



See-Kiong Ng, National University of Singapore

















PATIENTS. AT THE HE RT OF ALL WE DO."



### **Growing Prevalence of DHL**

### Primary Care is the first contact and principal point of continuing care for the chronic patients Near to 2 million visits to polyclinics (SHP) per year • Majority are for chronic conditions like DHL





Stroke  $\rightarrow$  Handicapped Kidney failure  $\rightarrow$  Dialysis



Diabetic eye disease → blindness



Vascular disease → amputation SingHealth DukeNUS



### **AI in Health Grand Challenge**

"How can Artificial Intelligence (AI) help primary care teams stop or slow disease progression and complication development in DHL patients by 20% in 5 years?"



FAMILY MEDICINE

**AI SINGAPORE** 

### Al-enabled Chronic Care – The 3 `P's

#### 1. Reactive care to <u>P</u>redictive care



Source: Robert Graham Center – The Contemporary Ecology of US Medical Care

Classification task to identify at-risk patients



Low care needs

### Al-enabled Chronic Care – The 3 `P's

### 2. One-size-fits-all to Personalized care

#### CHRONIC CARE ALGORITHMS DIABETES MELLITUS (DM): DM Medications (available

Biguanides Decreases hepatic gut, and increase i	glucose productio	n, decrease cu trail insulin sen	atohydrate absorption in the sitivity
Generic Name	Brand Name	Doses (min- max)	Prescribing notes/ caution
Metformin HCL	Glucophage, generic Metformin	500-3000 mg/day	Avoid in patients with low GFR and raised creatinine     May cause metallic sensation in the mouth and reduce appetite     Useful for obese patient     Recommended as first line monotherapy in most Type 2 DM patients

Sulphonylureas Stimulate increase	d insulin productio	n		
Generic Name	Brand Name	Doses (min/max)	Prescribing notes/ caution	
Gliclazide	Diamicron	80-320mg/day		
Glimepiride	Amaryl	1-8mgiday		
Glipizide	Glucotrol	2.5-40mg/day	15 mg bd optimal for most cases	
Glibenclamide	Diabeta, Glynase, Micronase	1.25-20mg/day	Long acting. Avoid in those > 60yo, CKD, Muslims (Ramadan)	
Tolazamide	Tolinase	100-250mg/day		
Tolbutamide	Orinase	1000- 3000mg/day	<ul> <li>Recommended in the elderly, less risk of hypoglycaemia</li> </ul>	

Pioglitizone	Actos	15-45mgiday	gain, edema, CHF, bone fractures (pogitazone, rosigitazone) Myocardial ischeme events (rosigitazon cation: Contraindicated in severe liver disease congestive heart failure. Need to monitor live enzymes Associated with bladder cancer
Rosiglitizone	Avandia	4-8mg/day	<ul> <li>Contraindicated in those with previous MI.</li> </ul>
Rosigitizone Alpha Glucosi Interferes with ca Generic Name	Avandia dase Inhibitors rbohydrate absor	4-8mg/day	those with previous MI.
			caution • Side effects: Gi effects (flatulence, dianthea)

	Insulins Injected to repla	ce or suppleme	ent natural insulin	
	Generic Name	Brand Name	Mode of action	Prescribing notes caution
	insulin aspart	Novolog, NovoRapid	Very fast	Hypoglycemia, weight gain for all insulin
8	insulin lispro	Humalog	Very fast	
Analo	glulisine	Apidra	Very fast	
	insulin	Lantus	Very slow	Pen
	insulin detemir	Levernir	Very slow	Pen
(es	Motard	70/30,50/50, 75/25	fast and intermediate	Penfill or vial
-e-u-	Novomix	70/30	fast and intermediate	Pen
	Insulio	Humulio		
Human recombinant insulins (rDNA)	Regular, Actrapid		Fast	Vial
		NPH(N), Insultard	Intermediate	Vial

#### **Optimization task**

Look for best effectiveness for least chance of side effect based on each patient's profile





FAMILY MEDICINE

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Glipizide	Meta	glip	250-2.5/2	000-20	
Amylin	Syml	in	15ug-120	ug	
Extenatide	Byett	a 5ug-10ug			
called increti insulin and in Generic	ns. Results shibits gluci Brand	in prolon agon in a Doses	ged action of glucose-depe (min/max)	latter, which indent way	Prescribing
Sitagliptin	Januvia	100 mg clearan 50 mg	OM (if creatin ce > 50 ml/mi OM (Cr Cl 30-	nine n) 50 ml/min)	Costly.
		50 mg (	OM (Cr OM (Cr	CI 30- CI <30	Cl 30-50 ml/min) Cl <30 ml/min)

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### Al-enabled Chronic Care – The 3 P's

### 3. Passive to Em<u>P</u>owered patients



 → ownership for health decisions and own health outcomes
 → Motivation to comply with treatment

Motivation to participate in **self-monitoring and self-care** (e.g. self-monitoring of blood glucose)



# JARVIS<sub>DHL</sub> Objective



for right-siting of at-risk individuals.



3.

From passive to em<u>P</u>owered patients





JARVIS<sub>DHL</sub>
 360° knowledge about
 patient with clinical +
 patient reported data.

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# **JARVIS** ("Just" A Rather Very Intelligent System)



### **Data-driven Al**



- Continuously learn from local primary care DATA to provide individualized evidence-based decision support to physicians to facilitate shared-decision making (SDM) with patients
- Harvest next-generation healthcare and lifestyle tracking DATA to include behavior and lifestyle data for <u>360-degree 24/7 view</u> of the patient



Al algorithms that are efficient, robust, and explainable to

- quantify benefits of treatment and risk of complications
- adapt customized treatment regimen according to lifestyle
- alleviate patient anxiety over perceived side effects
- support robust clinical decision-making
- recommend evidencebased treatment options



### **AI for Chronic Care: Considerations**

### 1. Efficiency

 Deep neural architecture with small footprint and high accuracy

### 2. Robustness

 Robust learning with self-regularization and non-linear kernels

### 3. Complexity

Multi-objective learners for understanding complex interactions

### 4. Explainability

 Automatic generation of explanations based on machine learning and database techniques

### 5. Causality

 Inference of models from clinical and lifelog data



### **Stage 1: Research Findings**

Predicting high risk pts for DM complications	<ul> <li>Developed RNN-Survival based on Temporal Point Process Model to identify diabetes patients who are at-risk of MACE complications in 1, 2, 5 years.</li> <li>Measure the risk of both new and repeated MACE events and predict the next event time.</li> <li>Validated on Singhealth Diabetes Registry (SDR) Data.</li> <li>Out-performs state-of-the-art model in terms of c-index for MACE complications in SDR and MIMIC-III dataset.</li> <li>Dashboard for prediction of diabetes complication is done and demonstrated.</li> <li>Next: Extend prediction to Kidney, eye and foot complications</li> </ul>
Patient similarity analytics for shared decision making	<ul> <li>Designed and developed machine learning method to infer the distance metric for the identification of similar patients for shared decision making.</li> <li>Initial results have shown a substantial agreement of 0.707 between the learned distance metric and 2 physicians</li> </ul>
Personalized treatment effectiveness for local population	Local data on statin treatment effectiveness based on real-world data varies from what is known from trial-based studies mostly conducted on Caucasian populations. (e.g. trial-based = statin initiation lowers LDL by 30-60%- ours was 20-30%, trial-based = doubling statin dose lowers LDL by about 6%, we found that uptitration lowered LDL by 12-24%) Next: To work on diabetic and hypertension medications.
Predicting CVD risk	Low cost CVD screening tool reduce unnecessary clinical tests and cardiac stress imaging for CVD risk stratification. [(questionnaire surveys variables, 24hours vitals monitoring, clinical blood investigation and data from wearable device)]
Diabetic screening using SIVA- DLS for automated measurement of retinal vessel calibers from retinal images	High agreement of between 082 to 0.95. SIVA-DLS found to have association with CVD risk factors, incident CVD and with mortality. Next: Linking of SIVA-DLS data with Diabetes main registry to prediction of macro and micro SingHealth DukeNUS vascular complications

## JARVIS<sub>DHL</sub> Timeline



2021	2022-24	2023-24
•	۲	•
•	۲	•
Fine-tuning of models and pilot interfaces for deployment	• Multi-site, adaptive, multi- modality, real-world, hybrid,	Evaluation of process, clinical and patient reported outcomes

- · Models/algorithms validated and improved
- Design of interventions finalized • based on each tool
- Study protocols finalized for each theme

implementation trial

- Deployment of tools in implementation trial
- Refinement of models, tools, platform etc.

- Evaluate outcomes
- Prepare for manuscripts
- Prepare for wider deployment and implementation at a health systems level.



# JARVIS<sub>DHL</sub> AI Tools





# Newsweek.

38.02.2017

#### THE DOCTOR WILL SEE YOU NOW

HOW AI IS GOING TO CURE OUR SICK HEALTH CARE SYSTEM

08321





### **Laypersons' Assumptions**



# Al Accuracy: What You Teach is What You Get



#### "Exploring the ChestXRay14 Dataset: Problems"

https://lukeoakdenrayner.wordpress.com/2017/12/18/the-chestxray14-dataset-problementh DukeNUS

### AI Ethics: Bias begets Bias (algorithmically!)



Source: U.S. Equal Employment Opportunity Commission. (n.d.). 2014 job patterns for minorities and women in private industry. Note: Figures do not add up to 100 percent due to rounding. "Barriers and Bias: The Status of Women in Leadership" (2016) SingHealth DukeNUS ACADEMIC MEDICAL CENTRE

### **Automated Propagation**



### Al Security: It's not as smart as you'd think!



Camouflage graffiti and art stickers cause a neural network to misclassify stop signs as speed limit 45 signs or yield signs

"Robust Physical-World Attacks on Desert Models" Evtimov et al (2017)



# Al Security: It's not as smart as you'd think!

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**Original image** 

Dermatoscopic image of a benign melanocytic nevus, along with the diagnostic probability computed by a deep neural network.





The patient has a history of back pain and chronic alcohol abuse and more recently has been seen in several...

#### **Opioid abuse risk: High**



#### Adversarial noise



Perturbation computed by a common adversarial attack technique. See (7) for details.

#### Adversarial example



Combined image of nevus and attack perturbation and the diagnostic probabilities from the same deep neural network.



272.2 Hyperglyceridemia429.9 Heart disease, unspecified278.00 Obesity, unspecified



**Reimbursement: Approved** 

### Adversarial attacks on medical machine learning

BY SAMUEL G. FINLAYSON, JOHN D. BOWERS, JOICHI ITO, JONATHAN L. ZITTRAIN, ANDREW L. BEAM, ISAAC S. KOHANE SCIENCE22 MAR 2019 : 1287-128









SingHealth DukeNUS

# JARVIS<sub>DHL</sub> Team

Collaboration between:



Institute of Data Science



School of Computing











Wynne Hsu (Main PI) Ng





Mong Li Chee Yong Chan Lee

Hock Hai

Тео



Lian Leng Low





SingHealth



Marcus Ong



Ngiap Chuan Tan



Tien-Yin Wong



Amanda Lam



Khung Keong Yeo







