16T09:20:05Z	b44e0d21	b1c428d6	6e0a0b1e	313782	Acetaminophen 325 MG Oral Tablet	212.34	Acute bronchitis (disorder
2012-12-06T04:54:31Z	2012-12-21T04:54:31Z	a4ffdc0b	b1c428d6	e9b9e36b	198405	Ibuprofen 100 MG Oral Tablet	136.66	
2013-02-28T13:34:24Z	2013-03-10T09:34:24Z	a4ffdc0b	b1c428d6	9c905a18	834061	Penicillin V Potassium 250 MG Oral Tablet	244.33	Streptococcal sore throat
2019-11-25T06:12:31Z		a4ffdc0b	b1c428d6	f269def7	861467	Meperidine Hydrochloride 50 MG Oral Tablet	4772.04	



## Generation of 117,258 synthetic patients (QLD)

#### Diabetes Hypertension 100 100 Prevalence of hypertension (%) Prevalence of diabetes (%) 75 75 50 50 25 25 Age groups (years) Age groups (year Alzheimer's disease Chronic kidney dis Prevalence of chronic kidney disease (%) Prevalence of Alzheimer's disease (%) 100 75 50 25 6.6.6.6.6.6.6.6.6.6.6.6. Age groups (years) Age groups (years)

Example showing four co	ommon chronic conditions	Patient characteristics within disease cohorts				
Diabetes	Hypertension					
	Lion- 100- 75- 25- 25- 25-	Diabetes	Chronic kidney disease	Alzheimer's disease		
		<ul> <li>70% metabolic syndrome</li> <li>63% diabetic renal</li> </ul>	<ul> <li>67% prescribed oral hypertension treatment (Lisinopril 10mg tablet)</li> </ul>	•100% dementia management plan		
Age groups (years)	Age groups (years)	disorder				
Alzheimer's disease	Chronic kidney disease	<ul> <li>51% diabetes-related microalbuminuria</li> </ul>				
tevalence of Alzheimer's disease (%)	ysp 75- typologic kidnes 50- 50- 25-					
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Australian e-Health

**Research Centre** 

CSIRO

### Summary

Synthea's methodology follows expert-curated patterns

- realistic without requiring real data
- reduced burden of administrative requirements for access



Limitations of disease modules based on literature

model may deviate from Australian healthcare intricacies



Limitations of current Synthea architecture

does not capture disease relationships outside each module



Current work: machine learning-based data generation

to capture clinical complexities present in real-world data





# Thank you

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### Health Intelligence @ CSIRO AEHRC



Health System Productivity & Efficiency Operational & Clinical Decision Support Evidence-driven Policy & Healthcare Delivery