# aiTRIAGE™

### INTELLIGENT TRIAGING SYSTEM FOR PATIENTS

AUTOMATIC & REAL-TIME RISK STRATIFICATION



## Background

- Triage is the clinical process of rapidly screening large numbers of patients to assess severity and assign priority of treatment
- Fast and accurate risk stratification is important to quickly identify patients of higher severity presented to the Emergency Department
- Currently, triage is generally done by nurses and depends on traditional vital signs and other physiological parameters



Chest Pain (CP) Patients in the Emergency Department (ED)

Main questions include:

- Is it life-threatening?
- Monitoring required?
  - Intervention required?
  - Safe to discharge?

# We need answers to these Questions!



### **Motivation**

- Medical resources are limited. Numbers of doctors, nurses, medical facilities may not be sufficient for fluctuating demand
- Traditional vital signs used in triage are not shown to correlate well with short-term or long-term outcomes
- Heart rate variability (HRV) shows potential for predicting hospital outcomes





## Competition

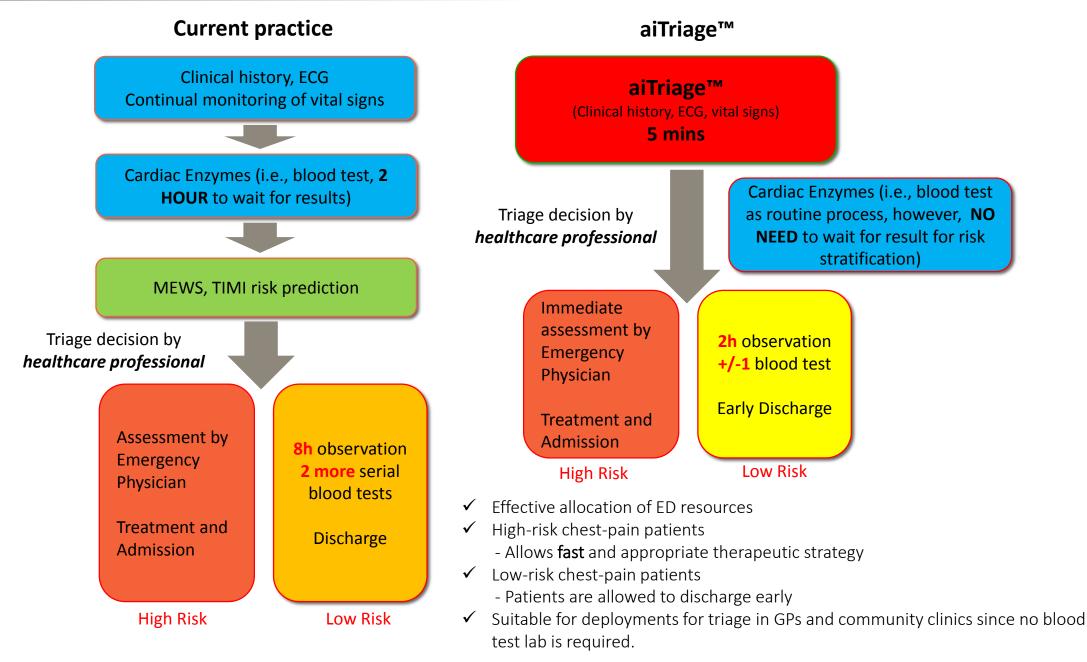
	aiTRIAGE™	MEWS (Gold standard)	ΤΙΜΙ
Parameters	12-Lead ECG, HRV, Blood Pressure, Respiration rate	ECG, Systolic blood pressure, Respiration rate, Temperature, AVPU score	Age, CAD risk factors, Known CAD, ASA used in past 7 days, Severe Angina, ECG ST changes, Positive Cardiac Mark
Equipment	One highly-integrated device	Separate equipment	Separate equipment
Blood Test	No	No	Yes
Time	5 minutes	5 minutes	1 hour (wait for blood test result)
Performance in AUC*	0.76	0.56	0.67

**HL7 Gateway:** CARESCAPE Gateway (GE Healthcare), NIHON KOHDEN HL7 Gateway Server, Infinity<sup>®</sup> Gateway **Disadvantages:** bulky size, mainly used for link with their proprietary monitoring system, costly





### Current practice and new workflow



## Market Opportunity

#### Customer

The system is suitable for large-scale deployment across healthcare facilities, such as **hospital Emergency Departments** (EDs), **GPs, community clinics.** 

#### **Market Size**

- >1 million visits to EDs across Singapore every year
- In the U.S, chest pain is the most common chief complaint in patients ages 65 years and older and second most common in patients ages 15 to 65 years treated in emergency departments. It accounts for over 6 million ED visits in 2001 and increases to over 7 million ED in 2011. Costs are more than \$10 billion/year.
- The worldwide market for cardiac monitoring and diagnostic devices is forecast to grow to \$2.3B by 2017
- With compound annual growth of 10% in the APAC region

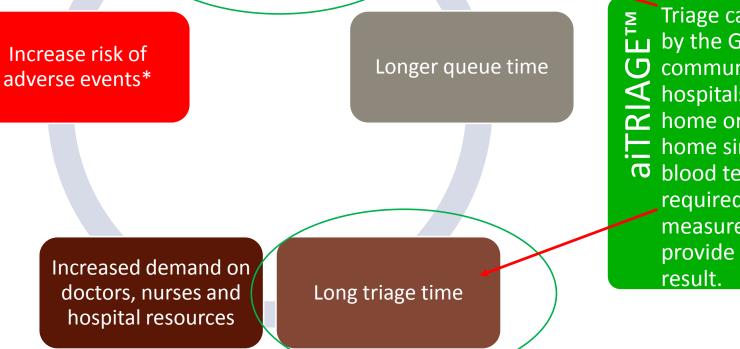
#### **Competitive landscape**

There are **NO commercially available devices** or systems that can provide real time prediction/stratification services for triage.

## Pain points

\* Research shows that the risk of adverse events increased with the mean length of stay of similar patients in the same shift in the emergency department (ED).

Increasing number of chest-pain patients visiting ED



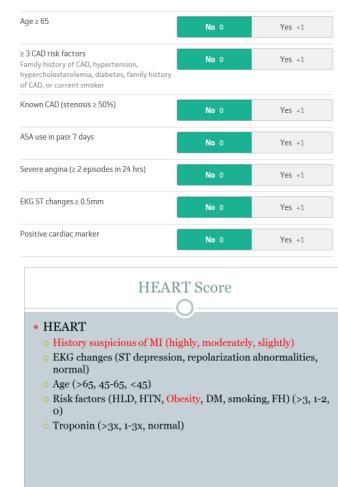
Triage can be done Triage can by the GP, C community A hospitals, nursing home or even at home since NO **r** blood test is required. 5-minutes measurement to provide triage

## Gold standards

#### Modified Early Warning Score (MEWS)

Systolic BP	≤70 mmHg	+3
	71-80 mmHg	+2
	81-100 mmHg	+1
	101-199 mmHg	0
	≥200 mmHg	+2
Heart rate	<40 bpm	+2
	41-50 bpm	+1
	51-100 bpm	0
	101-110 bpm	+1
	111-129 bpm	+2
	≥130 bpm	+3
Respiratory rate	<9 bpm	+2
	9-14 bpm	
	15-20 bpm	+1
	21-29 bpm	+2
	≥30 bpm	+3
Temperature		
	<35°C / 95°F	+2
	35–38.4°C / 95–101.1°F	0
	≥38.5°C / 101.3°F	+2
AVPU Score	Alert	0
	Reacts to voice	+1
	Reacts to pain	+2
	Unresponsive	+3

#### **TIMI Risk Score**

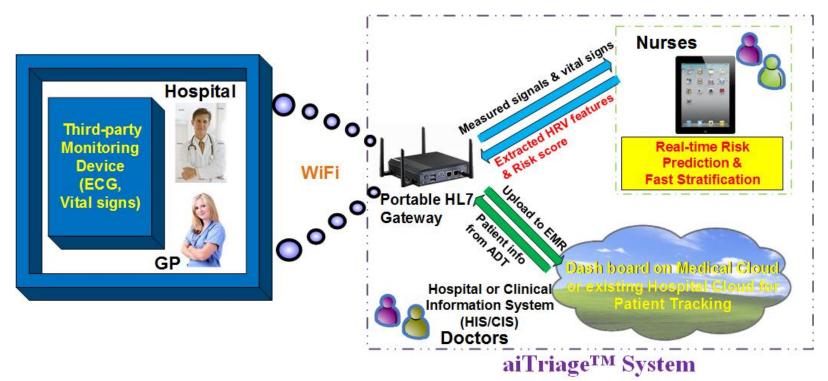


## Solution



#### **Solution**

aiTriage<sup>™</sup>: an intelligent cardiac risk stratification system, incorporates clinical information, heart rate variability (HRV), ECG parameters and vital signs into a scoring system for rapid, real-time risk stratification of MACE



#### **Hardware**

Portable HL7 gateway

#### <u>Software</u>

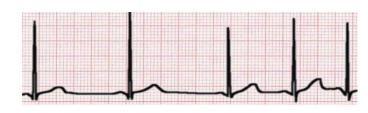
- PAD-based App for feature extraction & risk stratification
- A new dashboard or a module integrate into current existing dashboard

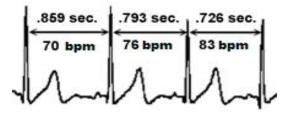
#### <u>Firmware</u>

Link with HIS/CIS for downloading patient info and uploading the risk score in HL7 format

## **Heart Rate Variability**

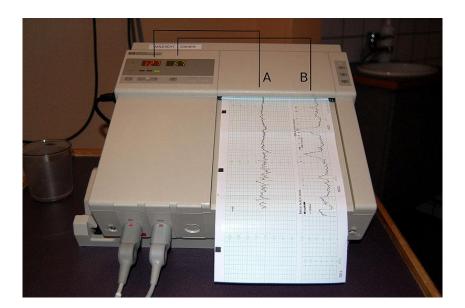
- HRV is the beat-to-beat variation in time interval between heart beats (RR interval) under control of autonomic nervous system
- HRV has shown significant relationship between autonomic nervous system and cardiovascular mortality
- We have previously shown that HRV outperforms vital signs in risk stratification and a combined use of both performs even better



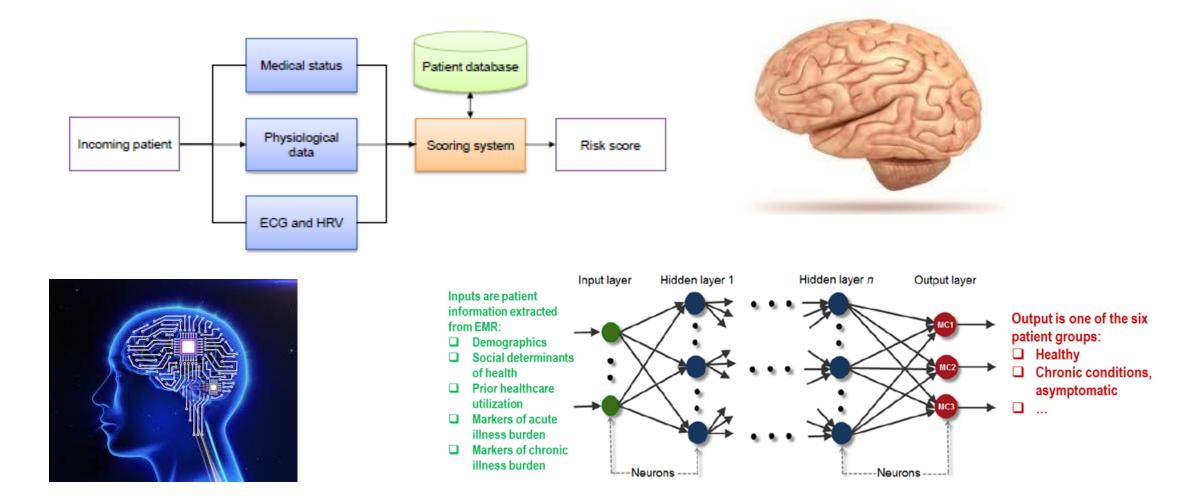


### **Fetal Heart Rate Variability**

- The clinical relevance of HRV was first appreciated in Hon and Lee (Am J Obstet Gynec 1965, 87:814-26) that HRV was correlated to fetal distress
- Cardiotocography (CTG),
  invented by Doctors Alan
  Bradfield, Orvan Hess and
  Edward Hon, is widely used in
  O&G department for fetal
  heartbeat monitoring



## Machine Learning/Artificial Intelligence



### **Our Journal Publications in MACE Prediction**

- 1. Ong MEH, et al. *Resuscitation* 2008; 78: 289-297.
- 2. Liu N, et al. Journal of Signal Processing Systems 2011; 64(2): 265-278.
- 3. Liu N, et al. *IEEE Transactions on Information Technology in Biomedicine* 2012; 16(6): 1324-1331.
- 4. Ong MEH, et al. *Critical Care* 2012; 16(3): R108.
- 5. Ong MEH, et al. American Journal of Emergency Medicine 2013; 31: 1201-1207.
- 6. Liu N, et al. BMC Medical Informatics and Decision Making 2014; 14(1): 75.
- 7. Liu N, et al. International Journal of Cardiology 2014; 176(3): 1091-1093.
- 8. Liu N, et al. *Mathematical Problems in Engineering* 2014; 2014: Article ID 248938.
- 9. Liu N, et al. *IEEE Journal of Biomedical and Health Informatics* 2014; 18(6): 1894-1902.
- 10. Liu N, et al. International Journal of Cardiology 2014; 177(3): 1095-1097.



Contents lists available at SciVerse ScienceDirect

American Journal of Emergency Medicine

### American Journal of Emergency Medicine

#### journal homepage: www.elsevier.com/locate/ajem

**Original Contribution** 

Heart rate variability risk score for prediction of acute cardiac complications in ED patients with chest pain  $\overset{\text{de}}{\xrightarrow{}}, \overset{\text{de}}{\xrightarrow{}}, \overset{\text{de}}{\xrightarrow{}}$ 

Marcus Eng Hock Ong MBBS <sup>a,\*</sup>, Ken Goh MD <sup>b</sup>, Stephanie Fook-Chong <sup>c</sup>, Benjamin Haaland PhD <sup>d</sup>, Khin Lay Wai MBBS <sup>e</sup>, Zhi Xiong Koh <sup>a</sup>, Nur Shahidah <sup>a</sup>, Zhiping Lin PhD <sup>f</sup>

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ARTICLE INFO ABSTRACT

## Initial Risk Prediction model for MACE

#### Table 5

Risk score\* for predicting severe complications within 72 hours of arrival at the ED

Characteristics	Transformed $\beta$ coefficients		Final score	
Heart rate, beat/min				
55-114	0	0	0	
<55	0.77	1	1	
≥115	1.14	1.48	1	
SBP, mm Hg				
>140	0	0	0	
90-140	1.88	2.44	2	
<90	3.21	4.17	4	
Respiratory rate, breath/min				
0-20	0	0	0	
>20	1,31	1.7	2	
LF/HF ratio				
>0.9	0		0	
0.3-0.9	1.33	1.73	2	
<0.3	2,4	3.12	3	

\* Risk score ranges from 0 to 10.

## Model Performance

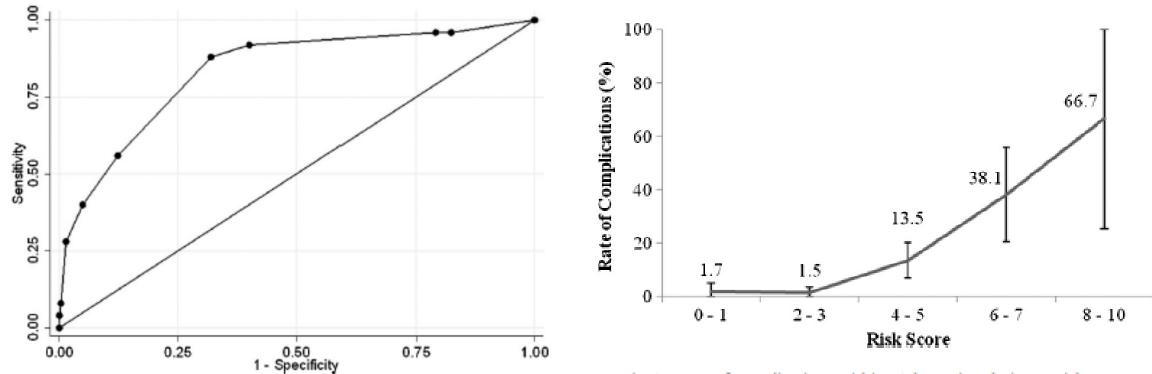
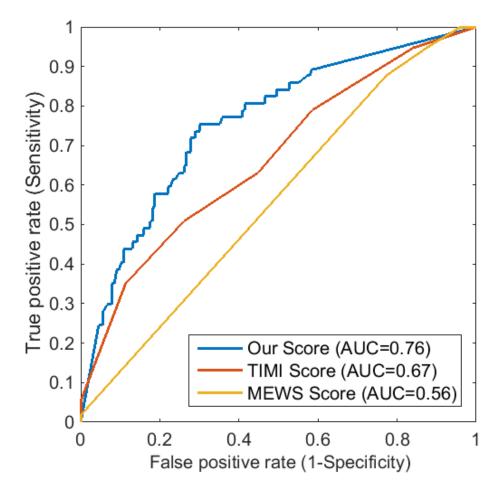


Fig. 1. Receiver operating characteristic analysis of risk score in predicting severe complications with 72 hours at the ED.

Fig. 3. Rates of complications within 72 hours in relation to risk score.

1. Collaborating with DxD in 6-month Exploratory Project, interim study using new data sets validated that aiTRIAGE<sup>™</sup> has superior performance than MEWS and TIMI



Model Derivation Set: 564 patients (data collected from 15 Sep 2010 to 16 Oct 2013)

Model Validation Set: 233 patients (data collected from 17 Oct 2013 to 10 Jul 2015) Outcomes: Major Adverse Cardiac Events (MACE) within 30 days

Note that due to small validation set, patient distributions in derivation set and validation set are different

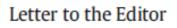
Patients	Derivation set	Validation set
Total	564	233
MACE	191 (34%)	57 (25%)
No MACE	373 (66%)	176 (75%)



Contents lists available at ScienceDirect

### International Journal of Cardiology

journal homepage: www.elsevier.com/locate/ijcard



Risk stratification for prediction of adverse coronary events in emergency department chest pain patients with a machine learning score compared with the TIMI score  $\stackrel{i}{\approx}$ 



CARDIOLOGY

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American Journal of Emergency Medicine

journal homepage: www.elsevier.com/locate/ajem

Integrating heart rate variability, vital signs, electrocardiogram, and troponin to triage chest pain patients in the ED

Jeffrey Tadashi Sakamoto, MD<sup>a,1</sup>, Nan Liu, PhD<sup>b,c,\*,1</sup>, Zhi Xiong Koh, BEng<sup>d</sup>, Dagang Guo, PhD<sup>d</sup>, Micah Liam Arthur Heldeweg<sup>e</sup>, Janson Cheng Ji Ng<sup>d</sup>, Marcus Eng Hock Ong, MBBS<sup>d,f</sup>

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\* Faculty of Medical Sciences, University of Groningen, Netherlands

<sup>f</sup> Health Services and Systems Research, Duke-NUS Medical School, Singapore

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ABSTRACT

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American Journal of Emergency Medicine Hock Ong et al. Critical Care 2012, 16:R108 http://ccforum.com/content/16/3/R108



### RESEARCH

Open Access

Prediction of cardiac arrest in critically ill patients presenting to the emergency department using a machine learning score incorporating heart rate variability compared with the modified early warning score

Marcus Eng Hock Ong<sup>1\*</sup>, Christina Hui Lee Ng<sup>2</sup>, Ken Goh<sup>3</sup>, Nan Liu<sup>1</sup>, Zhi Xiong Koh<sup>1</sup>, Nur Shahidah<sup>1</sup>, Tong Tong Zhang<sup>1</sup>, Stephanie Fook-Chong<sup>4</sup> and Zhiping Lin<sup>5</sup>

#### A NOVEL HEART RATE VARIABILITY BASED RISK PREDICTION MODEL FOR PATIENTS PRESENTING TO THE EMERGENCY DEPARTMENT WITH SEPSIS

Mas'uud Ibnu Samsudin<sup>1</sup>, Nan Liu<sup>1,2</sup>, M Sumanth<sup>3</sup>, Shuling Chong<sup>4</sup>, Zhi Xiong Koh<sup>2</sup>, R Rajesh<sup>3</sup>, Andrew Fu Wah Ho<sup>2</sup>, Marcus Eng Hock Ong<sup>1,2</sup> <sup>1</sup>Duke-NUS Medical School, Singapore; <sup>2</sup>Singapore General Hospital, Singapore; <sup>3</sup>National University of Singapore, Singapore; <sup>4</sup>KK Women's and Children's Hospital, Singapore





#### **Background**:

- Sepsis is highly prevalent condition presenting more in the Emergency Department (ED) than the wards with up to 20% inhospital mortality (IHM) rates.
- An accurate, objective, non-invasive, quantitative means of identifying high-risk septic patients early can potentially improve outcomes in the ED.
- Currently available risk assessment tools utilize either traditional vital signs alone or often require time-consuming laboratory investigations and subjective physician assessment of patients.
- Heart rate variability (HRV) analysis has been shown to correlate with mortality in critically ill patients.

#### Aims:

- Identify significant predictors of 30-day IHM in septic patients presenting to the ED using patient demographics, vital signs and HRV parameters and develop a risk prediction model (SGH ED Sepsis, SEDS)
- Compare its performance with the Modified Early Warning Score (MEWS), National Early Warning Score (NEWS) and quick Sequential Organ Failure Assessment (qSOFA) score.

#### Patients & Methods :

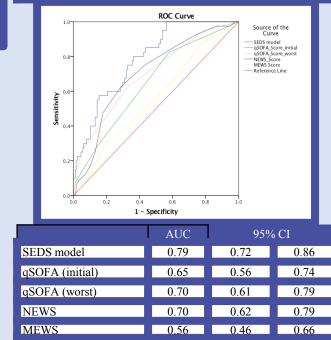
- All patients clinically suspected to have sepsis and met the Systemic Inflammatory Response Syndrome (SIRS) criteria were included.
- Routine triage 6-minute ECG segments were collected and processed to obtain HRV variables.
- The primary endpoint was a 30-day in-hospital mortality (IHM).
- Variables were selected by univariate analyses for significance. Multivariate logistic regression method was used to derive the risk prediction model.
- MEWS, NEWS and qSOFA (based on initial and worst measurements in the ED) scores were computed for each patient.
- Predictive performance of our model and the computed scores were compared using the the receiver operating curve (ROC).

#### **Results:**

- Out of 214 patients, 40 (19%) met the primary outcome.
- 22 variables including 2 demographic parameters, 4 vital signs and 16 HRV parameters were selected as covariates in developing the prediction model.
- The final SEDS model comprise of 5 variables including 2 HRV parameters.
- The SEDS model performed with AUC of 0.78 (95%CI: 0.72–0.86), compared to AUC of 0.65 (95%CI: 0.56–0.74), 0.70 (95%CI: 0.61–0.79), 0.70 (95%CI: 0.62–0.79), 0.56 (95%CI: 0.46–0.66) by the qSOFA (initial), qSOFA (worst), NEWS and MEWS respectively.

No 30-day IHM (n=174)30-day IHM (n=40)p-valueDemographics $Age, mean (SD)$ $65.0 (16.0)$ $75.0 (14.0)$ $0.001$ Medical History, n (%)Ischemic Heart Disease $38 (21.8)$ $14 (35.0)$ $0.080$ Vital signs, mean (SD)118.9 (20.9) $113.4 (24.4)$ $0.149$ Heart rate (bpm) $20.1 (3.7)$ $22.7 (5.1)$ $0.004$ Systolic BP (mm Hg) $118.8 (32.3)$ $110.0 (32.2)$ $0.124$ GCS (3-15) $13.5 (2.8)$ $11.9 (4.2)$ $0.025$ HRV parameters, mean (SD)Time domain $Mean NN (s)$ $553.8 (108.2)$ $590.6 (145.7)$ $0.072$ SD NN (s $24.5 (27.2)$ $39.9 (38.0)$ $0.019$ Mean HR (bpm) $112.6 (20.2)$ $108.0 (24.4)$ $0.211$ SD HR (bpm) $5.4 (6.2)$ $7.9 (7.8)$ $0.030$ RMSSD (s) $30.4 (41.0)$ $53.3 (57.0)$ $0.021$ NN50 (count) $58.5 (127.6)$ $87.7 (131.5)$ $0.196$ pNN50 (%) $9.0 (19.5)$ $15.2 (22.7)$ $0.081$ NN Triangular index $4.3 (4.2)$ $5.5 (6.6)$ $0.148$ TINN $164.0 (169.1)$ $233.4 (203.0)$ $0.026$
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NN Triangular index      4.3 (4.2)      5.5 (6.6)      0.148
TINN $164.0(169.1)$ $233.4(203.0)$ 0.026
11111    104.0 (107.1)    255.4 (205.0)    0.020
Total Power (ms2)724.3 (2205.5)1728.8 (3953.5)0.128
Frequency Domain
VLF Power (ms2) 138.5 (370.7) 370.3 (1080.3) 0.188
LF power (ms2) 180.0 (607.3) 396.0 (985.5) 0.190
HF power (ms2) 402.6 (1270.7) 956.3 (2056.9) 0.109
LF power norm (nu) 46.5 (29.0) 32.9 (25.7) 0.005
HF power norm (nu) 52.8 (28.6) 66.4 (25.4) 0.004
Non-linear domain
Poincare plot SD1 (ms) 21.5 (29.0) 37.7 (40.4) 0.020
Poincare plot SD2 (ms) 25.7 (26.7) 40.4 (37.1) 0.022
DFA, $\alpha 1$ 0.7 (0.4) 0.6 (0.3) 0.127
DFA, $\alpha 2$ 0.9 (0.4) 0.6 (0.4) <0.001

SEDS model variables	Adjusted OR	95% CI	
Age (years)	1.03	1.00	1.06
Respiratory rate (bpm)	1.13	1.05	1.23
Systolic BP (mmHg)	0.99	0.97	1.00
Mean NN (s)	1.00	1.00	1.01
DFA (α2)	0.20	0.08	0.55



#### **Conclusion and Perspectives:**

- Both linear and non-linear HRV parameters have been shown to be important predictors of 30-day IHM in septic patients presenting to ED
- First study that shows the incorporation of HRV parameters into a risk prediction model for septic patients, together with traditional predictors such as patient demographics and vital signs can improve the risk prediction performance.

Comparison of a Heart Rate Variability and Complexity Model with other pre-hospital scoring systems in predicting the need for Life-Saving Interventions amongst Trauma patients

AA KUMAR<sup>1</sup>, L NAN<sup>2</sup>, KOH XZ<sup>3</sup>, J CHIANG<sup>3</sup>,

SOH Y<sup>1</sup>, WONG TH<sup>4</sup>, ME ONG<sup>2,3</sup>

<sup>1</sup>YONG LOO LIN SCHOOL OF MEDICINE, NUS, SINGAPORE <sup>2</sup>SINGHEALTH HQ, SINGHEALTH RESEARCH CENTER <sup>3</sup> DEPARTMENT OF EMERGENCY MEDICINE, SGH <sup>4</sup>TRAUMA SERVICE, SGH

### **IP Position & Commercialization strategy**

**Current IP situation** 

- Method of predicting the survivability of a patient, US Patent 61313822, Filed on 15 March, 2010
- System and method of determining a risk score for triage, US Patent 13/791,764, Filed on 8 March 2013
- Another patent in draft

#### **Commercialisation Plan**

- Cardiac arrest prediction algorithm licensed to Zoll Medical Corp (2011). Commercial application now available
- Startup company
- License patent to develop into a product
- Looking for potential public / private investment

Working prototype is ready for more data collection and model refinement\*
 \*The data collection could be processed simultaneously with portable HL7 gateway development



3. Multi-site data collectionCGH (in-principle approval)KKH (in discussion)Hospitals in China (in discussion)

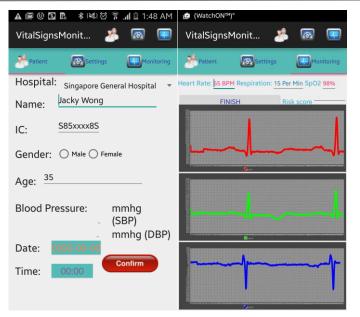
4. IP

- Two patent applications
- Published in > 10 journal papers

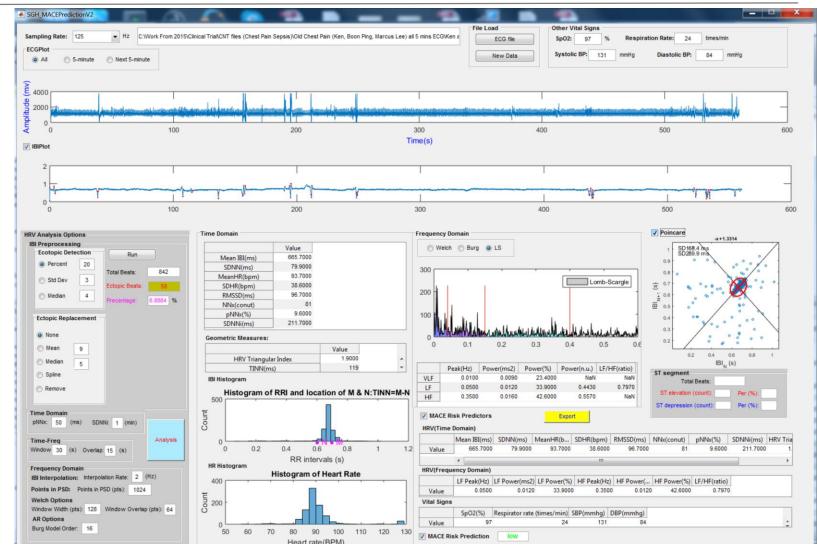
4. Android-based app with basic functions, data display and storage

#### 5. Labview-based signal display and data storage program





6. Matlab-based feature extraction and risk prediction program



### **Intelligent Risk Prediction**

### Wearable Data Acquisition (Portable device)

 Real-time ECG / Photoplethysmography(PPG) / SpO<sub>2</sub> / Continuous Blood Pressure



Prototype device



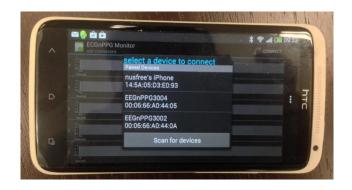
ECG sensor



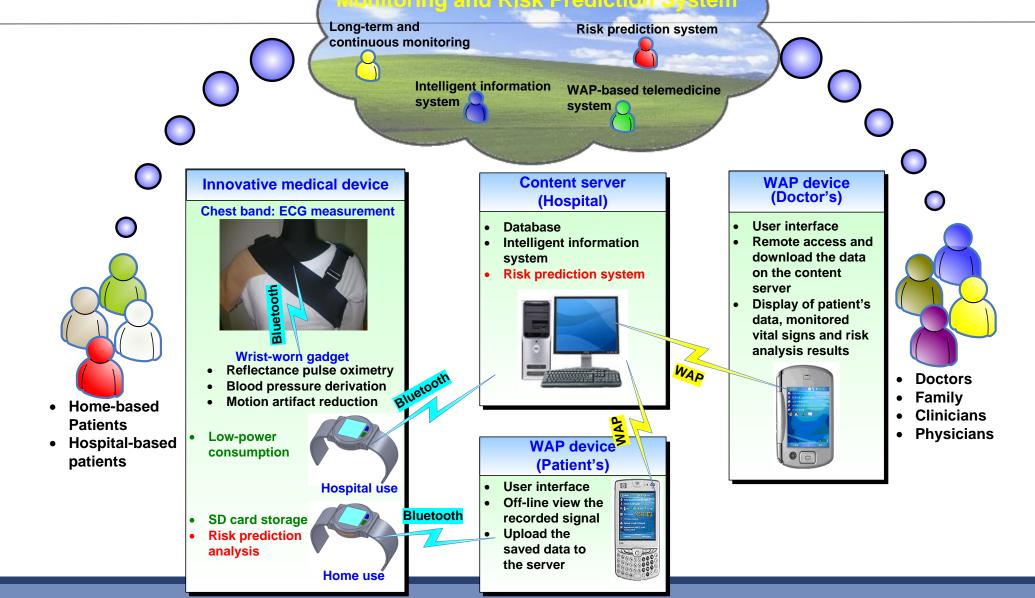
Pulse Oximetry Sensor

### **MACE risk prediction smartphone app**

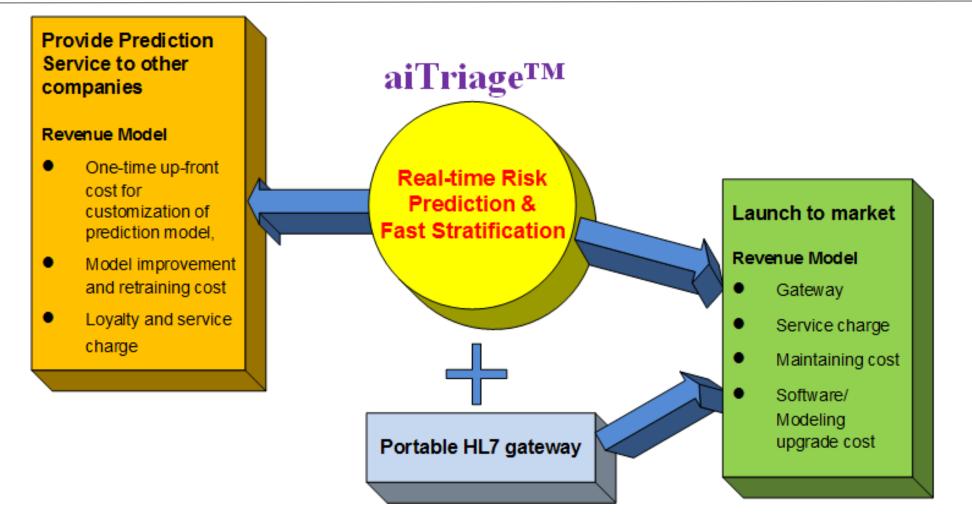
- Advance risk prediction algorithm
- Validated with large clinical database
- Outperform traditional clinical risk scores such as as TIMI score and MEWS



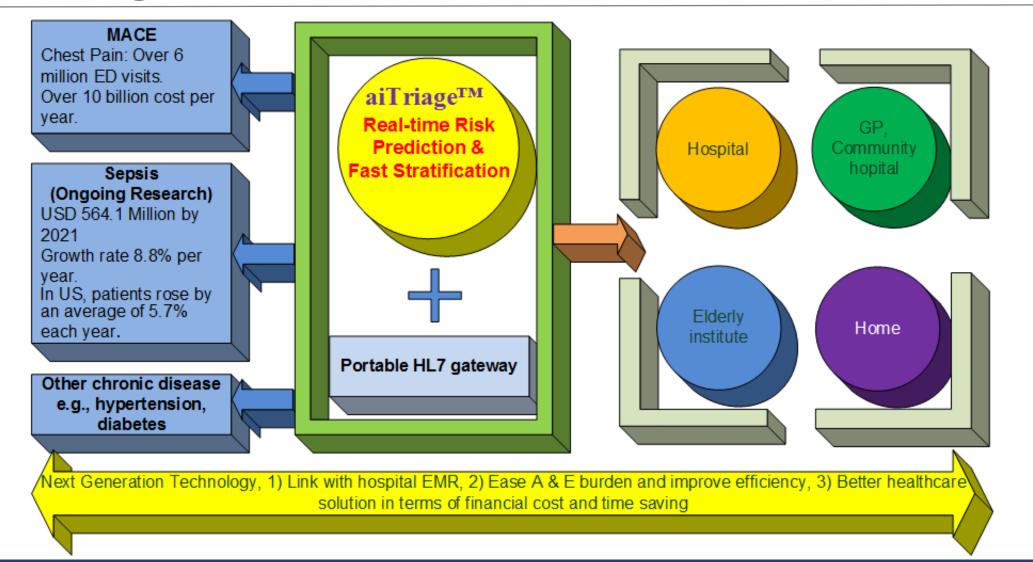
### Wearable, Ambulatory, Automatic Monitoring and Risk Prediction System



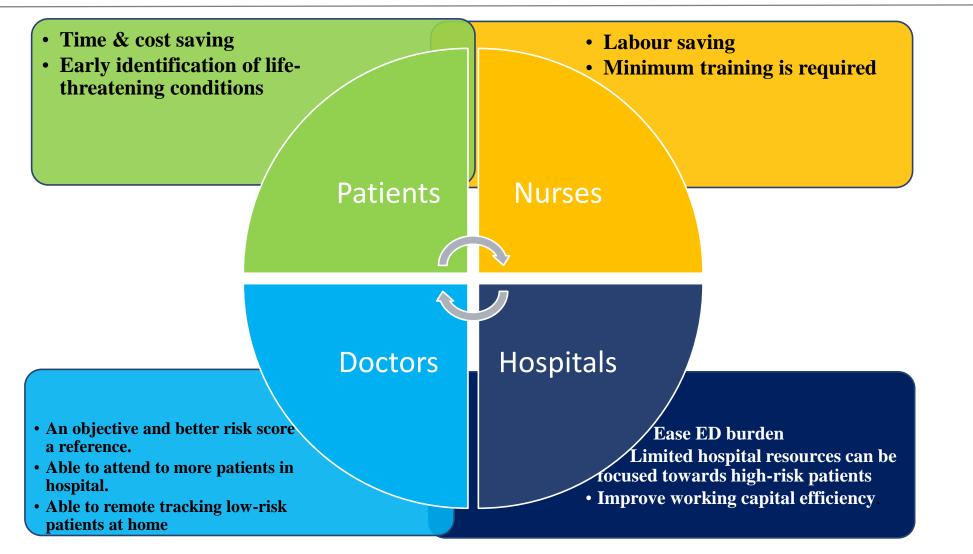
## **Business roadmap**



## Next generation



## Benefits



### Development of a Portable Device for Real-time Risk Stratification of Adverse Cardiac Events

PI: Associate Professor Marcus Ong (SGH)



#### **Clinical Need:**

- Chest pain patients may proceed to a Major Adverse Cardiac Event (MACE)
- Stratify chest pain patients re risk of MACE



#### Solution:

Intelligent software incorporating heart rate variability, ECG, vital signs for rapid real-time risk stratification of chest pain patients



#### Value Proposition:

Early intervention and intensive monitoring of only at-risk patients to reduce clinical workload

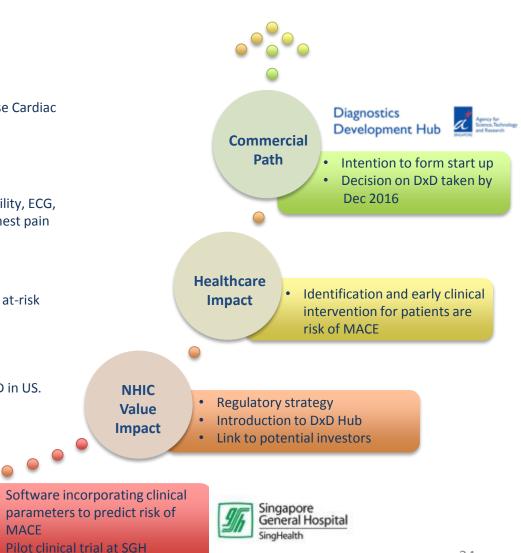


#### **Target Market:**

Chest pain is second principal reason for visits to ED in US. 129.8m visits in US; 120,000 at SGH

> Project Outcome

> > MACE



#### **Project Manager: Sharron Bennett**

## New local software gauges heart attack risk

#### BY MELISSA PANG

PATIENTS with chest pains who enter a hospital emergency room typically have their vital signs taken and are asked about their medical history and the symptoms they are experiencing.

One limitation to doing this is that people have different pain thresholds, so a stoic person may say he has only mild pain when he is really just a heartbeat away from a cardiac arrest.

Also, traditional vital signs such as pulse rate and blood pressure cannot accurately predict how critical the patient's condition is.

With the current mode of medical assessment quite subjective and fraught with limitations, researchers from the Singapore General Hospital (SGH) and Nanyang Technological University (NTU) have developed a computer program that gives an objective measure of a patient's risk of going into cardiac arrest.

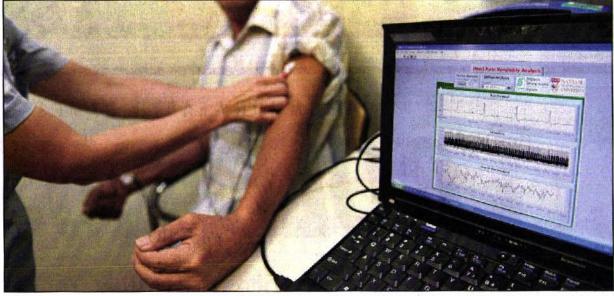
They are working with a commercial partner to incorporate this software into a portable machine to which a patient can be hooked up, so electric signals can be picked up. From these signals, the patient's heart rate variability – the time interval between heartbeats – can be calculated, and the risk of cardiac arrest objectively measured.

This data enables emergency room staff to decide which patient is seen to sooner, said Associate Professor Marcus Ong, consultant and director of research, and senior medical scientist in SGH's Department of Emergency Medicine. He worked with Associate Professor Lin Zhi Ping of NTU's School of Electrical and Electronic Engineering.

"The decision of who gets first priority or a lower priority – this is where the invention is targeted," said Prof Ong.

SGH's emergency room handles 300 to 500 patients a day, almost half with critical conditions such as heart attack, stroke and major trauma.

The professors will present their findings at a scientific congress this weekend.



A patient at a hospital emergency room can be hooked up to a machine running the software, which will calculate the time interval between heartbeats and give an objective assessment of his risk of going into cardiac arrest. It will allow emergency room staff to predict how critical the patient's condition is and prioritise all patients accordingly. ST PHOTO: JOYCE FANG

System and Method of Determining a Risk Score for Triage using Heart Rate Variability

Inventor's Name: A/Prof Marcus Ong Eng Hock Ong, Dr Liu Nan

ealth

## The Team



#### TIIM Pte Ltd (registered Nov 2016)

- ✓ In-licensing of aiTriage<sup>™</sup> from SGH currently in progress
- ✓ SGH, KKH and Changi General Hospital has been involved as clinical sites
- ✓ Collaboration with DxD (ETPL) on exploratory project

#### Founders

Senior Clinician: A/Prof Marcus Ong Eng Hock, Singapore General Hospital ✓ Senior consultant (Ministry of health), Director of Research, Head of Data Analytics in HSRC, Medical Director of UPEC

#### Business Development: Mr Cheng Keng Liang

✓ Over 20 years experience in business operation, creating & nurturing start-ups

#### Machine Learning Specialist: Dr Liu Nan

 $\checkmark$  Over 9 years experience in machine learning, statistics and signal processing

### Product Development: Dr Guo Dagang

✓ Over 10 years experience in wireless sensor network, biomedical device, firmware, hardware & software development

#### Clinical Trial Specialist: Mr Garion Koh Zhi Xiong

✓ Over 9 years experience in clinical trial study and management

**Yh** 

Singapore General Hospital SingHealth







## TIIM Healthcare Pte Ltd

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