Al in Action: Risk Prediction Using Wearable Technologies

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Advancing Heart Care Worldwide

Disclosures

• Employment: Biofourmis

 Consultant/ Advisory Board/ Ownership Interest: Avive, HealthTensor, HiLabs, Neuroglee, SwissRe





Overview / Learning Objectives

- 1. How does/can AI contribute to wearable technologies and physiological monitoring?
- 2. What roles does/will AI play in Hospital at Home?

3. How can AI be used for optimizing medical therapeutics?





Role of AI for Wearable Technologies and Physiological Monitoring





Wearable Technologies and Physiological Monitoring

Increasing Amounts of Health Care-related Data

- Over 23% of the U.S. population wore a smart wearable in 2021 according to eMarketer
- Wireless clinical grade wearables
 - Eases monitoring in H@H and acute care settings





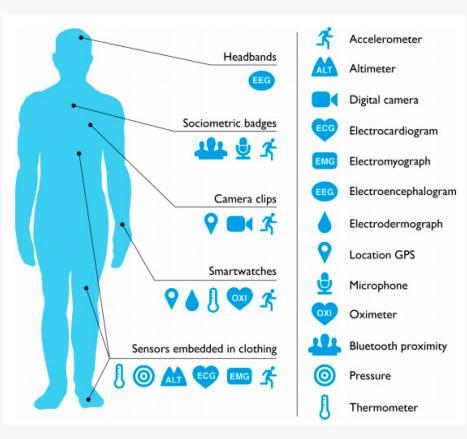






https://www.pewresearch.org/internet/fact-sheet/mobile/ https://www.insiderintelligence.com/insights/wearable-technology-healthcare-medical-devices/ Credit: https://thenounproject.com/

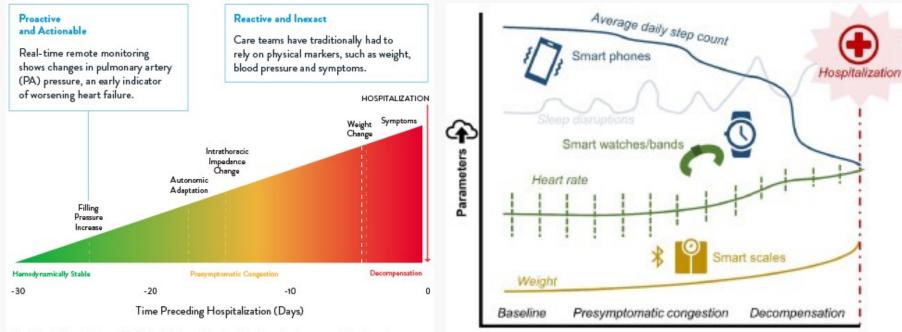
Wearable Health Systems Overview





https://www.ncbi.nlm.nih.gov/pmc/articles/PMC6111409/pdf/sensors-18-02414.pdf https://www.mdpi.com/1235214 ///////OUTFRONT ON EDUCATION

Intermittent vs. Continuous monitoring



Graph adapted from Adamson PB. Pathophysiology of the transition from ohronic compensated and acute decompensated heart failure: new insights from continuous monitoring devices. Current Heart Failure Reports. 2009;6:287-292.

Time

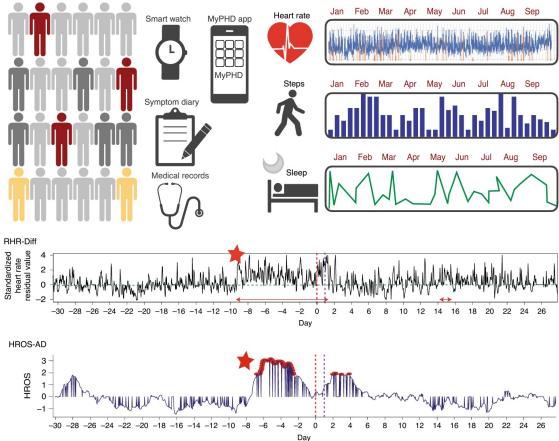
https://www.jhltonline.org/article/S1053-2498(20)31870-2/fulltext; https://www.cardiovascular.abbott/us/en/hcp/products/heart-failure/pulmonary-pressure-monitors/cardiomems/about.html





Article Published: 18 November 2020

Pre-symptomatic detection of COVID-19 from smartwatch data





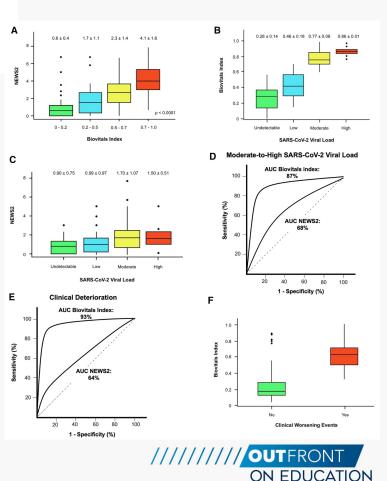
Observational study on wearable biosensors and machine learning-based remote monitoring of COVID- A 19 patients

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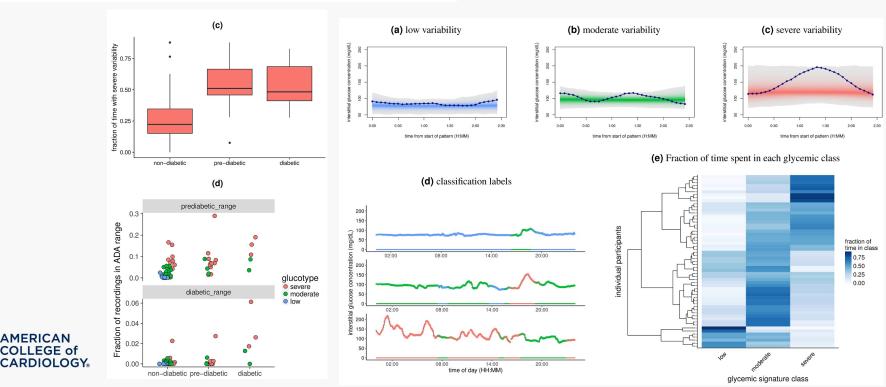




RESEARCH ARTICLE

Glucotypes reveal new patterns of glucose dysregulation

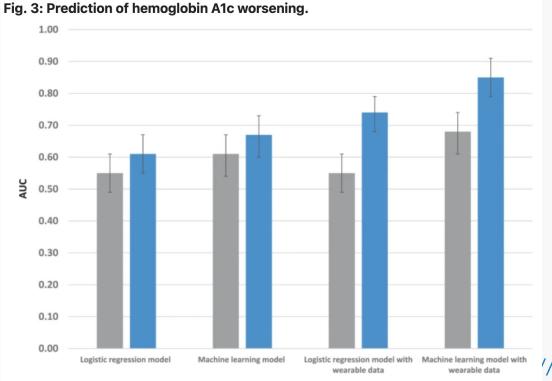
Heather Hall^{1,2®}, Dalia Perelman^{2®}, Alessandra Breschi^{2®}, Patricia Limcaoco², Ryan Kellogg², Tracey McLaughlin³, Michael Snyder²*



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Article Open Access Published: 21 December 2021

Predicting changes in glycemic control among adults with prediabetes from activity patterns collected by wearable devices



Wrist-Worn Arm

■ Waist-Worn Arm

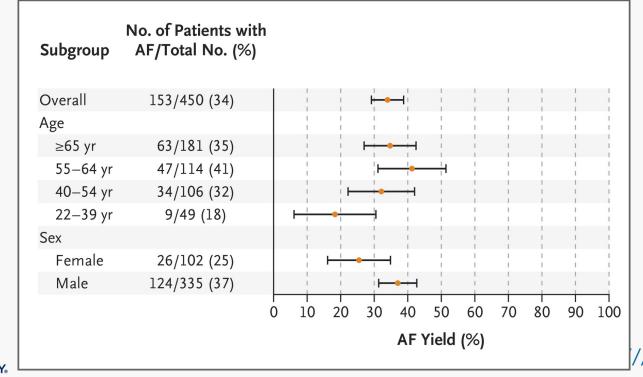




ORIGINAL ARTICLE

Large-Scale Assessment of a Smartwatch to Identify Atrial Fibrillation

Marco V. Perez, M.D., Kenneth W. Mahaffey, M.D., Haley Hedlin, Ph.D., John S. Rumsfeld, M.D., Ph.D., Ariadna Garcia, M.S., Todd Ferris, M.D., Vidhya Balasubramanian, M.S., Andrea M. Russo, M.D., Amol Rajmane, M.D., Lauren Cheung, M.D., Grace Hung, M.S., Justin Lee, M.P.H., et al., for the Apple Heart Study Investigators^{*}



OUTFRON

ON EDUCATION



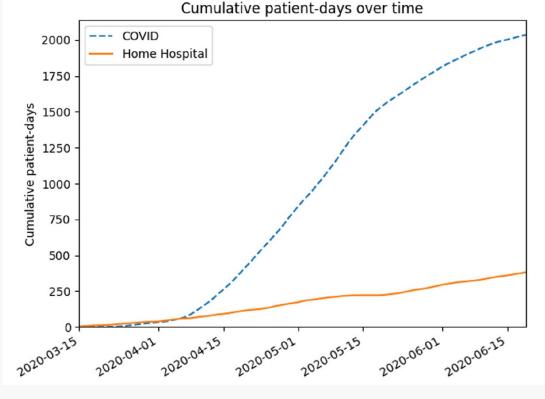
Role of AI for Hospital at Home





Hospital at Home Care During COVID-19 Pandemic

- Increase available hospital staff and resources for critical acute care (e.g. COVID-19 patients during surges in the pandemic)
 - Figure from pilot study, now available at hundreds of hospitals
- Cost of care significantly reduced compared to in-hospital costs
- Quality of patient outcomes better or similar to traditional hospital care
- Increased mobility of patients at home compared to in hospital setting



Acute Care at Home During the COVID-19 Pandemic Surge in Boston, Levine et al., 2021





Sample Hospital at Home Patient Journey

Admission day	Home hospital day 1	Home hospital day 2		Discharge day	TIMING OF STAY
Length of Stay Prediction	Time to Discharge Prediction	Time to Discharge Prediction		Unplanned 30-day Readmission Prediction	
SAMPLE ADMISSION REPORT Length of Stay Prediction > 5 Days	Sample Time to Discharge Prediction Probability of Discharge w/in 48hrs Low	ediction Discharge Prediction Probability of		SAMPLE READMISSION PREDICTION REPORT Risk of Readmission Low	
High Comorbidity Score	Continuous Monitoring with Biovitals Index, Smart Alerts and Rhythm Analytics			High Activity Level No Indication of Anxiety/Depression	
Increasing Weight				High Covariance Activity/HR	
	Day 1 at 9:30 am: " <u>Biovitals</u> Index is high" Day 1 at 12:30 pm: "Blood oxygen saturation below 90% for 15 min" Day 2 at 3:00 am: "Sinus Tachycardia"				





Application of Machine Learning Techniques in Hospital at Home

Model Types	Sample Techniques	Sample Use Cases
Classification	CNN Logistic regression SVM	Arrhythmia interpretation Heart failure subtype classification COPD severity classification Sleep apnea severity estimation
Time series forecasting	LSTM Neural networks Time-series regression	Disease severity and disease progression prediction
Clustering / Pattern recognition	Gaussian mixture models K-means	Activity and vitals pattern learning
Anomaly detection	K-nearest neighbors One-class SVM	Continuous risk score generation Clinical decompensation prediction
Natural language processing	Latent Dirichlet Allocation RNN LSTM	Clinician note interpretation Depression/anxiety detection EHR parsing





Role of AI for Hospital at Home (Example: ECG)

Rapid ECG arrhythmia interpretation

- Assisting clinician in interpreting long term ECG
- Reduce workload of clinician by deprioritise noise and focus only on important arrhythmia only
- Beneficial to patient because it allows to capture real time arrhythmia instead of single spot check

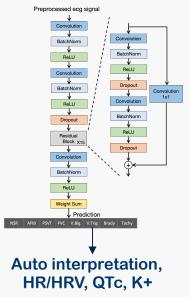
Auto measurement of QTc interval

- Allowing detection of sudden QTc prolongation from patient.
- Allowing new biomarker research of how QTc interval changes throughout patient journey
- Assisting clinician to diagnose patient with new real time event

Estimation of electrolyte abnormalities (K+ estimation from ECG)

- Allowing real time alert of abnormal lab value
- Assisting clinician by providing extra evidence of lab value
- Alert hyperkalaemia / hypokalaemia



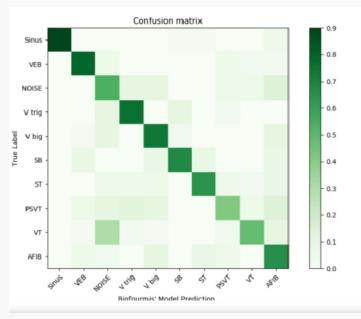






On Arrhythmia Detection by Deep Learning and Multidimensional Representation

	F1 scores				
	Biofourmis' Model	Model(49)	Model(50)	Cardiologists	
Normal Sinus Rhythm	0.924	0.932	0.951	0.911	
Atrial Fibrillation	0.838	0.697	0.752	0.724	
Sinus Tachycardia	0.824	0.794	0.741	0.806	
Sinus Bradycardia	0.847	0.853	0.818	0.827	
Ventricular Bigeminy	0.872	0.882	0.759	0.803	
Ventricular Trigeminy	0.880	0.855	0.731	0.780	
Ventricular Tachycardia	0.746	0.713	0.689	0.784	
PSVT	0.716	0.618	0.602	0.654	
Noise	0.779	0.707	0.632	0.713	
VEB	0.909	0.872	0.824	0.834	
Summary Results					
Specificity	0.982	0.973	0.935	0.952	
Sensitivity	0.908	0.887	0.842	0.860	
F1	0.834	0.792	0.749	0.784	







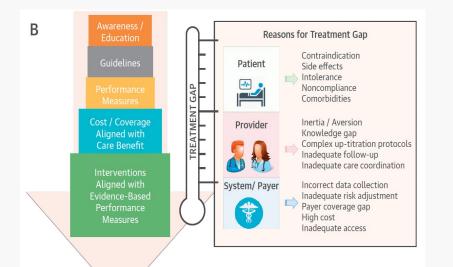
Role of AI for Optimizing Medical Therapeutics





AI for Optimizing Medical Therapeutics

Existing Gap between Therapeutics Guidelines and Clinical Practice



Al Optimized Therapeutics: Reduce the Gap and Optimize Outcome (Engagement, Tailored & Specific titration recommendations)



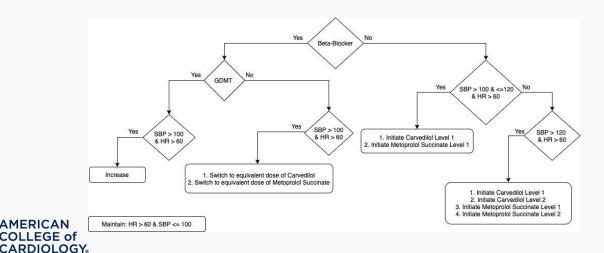


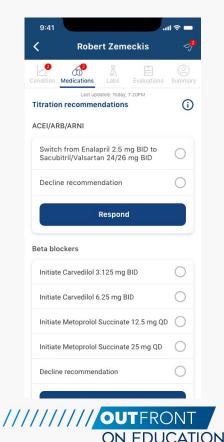


AI for Optimizing Medical Therapeutics (Example)

- Limited to recommendations of initiations and up-titrations of GDMT
- Drug recommendations are based on AHA guidelines and expert inputs
- Decisions to increase the dosage of GDMT or start HF medications will ultimately be made by the treating cardiologist, or qualified designated HCP.

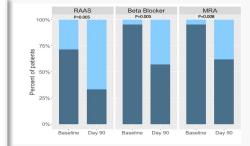
e.g., Titration Algorithm Example

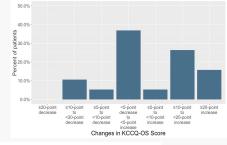


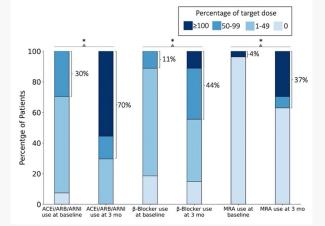


GDMT Optimization – Preliminary Evidence

- N=~30 participated in a run-in phase of a larger RCT
- Objective: To determine whether a remote, software algorithmdriven, medication optimization program can enhance implementation of GDMT in HFrEF.
- Patients were onboarded to the BiovitalsHF platform with surveillance of laboratories, physiology, and symptoms and recommendations made to the clinical team for approval of titration recommendation.
- Results¹:
 - At 3 months, patients on the BiovitalsHF platform experienced significant increase from baseline in utilization of all categories of GDMT (p<0.05).
 - The proportion of patients advanced to target doses of GDMT was also higher at 3 months as compared to historical controls/ registry data. (p<0.05)
 - At 3 months, patients on Biovitals-HF platform experience statistically significant and clinically meaningful improvement in KCCQ-OS.









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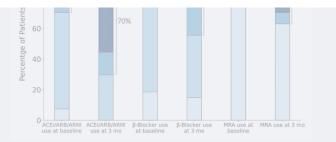
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Biofourmis receives FDA breakthrough device designation for heart failure "digital therapy"

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