AMDIS TED TALKS – 2019 EDITION - PART I

• SETTING EVIDENCE-BASED MEDICINE ON FHIR

BRIAN S. ALPER, MD, MSPH, FAAFP

PREDICTIVE ANALYTICS - IMPACT ON PATIENT CARE & THROUGHPUT

• RYAN BOUTIN, MD

• OPTIMIZATION STRATEGIES TO ENHANCE PHYSICIAN WELL-BEING AND ALLEVIATE EHR-RELATED BURNOUT

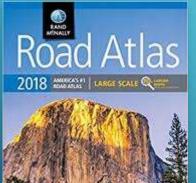
- SHADI HIJJAWI, MD, FACP, MBA, CHCQ
- THE DISEASES OF CLINICAL INFORMATICS
 - JAKE LANCASTER, MD, MSHA, MSACI

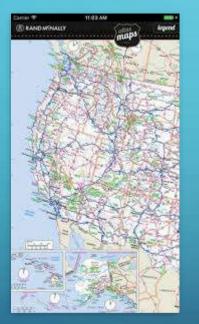
SETTING **EVIDENCE-BASED MEDICINE ON FHIR** ITEROPERARILITY FOR EBM66FHIR **EXTERNAL EVIDENCE**

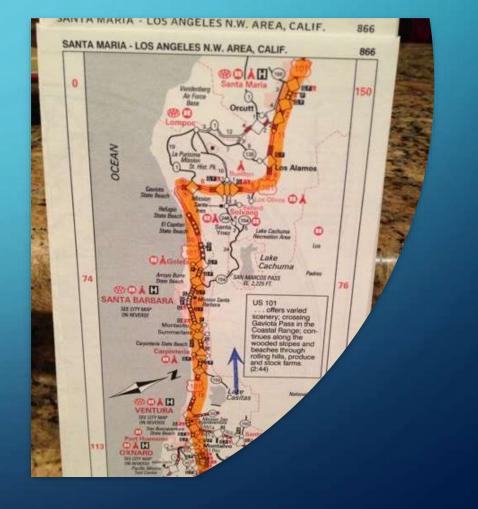
PRESENTER AND DISCLOSURES

- Brian S. Alper, MD, MSPH, FAAFP
- Board certifications: Family Medicine, Clinical Informatics
- Founder of DynaMed
- Vice President of Innovations and EBM Development, EBSCO Health
- Project Lead, EBMonFHIR
- Key Contributor AHRQ ACTS, PC CDS Learning Network, MCBK
- Member AAFP, ACP, AMDIS, AMIA, GRADE Working Group, G-I-N, HIMSS, HL7, ISDM, ISEHC









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Digital

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Executable







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BIOMEDICAL EVIDENCE IS NOT COMPUTABLE LIKE FINANCIAL KNOWLEDGE OR LOCATION KNOWLEDGE, SO

(-1)~

We can instantly know when to turn next to get to the restaurant and traffic is diverted, but we cannot instantly know what treatment to consider next for our health concerns -> major waste in time and resources; poor decisions and poor medical outcomes

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-computable

ge to find healthcare

JJIVIIMI

WHY IS BIOMEDICAL EVIDENCE NOT COMPUTABLE?

...standard for machine-interpretable expression ...interoperability (every group communicating it does it their own way) ...universal agreement about the right way to do it ...functional demonstration of how it can be done

FHIR SOLVES INTEROPERABILITY FOR PATIENT DATA

- Fast Healthcare Interoperability Resources (FHIR) is an HL7 standard
- Developed by US government (ONC, CDC, AHRQ, FDA, NIH, CMS), other governments, healthcare systems, payers (UHC, Aetna, etc), EHRs (Cerner, Epic, Allscripts, etc.), industry – all agreeing how to do it as a standard
- US likely to require by 2021 any person can get ALL their electronic health information in FHIR format required for any EHR

EHR Vendors will not be controlling data access and business rules much longer

FHIR 'AS IS' DOES NOT HANDLE BIOMEDICAL RESEARCH EVIDENCE

No other standards are ready to handle research evidence Large attempts include:

- Mobilizing Computable Biomedical Knowledge (MCBK) NLM-associated consortium
- CDC "Adapting Clinical Guidelines for the Digital Age"
- "Evidence Ecosystem" attempts in Europe

None of these attempts have directly addressed standards for data exchange (i.e. the actual thing that would enable interoperability)

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24	28	26	27	28	29	30

- GIN Alper takes on GINTech (EBM technical group) role to start efforts to define interoperability standards
- HL7 Alper learns enough about FHIR to understand how it works
- HIMSS Alper informally proposes extending FHIR to meet EBM needs
- HL7 Alper formally proposes HL7 project "FHIR Resources for Evidence-Based Medicine Knowledge Assets" (EBMonFHIR)
- HL7 Approves EBMonFHIR project (5 work groups and management committees)

BBM-ON-FHIR – HISTORY CONT.



HL7, GIN – Alper and Shahin have first EBMonFHIR connectation

- Evidence resource created to handle evidence about effects of interventions (focus on systematic reviews)
- Participating groups include Duodecim, MAGIC, HarmonIQ, ACC, EvidencePrime (GRADEpro) and more

BBM-ON-FHIR – HISTORY CONT.

 JANUARY 2019

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HL7 – Alper and Shahin have second EBMonFHIR connectathon

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- Evidence resource expanded to handle needs for research registries (associations of things, not just effects of interventions) – EBMonFHIR "absorbs" Clinical Profiles standard project
- CDC effort to adapt guidelines into recommendations (CDS artifacts) and HL7 CDS efforts combined to launch "Recommendations on FHIR" project (nicknamed CPGonFHIR and coordinated with EBMonFHIR)
- BRR group (FDA, NIH/NLM, CMS reps) suggest EBMonFHIR can become basis for required data formats for ClinicalTrials.gov, PubMed listing, journal publications
- Participating groups expand to include CDC, AHRQ, Johns Hopkins University, and more

BBM-ON-FHIR – HISTORY CONT.

 FEBRUARY 2019

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Evidence resource codifies 'statistic' and 'certainty'

 Despite statistic concepts being universally reported across biomedical publications and certainty concepts gathering "semi-standard" approach in healthcare (GRADE), there has been no well established method for reporting these things in machine-coded form

Sep Jan Feb May June Sep Jan Feb

EBMonFHIR makes computable expression achievable for biomedical research evidence

PORTION OF STATISTIC RESOURCE

Each concept has explicit coding for unambiguous machine-interpretable expression

- 🎯 statisticType
- 🕥 quantity
- 词 sampleSize
- 💷 description
- 🕥 note
🛄 numberOfStudies
- 📖 numberOfParticipants
- 📖 knownDataCount
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- 🛅 precisionEstimate
- 📖 description
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The effect or risk estimate type StatisticStatisticType (Extensible) The statistic value Population sample size Textual description of population sample size Footnote or explanatory note about the sample size Number of contributing studies Cumulative number of participants TBD TBD An estimate of the precision of the statistic Textual description of the estimate Footnote or explanatory note about the estimate The estimate type StatisticPrecisionEstimateType (Extensible) Level of confidence interval Lower bound Upper bound

certainty

--·() note --·() rating

a certaintySubcomponent

- 🛄 description

🔘 note

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rating

- BackboneElement 0..* 0..1 string 0..* Annotation 0..* CodeableConcept 0..* BackboneElement 0..1 string 0..* Annotation 0..* CodeableConcept
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How certain is the effect Textual description of the certainty Footnote or explanatory note about the statistic certainty Certainty rating StatisticCertaintyRating (Extensible) A component that contributes to the overall certainty Textual description of the subcomponent Footnote or explanatory note about the statistic certainty subcomponent Type of subcomponent of certainty rating StatisticCertaintySubcomponentType (Extensible) Subcomponent certainty rating StatisticCertaintySubcomponentRating (Extensible)

CERTAINTY ENCODED

QUALITATIVE CONCEPTS HAVE EXPLICIT CODING FOR UNAMBIGUOUS MACHINE-INTERPRETABLE EXPRESSION

GET INVOLVED

- Website confluence.hl7.org/display/CDS/EBMonFHIR
- GoogleGroups email groups.google.com/forum/#!forum/ebmonfhir
- Open meetings via WebEx
 - Tuesdays 4 pm Eastern
 - Thursdays 9 am Eastern
- Email balper@ebsco.com

Predictive Analytics - Impact on Patient Care & Throughput



Dr. Ryan Boutin

Assistant Chief, Hospital Medicine Physician Informatacist / IT Physician Liaison

Middlesex Health includes a primary care network within Central and Southern CT as well as Urgent Care centers, 2 satellite EDs and Middlesex Hospital.

Middlesex Hospital is a 300 bed non-profit community hospital in Middletown, CT in central CT.

Early Warning Analysis

 Develop a real time early warning analysis at the point of care that physicians and care teams can utilize to monitor developing acute disease states, throughput measures, readmission risk and utilization review.

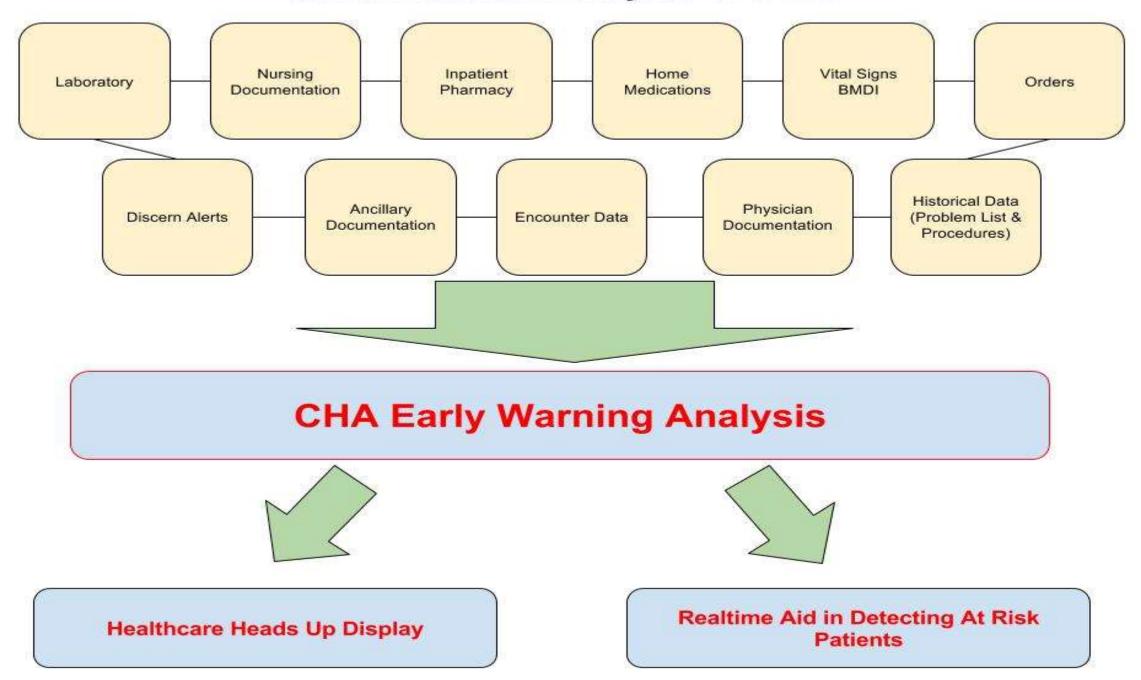


Why Develop An Early Warning Analysis

- A percentage of developing acute diseases can be **predicted** (and potentially prevented) by utilizing the data that is currently in the EMR. Potential to decrease M&M.
- The benefits of utilizing **Standardized protocols** to treat/prevent developing disease states is well documented.
- Potential for reduced cost by decreasing length of stay, decreasing readmission risk and improving utilization review



Clinical Healthcare Analytics Overview



Early Warning Analysis Development

Clinical Protocols:

- Acute Kidney Injury
- Alcohol Withdrawal
- Sepsis

• Discharge / Throughput Protocols:

- Readmission Risk
- Discharge Anticipation
- Discharge Readiness
- Level of Care Discrepancy



Healthcare Heads Up Display - HHUD

- High Level Information
- Located Within Existing Physician Workflow
- Easy to Utilize, Minimal Training Needed
- Non-Interruptive
- Drill Down Capability
- Actionable
- Red / Yellow / Green Formatting (when applicable)





Easy to Use, High Level Information within Workflow

Menu	ą	5 3 * 1	A Heads Up Dis	play						
Heads Up Display			▶ 🔍 🔧 100%							
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36 Hour Order Review		Lymph %:								
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Non-Interruptive Early Warning System

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ounds Report		WBC:	~ 13.1 H	UA RBC:	0-2			
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Drill Down Capability

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Actionable

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Hospitalist Workflow

Red / Yellow / Green Formatting

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lour Order Review										

Realtime Aid in Detecting At Risk Patients RADAR

• Keys to success:

- High Level Information
- Easy to Utilize
- Drill Down Capability
- Red / Yellow / Green Formatting
- Actionable
- Customizable by Role / User



Easy to Use, High Level Information

Patients for NORTH FIVE

how 100	✓ en	itries									Search:	
Rm/Bed	Age	Visit Reason	Primary Nurse	Admitting Physician	Conditions	Last Report	LOS	Status	Readmit	DC Anticipation	DC Readiness	Notes
651 - D	79	UTI-UTI?-ER/IP				2/1 11:49 AM	131	Inpatient	Low (9)	Possibly Tomorrow	Almost Ready	
540 - D	59	SMALL BOWEL OBSTRUCTION-N/V-ER/ADMIT				4/11 01:19 PM	127	Inpatient	Elevated (11)	Not Ready	Armost Ready	222.5
409 - D	79	-ANEMIA KIDNEY INFECTION				3/22 03:09 PM	91	Inpatient	Elevated (13)	Not Ready	Almost Ready	110
552 - D	57	ARF/DEHYDRATION-ABNORMAL LABS- OER/ADMIT IP	Haynes RN, Amy	ZACK MD, CATHY J	Acute Kidney Injury	6/6 02:59 PM	7.4	Inpatient	Elevated (15)	Possibly Tomorrow	Not Ready	(***
543 - D	39	APPENDICITIS-PER TASK IP FROM THE BEG- NAUSEA-OPS/OCP	Ross RN, Gwen	PARKER MD, JAMES MICHAEL		6/5 09:20 AM	5.8	Inpatient	Low (7)	Possibly Tomorrow	Not Ready	i i i i i i i i i i i i i i i i i i i
556 - D	51	ACUTE SIGMOID DIVERTICULITIS W/ABSCESS- ABD PAIN-ER/ADMIT	Lutecki RN, Martha	ROSENER MD, STEPHANIE E	Acute Kidney Injury	6/8 12:37 PM	4.6	Inpatient	Low (7)	Not Ready	Not Ready	
553 - D	64	PNEUMONIA-DIFF BREATHING-OER/IP	Haynes RN, Amy	OCHOLA-TINKER MD, LISA A		6/7 03:25 PM	4.3	Inpatient	Elevated (12)	Not Ready	Not Ready	
540 - D	84	C DIFF COLITIS-N/V/D-MMCS ADMIT	Doty RN, Zachary	MACHADO DO, JOHN D		6/8 12:41 PM	3.7	Inpatient	Low (10)	Possibly Tomorrow	Almost Ready	(***)
544 - D	55	SBO, HYPERTENSION, ABN EKG-MMCS ADMIT- SEVERE ABD PAIN	Ross RN, Gwen	HARTMANN MD, KARL T		6/7 08:24 AM	3.4	Inpatient	Low (6)	Possibly Tomorrow	Not Ready	(***)
542 - D	56	SEVERE PANCREATITIS-CP/VOMITING-OER/IP ADMIT	Doty RN, Zachary	DOUGLASS MD, ALAN B		6/8 12:44 PM	3.2	Inpatient	Low (7)	Not Ready	Not Ready	(444)
558 - D	47	FEVER-101.1 FEVER-ER/ADMIT	Robichaud RN, Teresa	BALAZADEH MD, SETAREH L	Acute Kidney Injury	6/8 12:11 PM	2.6	Inpatient	Elevated (14)	Possibly Tomorrow	Not Ready	n Taratan Taratan
541 - D	67	RIGHT RENAL CELL CARCINOMA-RIGHT PARTIAL NEPHRECTOMY OPEN-NCO	Lutecki RN, Martha	MYER MD, EDWARD G		6/8 03:14 PM	2.1	Inpatient	Low (6)	Possibly Tomorrow	Not Ready	
557 - D	80	PVD-RIGHT FEMORAL DISTAL BYPASS-EST CO PAID-**AUTH GOOD FOR 1DAY**	Lutecki RN, Martha	SAM MD, ALBERT D	*Beta:Protocol	6/8 02:07 PM	2.1	Inpatient	Low (10)	Possibly Tomorrow	Not Ready	1111
545 - D	52	HYPOMAGNESEMIA/HYPOCALCEMIA/HYPERKAL PER TASK OCP TO IP-Potassium LEVEL IS LOW- ER/OCP	Ross RN, Gwen	ZACK MD, CATHY J		6/7 10:26 AM	1.8	Inpatient	Low (7)	Today/Tomorrow	Not Ready	(***)
549 - W	91	DISTAL TIBIA AND FIBULAR FX-OCP TO IP PER TASK LIST-FALL-MMCM/OCP ADMIT VIA AMBULANCE	Ross RN, Gwen	ZACK MD, CATHY J		6/8 12:09 PM	.1.7	Inpatient	Low (5)	Possibly Tomorrow	Not Ready	5113
550 - D	31	INTRACTABLE ABD PAIN-DIFF BREATHING-	Haynes RN, Amy	PARKER MD, JAMES MICHAEL			1.5	Observation!!	Low (2)	Possibly Tomorrow	Not Ready	



Drill Down Capability

ZACK MD, CATHY J

6			
Rm/Bed	Age	Visit Reason	Primary Nurse
651 - D	79	UTI-UTI?-ER/IP	
540 - D	59	SMALL BOWEL OBSTRUCTION-N/V-ER/ADMIT	
409 - D	79	-ANEMIA KIDNEY INFECTION	
552 - D	57	ARF/DEHYDRATION-ABNORMAL LABS- OER/ADMIT IP	Haynes RN, Amy
543 - D	39	APPENDICITIS-PER TASK IP FROM THE BEC- NAUSEA-OPS/OCP	Ross RN, Gwen
556 - D	51	ACUTE SIGMOID DIVERTICULITIS W/ABSCESS- ABD PAIN-ER/ADMIT	Lutecki RN, Martha
553 - D	64	PNEUMONIA-DIFF BREATHING-OER/IP	Haynes RN, Amy
540 - D	84	C DIFF COLITIS-N/V/D-MMCS ADMIT	Doty RN, Zachary
544 - D	55	SBO, HYPERTENSION, ABN EKG-MMCS ADMIT- SEVERE ABD PAIN	Ross RN, Gwen
542 - D	56	SEVERE PANCREATITIS-CP/VOMITING-OER/IP ADMIT	Doty RN, Zachary
558 - D	47	FEVER-101.1 FEVER-ER/ADMIT	Robichaud RN, Teresa
541 - D	67	RIGHT RENAL CELL CARCINOMA-RIGHT PARTIAL NEPHRECTOMY OPEN-NCO	Lutecki RN, Martha
557 - D	80	PVD-RIGHT FEMORAL DISTAL BYPASS-EST CO PAID-**AUTH GOOD FOR 1DAY**	Lutecki RN, Martha
545 - D	52	HYPOMAGNESEMIA/HYPOCALCEMIA/HYPERKAL PER TASK OCP TO IP-Potassium LEVEL IS LOW- ER/OCP	Ross RN, Gwen
549 - W	91	DISTAL TIBIA AND FIBULAR FX-OCP TO IP PER TASK LIST-FALL-MMCM/OCP ADMIT VIA AMBUILANCE	Ross RN, Gwen

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6/8 12:09 PM

1.7

Inpatient

Low (5)

Notes

Not Ready



Red / Yellow / Green Formatting

Rm/Bed	Age	Visit Reason	Primary Nurse	Admitting Physician	Conditions	Last Report	LOS	Status	Readmit	DC Anticipation	DC Readiness	Notes
651 - D	79	UTI-UTI?-ER/IP				2/1 11:49 AM	131	Inpatient	Low (9)	Possibly Tomorrow	Almost Ready	
540 - D	59	SMALL BOWEL OBSTRUCTION-N/V-ER/ADMIT				4/11 01:19 PM	127	Inpatient	Elevated (11)	Not Ready	Almost Ready	***
409 - D	79	-ANEMIA KIDNEY INFECTION				3/22 03:09 PM	91	Inpatient	Elevated (13)	Not Ready	Almost Ready	
552 - D	57	ARF/DEHYDRATION-ABNORMAL LABS- OER/ADMIT IP	Haynes RN, Amy	ZACK MD, CATHY J	Acute Kidney Injury	6/6 02:59 PM	7.4	Inpatient	Elevated (15)	Possibly Tomorrow	Not Ready	
543 - D	39	APPENDICITIS-PER TASK IP FROM THE BEG- NAUSEA-OPS/OCP	Ross RN, Gwen	PARKER MD, JAMES MICHAEL		6/5 09:20 AM	5.8	Inpatient	Low (7)	Possibly Tomorrow	Not Ready	
56 - D	51	ACUTE SIGMOID DIVERTICULITIS W/ABSCESS- ABD PAIN-ER/ADMIT	Lutecki RN, Martha	ROSENER MD, STEPHANIE E	Acute Kidney Injury	6/8 12:37 PM	4.6	Inpatient	Low (7)	Not Ready	Not Ready	2 2 4 4
i53 - D	64	PNEUMONIA-DIFF BREATHING-OER/IP	Haynes RN, Amy	OCHOLA-TINKER MD, LISA A		6/7 03:25 PM	4.3	Inpatient	Elevated (12)	Not Ready	Not Ready	-
540 - D	84	C DIFF COLITIS-N/V/D-MMCS ADMIT	Doty RN, Zachary	MACHADO DO, JOHN D		6/8 12:41 PM	3.7	Inpatient	Low (10)	Possibly Tomorrow	Almost Ready	
544 - D	55	SBO, HYPERTENSION, ABN EKG-MMCS ADMIT- SEVERE ABD PAIN	Ross RN, Gwen	HARTMANN MD, KARL T		6/7 08:24 AM	3.4	Inpatient	Low (6)	Possibly Tomorrow	Not Ready	***
542 - D	56	SEVERE PANCREATITIS-CP/VOMITING-OER/IP ADMIT	Doty RN, Zachary	DOUGLASS MD, ALAN B		6/8 12:44 PM	3.2	Inpatient	Low (7)	Not Ready	Not Ready	•••
558 - D	47	FEVER-101.1 FEVER-ER/ADMIT	Robichaud RN, Teresa	BALAZADEH MD, SETAREH L	Acute Kidney Injury	6/8 12:11 PM	2.6	Inpatient	Elevated (14)	Possibly Tomorrow	Not Ready	
541 - D	67	RIGHT RENAL CELL CARCINOMA-RIGHT PARTIAL NEPHRECTOMY OPEN-NCO	Lutecki RN, Martha	MYER MD, EDWARD G		6/8 03:14 PM	2.1	Inpatient	Low (6)	Possibly Tomorrow	Not Ready	
557 - D	80	PVD-RIGHT FEMORAL DISTAL BYPASS-EST CO PAID-**AUTH GOOD FOR 1DAY**	Lutecki RN, Martha	SAM MD, ALBERT D	*Beta:Protocol	6/8 02:07 PM	2.1	Inpatient	Low (10)	Possibly Tomorrow	Not Ready	
545 - D	52	HYPOMAGNESEMIA/HYPOCALCEMIA/HYPERKAL PER TASK OCP TO IP-Potassium LEVEL IS LOW- ER/OCP	Ross RN, Gwen	ZACK MD, CATHY J		6/7 10:26 AM	1.8	Inpatient	Low (7)	Today/Tomorrow	Not Ready	1999 19 84 1997
49 - W	91	DISTAL TIBIA AND FIBULAR FX-OCP TO IP PER TASK LIST-FALL-MMCM/OCP ADMIT VIA AMBULANCE	Ross RN, Gwen	ZACK MD, CATHY J		6/8 12:09 PM	1.7	Inpatient	Low (5)	Possibly Tomorrow	Not Ready	
550 - D	31	INTRACTABLE ABD PAIN-DIFF BREATHING-	Haynes RN, Amy	PARKER MD, JAMES MICHAEL			1.5	ObservationII	Low (2)	Possibly Tomorrow	Not Ready	-



Actionable

RTH FIVE		✓ 15 minutes ■ [⊞ ∲ P I O	L₿Ľ♠Ŧ									
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Rm/Bed	Age	Visit Reason	Primary Nurse	Admitting Physician	Conditions	Last Report	LOS	Status	Readmit	DC Anticipation	DC Readiness	Notes	
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553 - D	64	PNEUMONIA-DIFF BREATHING-OER/IP	Haynes RN, Amy	OCHOLA-TINKER MD, LISA A		6/7 03:25 PM	4.3	Inpatient	Elevated (12)	Not Ready	Not Ready		
540 - D	84	C DIFF COLITIS-N/V/D-MMCS ADMIT	Doty RN, Zachary	MACHADO DO, JOHN D		6/9 10:00 AM	3.7	Inpatient	Low (10)	Possibly Tomorrow	Almost Ready		
544 - D		SBO, HYPERTENSION, ABN EKG-MMCS ADMIT- SEVERE ABD PAIN	Ross RN, Gwen	HARTMANN MD, KARL T		6/7 08:24 AM	3.4	Inpatient	Low (6)	Possibly Tomorrow	Not Ready	(11)	
542 - D		SEVERE PANCREATITIS-CP/VOMITING-OER/IP ADMIT	Doty RN, Zachary	DOUGLASS MD, ALAN B		6/8 12:44 PM	3.2	Inpatient	Low (7)	Not Ready	Not Ready	##??	
558 - D	47	FEVER-101.1 FEVER-ER/ADMIT	Robichaud RN, Teresa	BALAZADEH MD, SETAREH L	Acute Kidney Injury	6/8 12:11 PM	2.6	Inpatient	Elevated (14)	Possibly Tomorrow	Not Ready		
541 - D	67	RIGHT RENAL CELL CARCINOMA-RIGHT PARTIAL NEPHRECTOMY OPEN-NCO	Lutecki RN, Martha	MYER MD, EDWARD G		6/8 03:14 PM	2.1	Inpatient	Low (6)	Possibly Tomorrow	Not Ready	l	

Benefits

- Early Warning Analysis, HHUD and RADAR are within the EMR
- Clinicians do not have to learn or utilize a separate system
- HHUD can be customized for each care group / facility
- Clinical Protocols developed specifically for acute disease states



Optimization Strategies to Enhance Physician Well-being and Alleviate EHR-related Burnout

> Shadi Hijjawi, MD, FACP, MBA, CHCQM Chief Medical Information Officer CaroMont Health Gastonia, NC





CaroMont Health

Non-profit Organization 435-Bed Tertiary Care Hospital Level 3 Trauma Center Free Standing ED/Urgent Care

50+ Physician Practices 500 + Physicians & ACPs 1,200 + Nurses

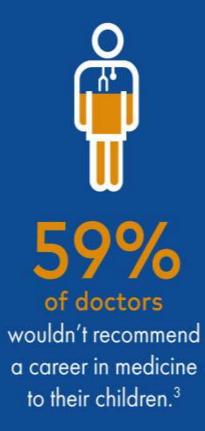
Annual Visits Admissions: 20,000+ ED Visits: 108,000+ Ambulatory/ OP visits: 817,000+





Physician Burnout





Mayo Clinic 2014.
 VITAL WorkLife & Cejka Search Physician Stress and Burnout Survey 2015.
 Jackson Healthcare; 2013 Physician Outlook and Practice Trends.

Medscape Survey 2019

Are Physicians Burned Out or Depressed?

Burned out 44%

Colloquially depressed 11%



Clinically depressed 4%

How much does it cost USA?

- \$4.6 billion in costs related to physician turnover and reduced clinical hours is attributable to burnout each year in the United States.
- At an organizational level, the annual economic cost associated with burnout related to turnover and reduced clinical hours is approximately \$7600 per employed physician each year.

Ann Intern Med. 2019;170(11) :784-790.

How to Tackle this?



Optimization and Improvement Strategies

- Expert Help: Consultant Visit
- Leadership Planning
- Informatics Team Formation and Marketing

- Strategic Project: PEP
- Revamped training
- Outreach Programs

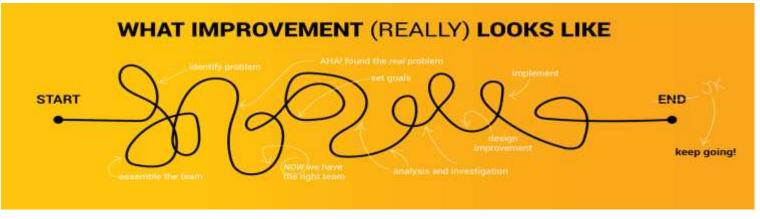


Photo Credit: Univ. of Utah Health

How to do that?



Let us show YOU how WE CARE!

Informatics Team

Mission: To Provide Exceptional Support to CaroMont Epic Users

Vision: To be CaroMont's Trusted Champions for Epic Users

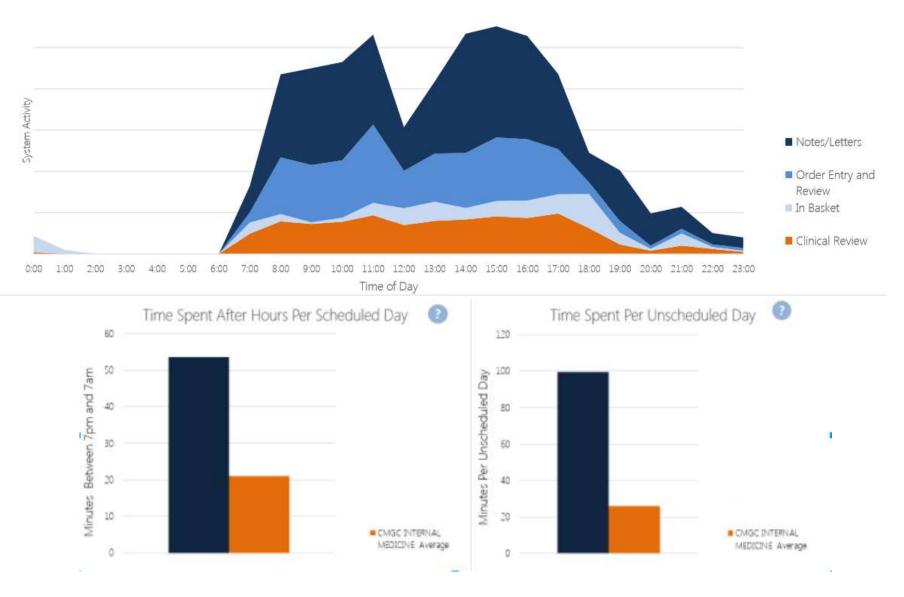
CaroMont's CARES Values

Compassion Accountability Reliability Excellence Safety



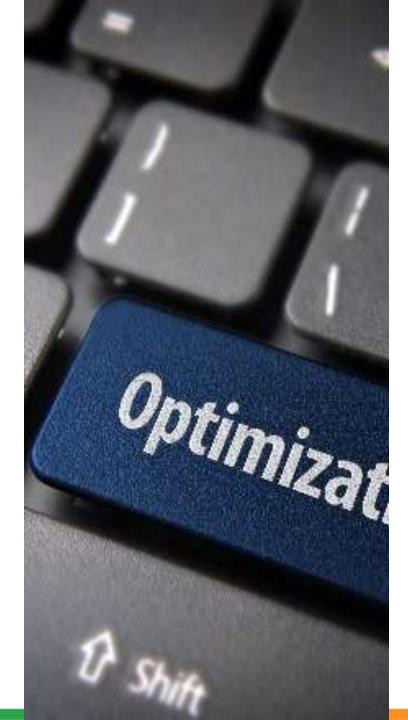


Data Analytics: PEP and Signal of *Epic*



Data Collection

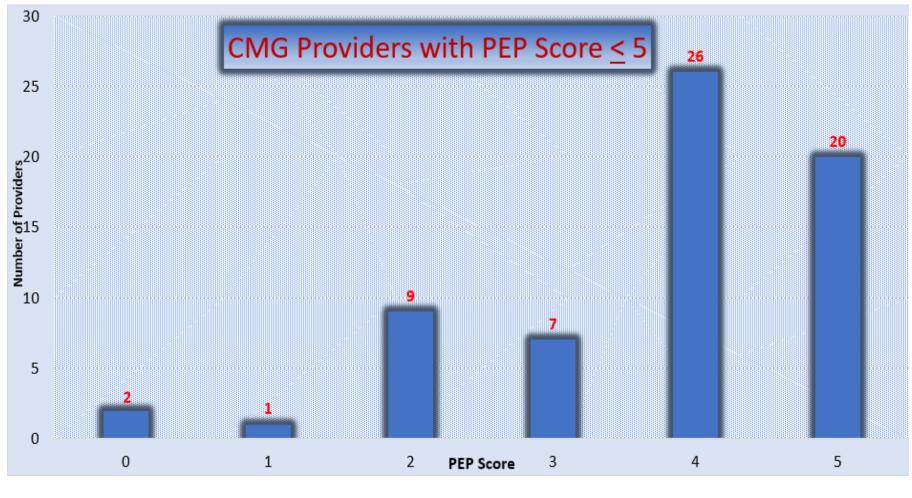




Optimization Project FY17/18

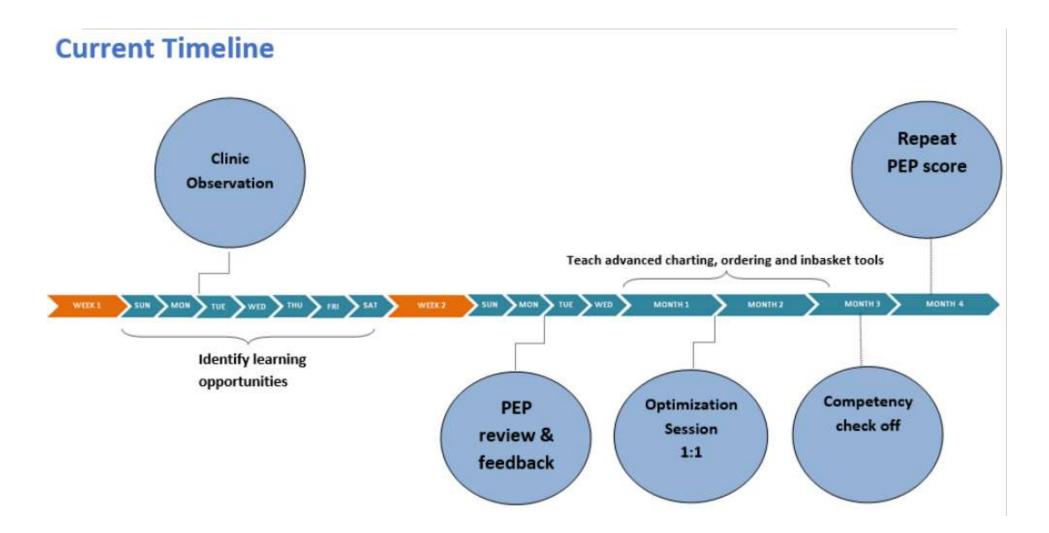
- Intervention designed for some *Ambulatory* providers
- Used PEP data
- A 16-week plan designed after feedback from providers
- Main Objective is to address Providers' Burnout

Enrollment: Providers with PEP < 5



Total 65

Intervention Plan





- Finished > 350 1:1 sessions
- More than 500 hrs. of 1:1 training
- Filled PRE and POST training intervention Surveys
- Response Rate 74% on the PRE, and 65% on the POST
- Completed training 57 providers (19 ACPs, and 38 Physicians)

Subjective Data (Survey)

Burnout was reduced in > 70% after optimization

Outcomes After	Undergoing Optimization	n (n=32)	outo	f 57	(56%)

Feeling MORE confident in proficiency to use Epic effectively	97%
Agreed for needing more optimization	84%
ALLEVIATED work-related burnout *	(See footnote)
Using epic functions more appropriate	97%
Signifcant improvement in effeicency in the following:	
Finding information and reviewing chart	84%
Office visit, consult & procedure note templates	88%
Documenting problem lists	72%
Ordering medications, labs, imaging, referrals	78%
Health Maintenance, Dashboard and Quality measures documentation	75%
InBasket workflows such as Results, MyChart, Refill requests	88%
* 34% had no burnout, > 71.4% of the remaining had alleviated burnout	

Objective Outcomes

Follow up PEP data after intervention – 52 providers

	Increased > 1	Overall Increase
Efficiency (PEP)	25%	56%
Proficiency	44%	69%

Efficiency and Proficiency Average Scores

	Efficiency	Proficiency
Pre Optimization	3.7	6.0
Post Optimization	3.9	7.0
Change	0.2* or 5.0% improvement	1.00* or 16.0% improvement

• *p*-Value 0.13 • *p*-Value 0.000022

Minutes

Average minutes spent by each provider per patient / encounter in main chart sections

	Clinical Review	Ordering	Notes/Letters	Total
Pre Optimization	3.01	3.67	6.85	13.53
Post Optimization	2.75	3.56	5.96	12.27
Change per Encounter	0.26	0.11	0.89	1.26 saved minutes per encounter*

*On average, if the provider sees 20 patients a day, he\she can save 25 minutes in the EMR per day.

 \rightarrow This is at least 84 hours less in the EMR per year per provider

 \rightarrow That is more than 2 weeks of less work per year per provider

Days of Working Late (after 5 pm)

	Avg. days of late activity per provider^
Pre Optimization	9.8 days
Post Optimization	5.2 days
Change per provider	4.6* days

^during monitoring period ~ 3 wks

- **p*-value =3.32E-08 (0.000000332)
- On average, each provider reduced his\her days of working late by half after optimization !!

Provider Outreach Programs

- Clinic Rounding
- 1:1 sessions
- Epic Thursdays
- Workflow analysis



Coordinating with different Teams

- Analysts
- Coders
- Quality
- Leadership







Are You Ready?

Thank you !



Shadi Hijjawi, MD, FACP, CHCQM, MBA CMIO, CaroMont Health Shadi.Hijjawi@CaroMontHealth.org

The Diseases of Clinical Informatics

PRESENTED BY: JAKE LANCASTER, MD, MSHA, MSACI CMIO WEST TENNESSEE HEALTHCARE

Problem Statement

Clinical Informatics is a recognized clinical subspecialty of medicine but lacks many key features of other specialties including procedures, billing codes, diagnostic tests...



What is Clinical Informatics?

The diagnosis and treatment of diseases related to information systems

CC: "I'm spending too much time in the chart"

History: I've been using this thing for years but I am still can't see as many patients as I did on paper. I spend my nights finishing notes

Physical: Hunt and peck method of typing, no saved favorites, frequent jumping between screens

Workup: EHR provider efficiency report shows doc spends 20 more minutes per patient than peers in same specialty. Bulk of time documenting and in orders

Diagnosis: Diabetes informatio

Plan: Setup with auto text and order favorites. Setup with voice recognition transcription software.

Check progress in 3 months.

If no improvement consider Scribe

CC: "The notes don't make sense anymore"

History: Since going live with the new EHR, the notes have become progressively longer and you can no longer find any of the info you need.

Physical: Audit of multiple notes from different providers shows overuse of copy forward as well as long autotext and other templates.

Workup: Additional testing shows length of notes has doubled over past 8 years

Malignant documentation informationoma (Note Bloat)

Plan:

- Develop standards for what should and should not be included in notes by med staff and HIM
- Educate about legal impact of having erroneous info in notes
- Encourage movement to workflow pages (reduces note bloat)
- Turn off copy forward

CC: I can't get through an admission without 4-5 pop-up alerts

- History: Every time time admit orders are placed, multiple alerts display for lab duplicates, imaging duplicates, drug-drug interactions, and drug allergies
- Physical: Able to reproduce some of the alerts on a test patient including one for duplicate CBCs though ordered a day apart
- Workup: Report is run on alerts that are fired the most and have very high override rates.

Status Informaticus

Plan:

- Form best practices alerts group to review and streamline existing and incoming alerts
- Explore new features for suppressing redundant alerts in an encounter
- Offload some alerts to passive alerts
- Change culture of solving every problem with an alert

CC: My computer is asking me to send it bitcoin

History: Physician opened a link in an email from Jeff Bezos that asked if he wanted to be the new CMO of Amazon Health

Physical: All files are frozen on his computer and pop-up box with count down timer has instructions for how to deposit the bitcoin

Workup: Security assessment shows that threat is local to that machine only. All local files are either backed up or disposable

iBola Virus

Plan:

- Quarantine computer and remove from network
- Restore and recover files
- Continue to educate staff to not open emails from untrusted third parties
- Yearly security assessments

CC: Everyone needs to switch from using notes to the workflow pages

- History: EHR vendor is recommending that clients move to using the workflow pages instead of the commonly used notes page. They will only be adding new features to the workflow pages and plan to retire the notes page.
- Physical: Most of current physicians on notes page. Some of the new workflows note optimized for the organization's current physicians. Mood of physicians not very receptive to the change
- Workup: Workflow pages may save a minute or two per patient. Numerous hurdles to overcome.

Informatiolithiasis

Plan:
Optimize workflow page environment
Let transition occur as naturally as possible
If adoption halts or retirement date announced then bring on support for emergent conversion

Questions?

Jake.Lancaster@wth.org

AMDIS TED TALKS - 2019

• The Killing Paradox • Jason Schaffer, MD, MBI, FACEP Habits of Highly Effective Alerts • Emily C. Webber, MD FAAP FAMIA Beyond Secure Messaging • Jason Schaffer, MD, MBI, FACEP

The Killing Paradox

Electronic Health Records, Clinician Burnout, and the Paradox of Choice

Jason Schaffer, MD, MBI, FACEP



Indiana University Health

Success Metrics

- Documentation and total EHR time has fallen dramatically
- Governance time from request to decision has decreased by months
- Performance metrics have been improved from worst in the world to best-in-class
- Alerts and rules have been decreased by 80%
- Physician burnout has dropped by over 30% (measured by the Mayo Clinician Wellness Index)
- Patient quality and safety metricsf have all improved (as measured by Vizient)



Habits of Highly Effective Alerts

Emily C. Webber, MD FAAP FAMIA

AMDIS Physician Computer-Connection Symposium

June 2019



Indiana University Health

May 28, 2019, 08:00am | Views: 7,902

Electronic Health Records Are Broken

🗶 U.S. Department of Health and Human Services



Agency for Healthcare Research and Quality Advancing Excellence in Health Care

Although there are few studies that quantify adverse events related to alert fatigue, this phenomenon has been implicated as a significant cause in several high-profile errors. A 2011 **Boston Globe investigation** identified more than 200 deaths over a 5-year period attributable to failure to appropriately heed alarms from physiologic monitoring systems. A recent book by a prominent patient safety leader details how a hospitalized teenager received a 38-fold overdose of an antibiotic, in large part because the ordering physician had been advised by colleagues to "just ignore the alerts."

ANNALS OF MEDICINE

WHY DOCTORS HATE THEIR COMPUTERS

Digitization promises to make medical care easier and more efficient. But are screens coming between doctors and patients?

By Atul Gawande November 5, 2018

Study Published December 2013

Are we heeding the warning signs? Examining providers' overrides of computerized drug–drug interaction alerts in primary care.

"Exnovation" and "The Purge"

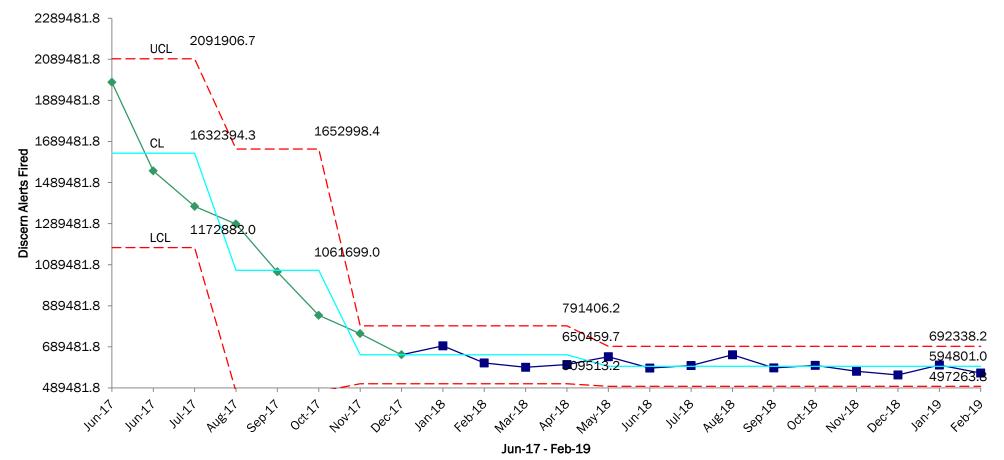
- Exnovation
 - An opposite of innovation
 - Occurs when products and processes that have been tested and confirmed to be best-in-class are <u>standardized</u> to ensure that they are not innovated further

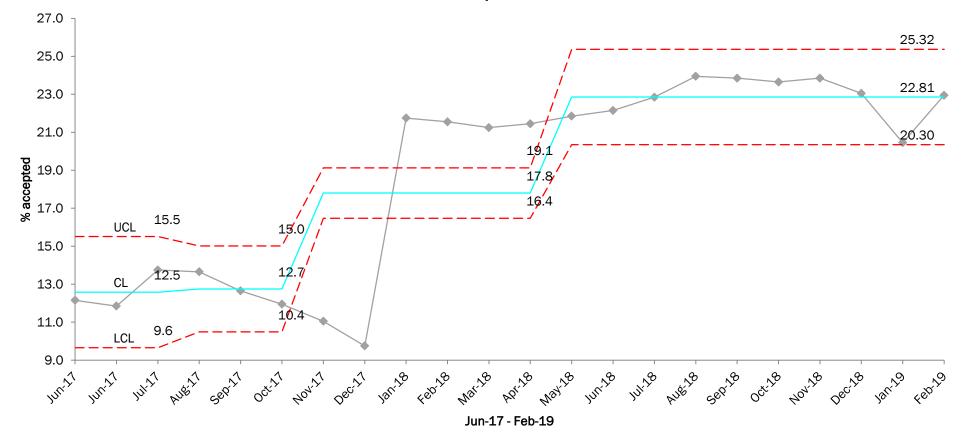
Does this work?

- Do you need a new solution?
- Did you sunset the thing you replaced?



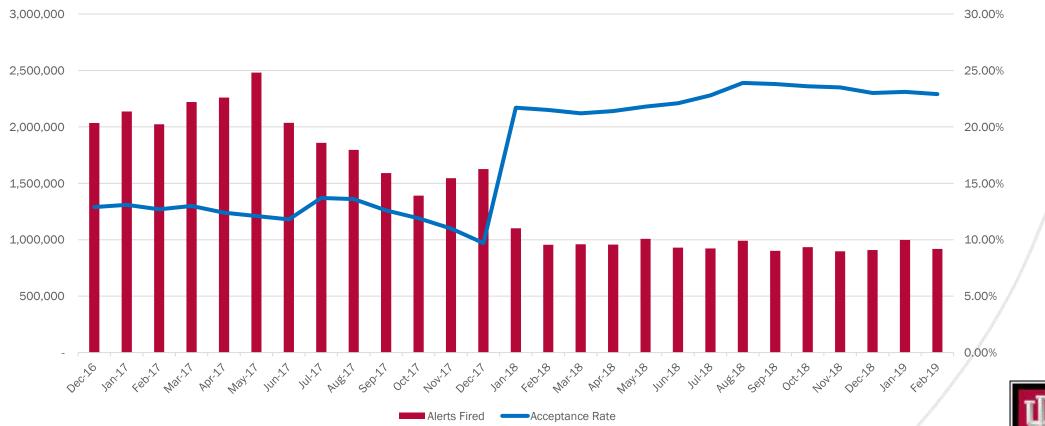
Discern Alerts Fired - X Chart





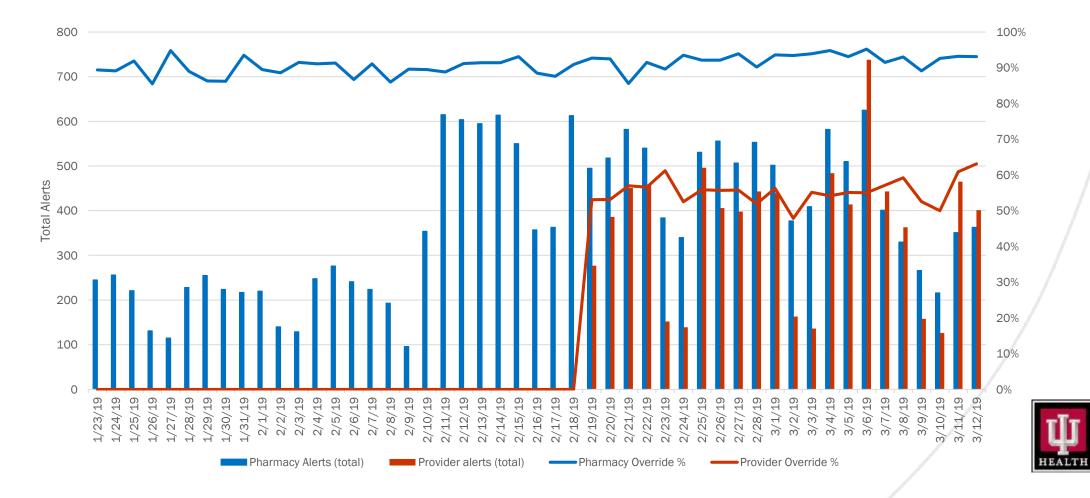
% Alerts accepted - X Chart

Alert acceptance

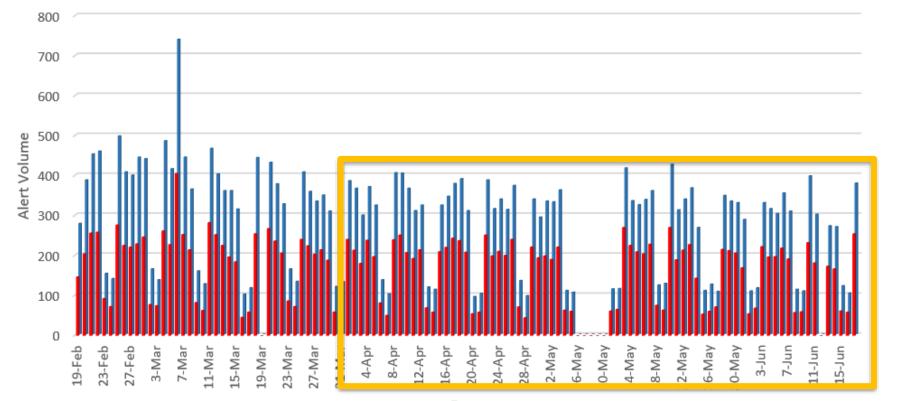




Pharmacy and provider acceptance of DRC



DRC Alert Volume





Key Drivers of Success

- Disciplined approach to intent
- Clinical entrenchment
- Agile removal and curation
 - Alert SWAT team: average 72 business hours











References

- 1. <u>Saiyed SM</u> et al. Optimizing drug-dose alerts using commercial software throughout an integrated health care system. <u>J Am Med Inform Assoc.</u> 2017 Nov 1;24(6):1149-1154. doi: 10.1093/jamia/ocx031.
- 2. Institute for Safe Medication Practices (ISMP). High alert medication assessment. https://www.ismp.org/assessments/high-alert-medications
- **3.** <u>Sirajuddin AM</u> et al, Implementation pearls from a new guidebook on improving medication use and outcomes with clinical decision support. Effective CDS is essential for addressing healthcare performance improvement imperatives. J Healthc Inf Manag.</u> 2009 Fall;23(4):38-45.j



Beyond Secure Messaging

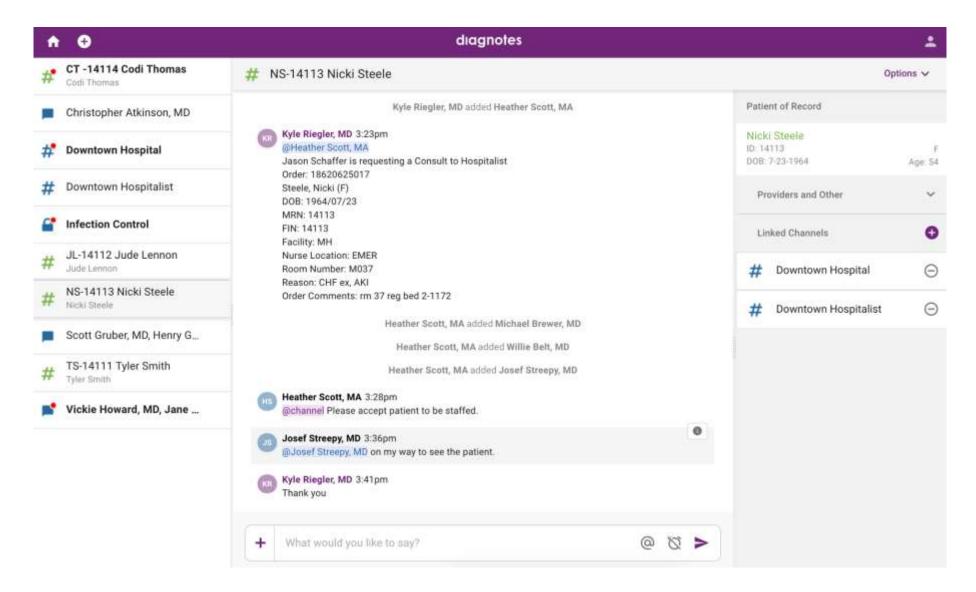
Health Care Communication for a new Age

Jason Schaffer, MD, MBI, FACEP





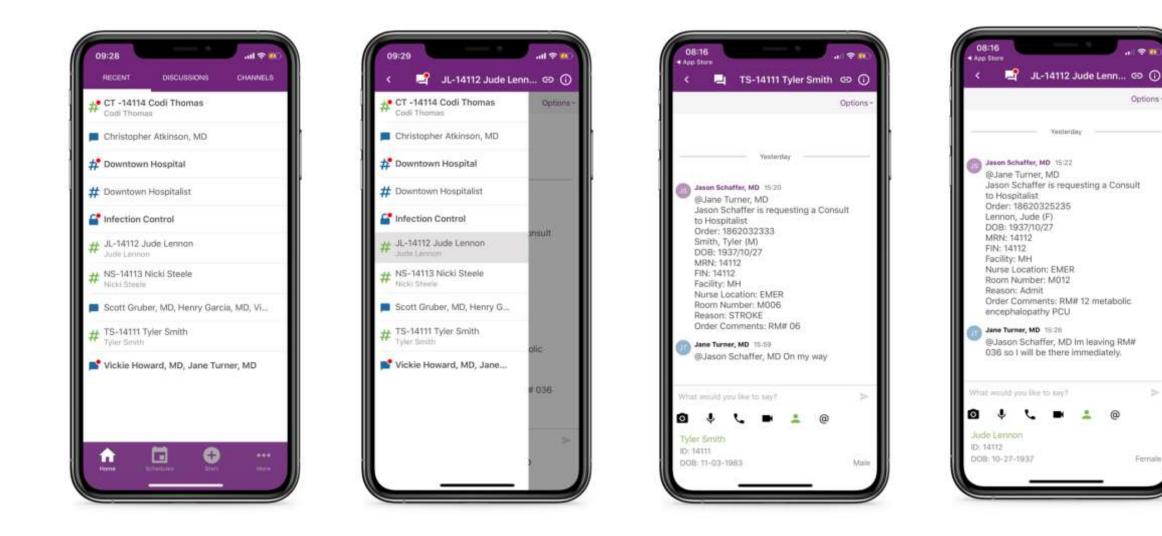
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Options

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AMDIS TED TALKS – 2019 CLINICAL FELLOWS EDITION

CMIO 3.0
Monique Diaz M.D.
Digital Phenotyping
John Zulueta, MD

CMIO 3.0

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MONIQUE DIAZ M.D.

UNIVERSITY OF ILLINOIS HOSPITAL AND HEALTH SCIENCES SYSTEM CHICAGO, IL



The Rise of the Second-Generation CMIO

Physician leaders shift to more strategic uses of data

December 1, 2014 by David Raths

In arranging interviews with health IT leaders this year, I have noticed a profusion of new titles, such as chief health information officer, medical director of informatics, and chief innovation officer. Hillary Ross, a consultant for the executive search firm Witt/ Kieffer, who specializes in recruiting chief medical information officers and other senior-level IT executives, believes these new titles are part of a wave she calls "second-generation CMIOs."

"The first-generation CMIO was

a change agent, an implementer," she said. That person did the operational heavy lifting with creating order sets, engaging physicians in new systems, and overseeing training and education. "This next generation is more strategic and visionary," she said. They are searching for the type of initiatives to leverage the healthcare system's investment in EHRs, focused on population health, improving patient safety and care and lowering costs.

Some first-generation CMIOs will make the transition to the second generation, while others



Hillary Ross, Witt/Kieffer And although health systems such as UPMC focus energy on commercializing innovations developed internally, Ross said often the innovation focus in a job title refers to physicians bringing new technologies, such as telemedicine, smartphones, and smart pump technology, to the organization and integrating them with existing technologies.

One change she has noted is in reporting structures. When EHRs were first being implemented, the CMIO typically reported to the CIO,

Ross said. "Now that the lion's share of initial EHR implementation work is done, and the focus is on optimizing their use, we are seeing a definite shift in their reporting to the chief medical officer."

CMIOs with the skills to focus on data and analytics are very much in demand, she said. "It is critical that you have the skill set but also the personal skills. You can be the most educated person in the world, but if you don't have a personal style that is a good fit with the organization you won't be successful." Personal style was important for first-generation CMIOs, she said, and

CMIO 3.0: THE GIST

CMIO 1st Generation + CMIO 2nd Generation SURE

CMIO 3.0: THE GIST

$\frac{\text{CMIO 3.0 TRUE}}{\text{WHERE IQ} = \text{EQ}}$

CMIO 3.0 CHARACTERISTICS

A Team-builder and (Interdisciplinary) Team Player



THE BIG IDEA

The Strategy That Will Fix Health Care

OCTOBER 2013

REPRINT R1310B

Providers must lead the way in making value the overarching goal by Michael E. Porter and Thomas H. Lee

Longitudinal Look-Stroke Dashboard

	Precipitating Event	ER	Acute Hospital Admit (OT Eval.)	Acute Rehab Admit	Home After 90 Days	Home After 6 months
Prompt		5B Right arm motor drift	Not applicable			
Response		+3 No effort against gravity	2. 'A lot' (patient requires maximum moderate assistance			
Scoring System		NIHSS	JHU AM-PAC			

INTERDISCIPLINARY TEAM MEMBERS & CONTRIBUTORS

Neurology & Rehab Residents	Neurology & Rehab Attendings	Nurses
Researchers	Data Scientists	Medical Librarians
Bio-visual designers	Stroke Survivors	Family Members

CMIO 3.0 CHARACTERISTICS

Designer (kinda)

90 Day Post-Stroke mRankin Score (Q2)



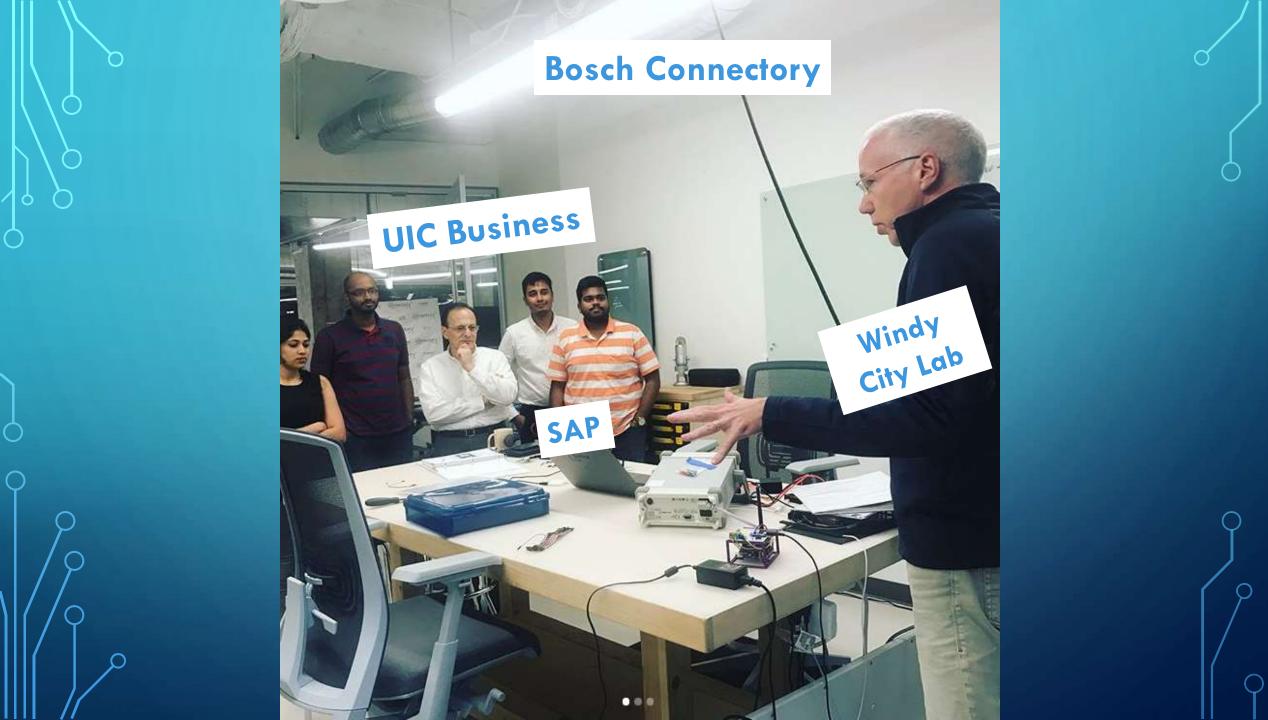
CMIO 3.0 CHARACTERISTICS

Strategic Partner

MARC HARRISON PRESIDENT AND CEO AT INTERMOUNTAIN HEALTHCARE BECKER'S HOSPITAL REVIEW MEETING APRIL 2ND 2019

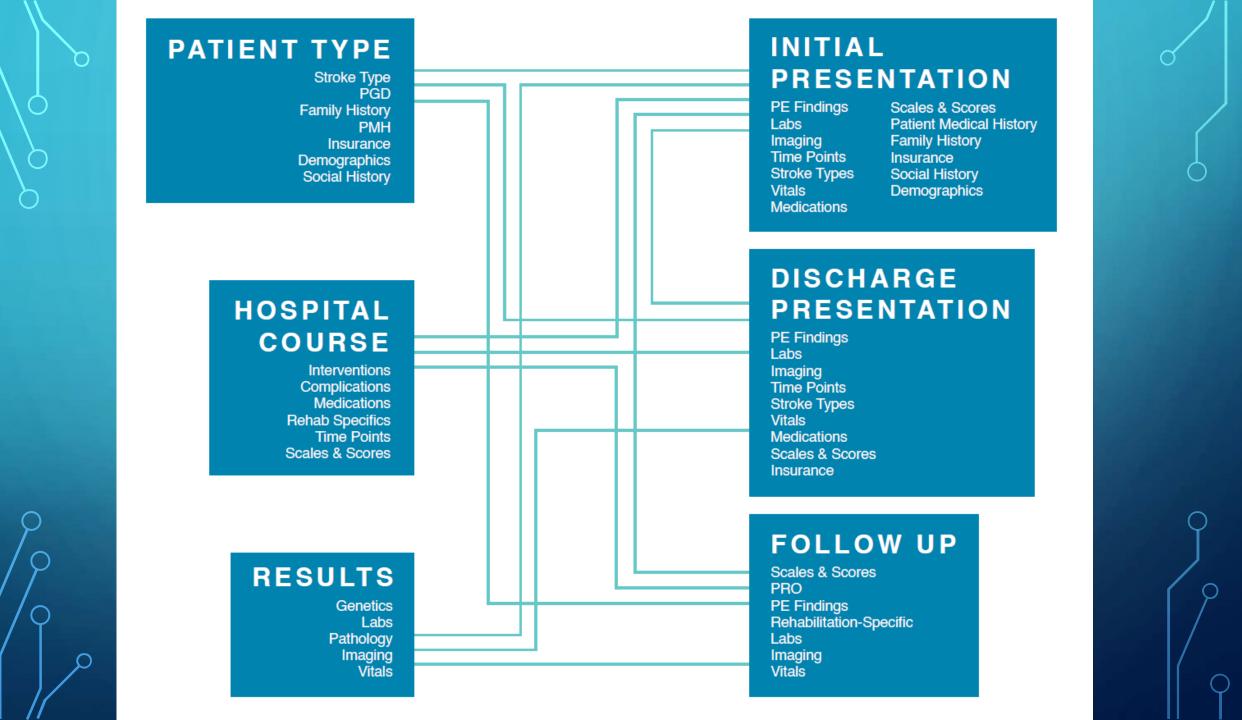


"The answer will not be mergers, it will be creative and strategic partnerships. Partnerships you would have never imagined just a few years ago."



CMIO 3.0 CHARACTERISTICS

Culturally Competent



Novant Health-Analysis and Insight

> Discharge Disposition Overutilization of Skilled Nursing Facility Underutilization of Hospice

> > Lapse in Days 0-7 days in surgical population Varied by medical condition

Reason for Readmission 50% were related to the medical reason of the index Complications from surgery

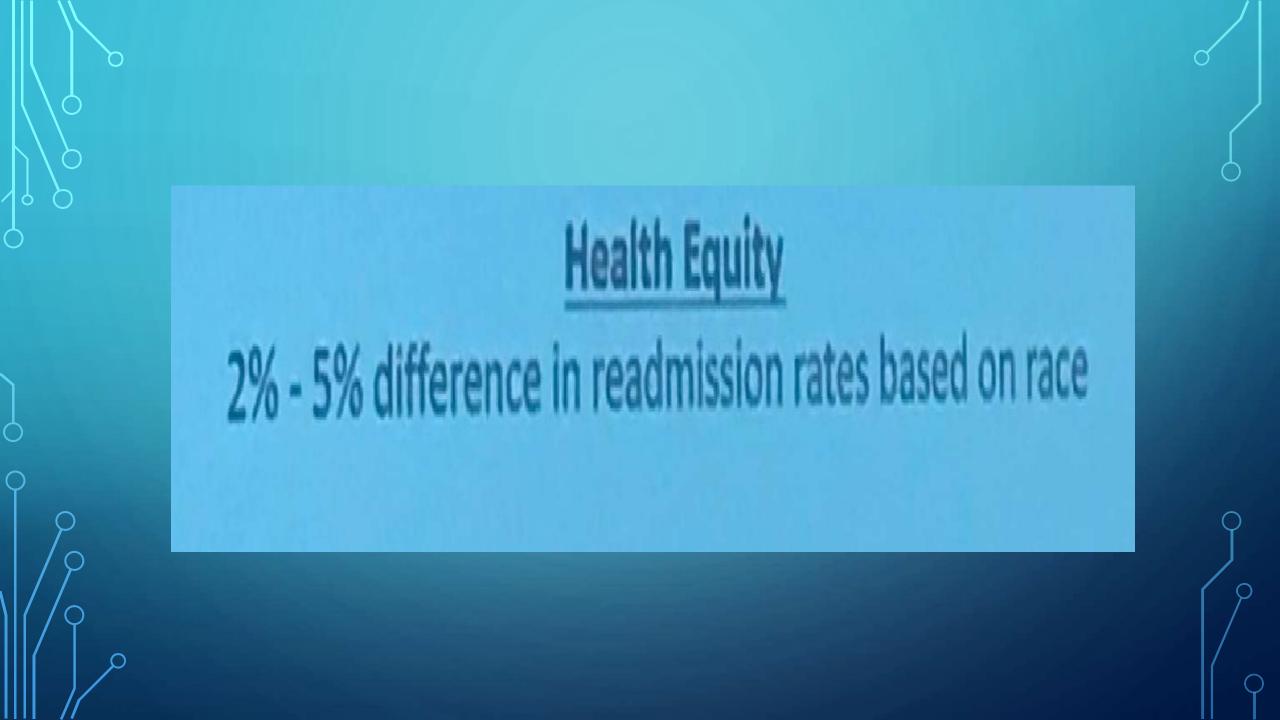
Readmission Facility [Novant/Non-Novant] 80% were Novant

Health Equity 2% - 5% difference in readmission rates based on race

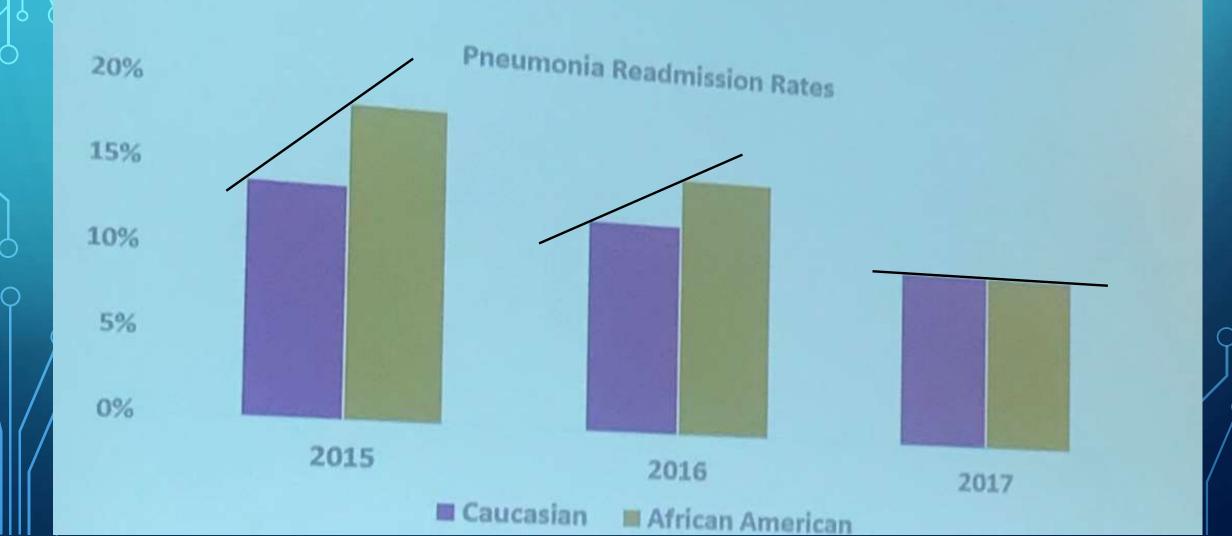


Novant Health

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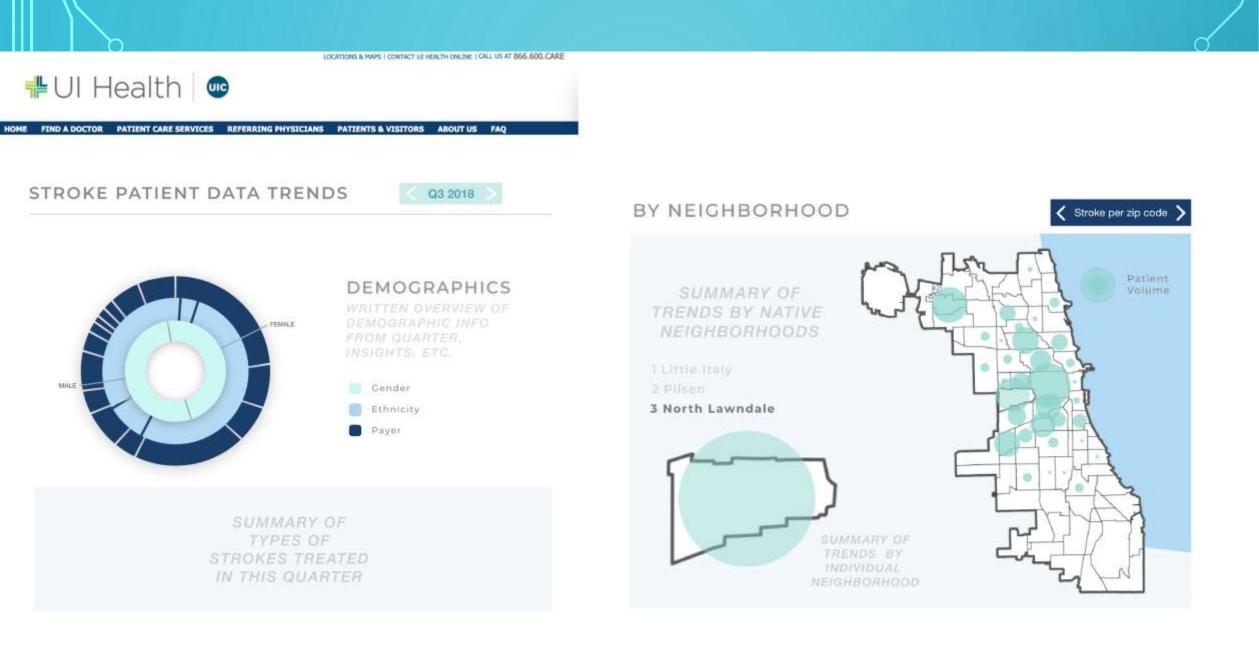


Novant Health Health Equity



CMIO 3.0 CHARACTERISTICS

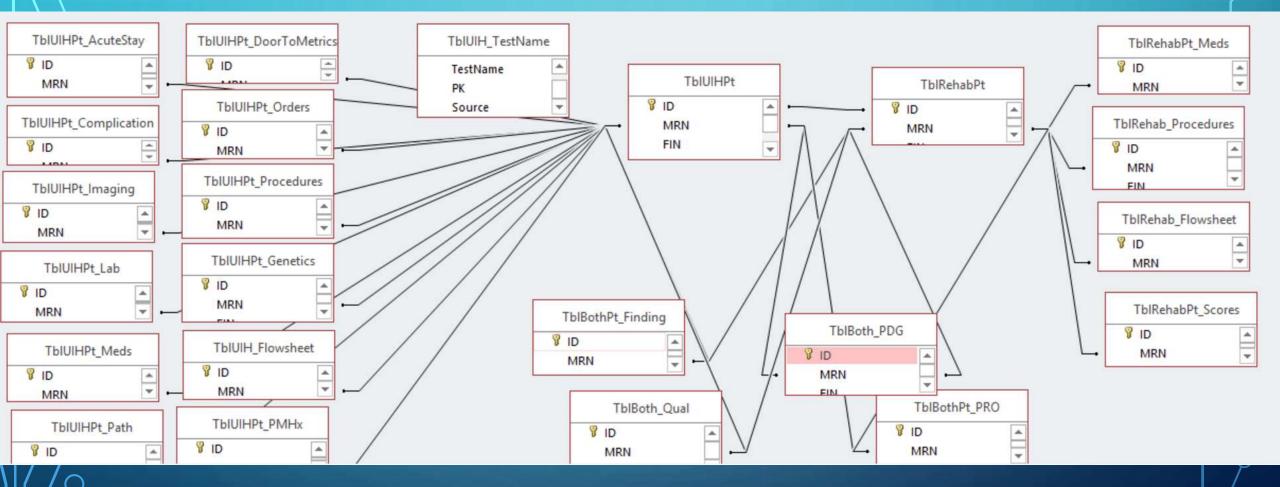
Programmer ?



Q

CMIO 3.0 CHARACTERISTICS

Data Curator



FUNCTIONAL INDEPENDENCE MEASURE (FIM) SCORES ARE A BETTER PREDICTOR OF 30-DAY READMISSION COMPARED TO COMORBIDITIES ALONE

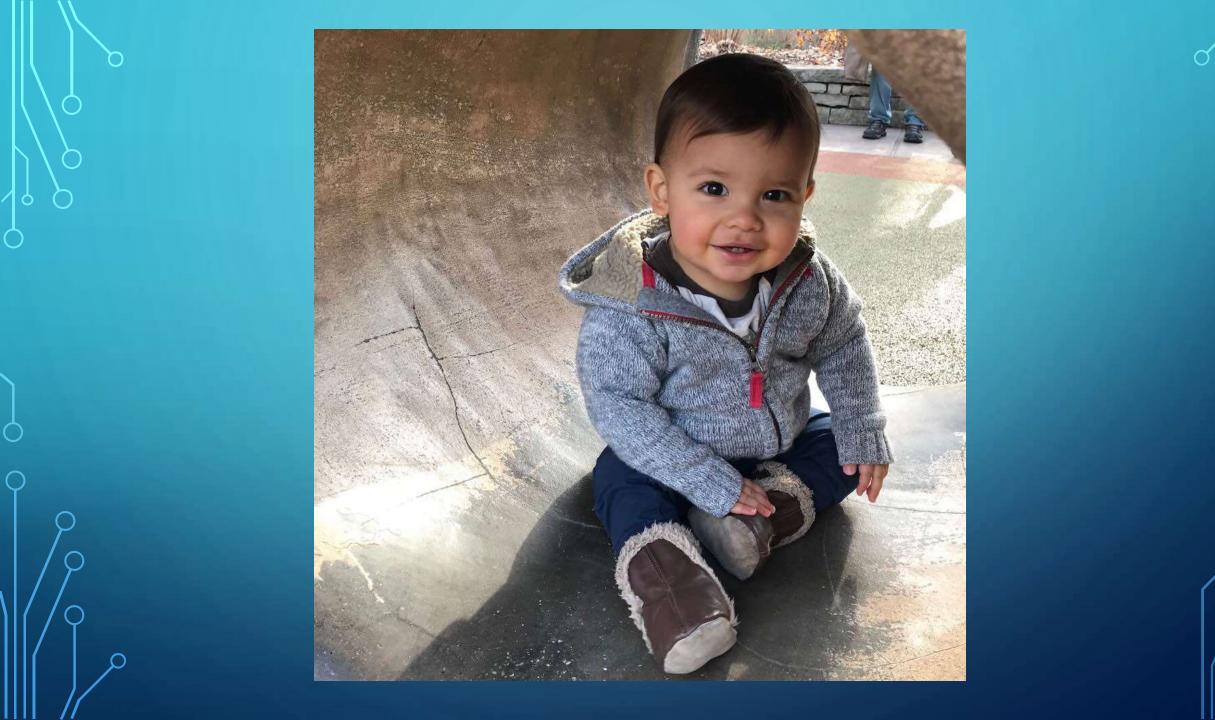
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- Shih SL, Zafonte R, Bates DW, et al. Functional status outperforms comorbidities as a predictor of 30-day acute care readmissions in the inpatient rehabilitation population. J Am Med Dir Assoc. 2016;17(10):921-926.
- Fisher SR, Graham JE, Krishnan S, Ottenbacher KJ. Predictors of 30-day readmission following inpatient rehabilitation for patients at high risk for hospital readmission. Phys Ther. 2016;96(1):62-70.]

DATA CURATOR

Physician Determined Data

(What weekly/monthly reports do clinicians want to see?)







HEALTH LAW

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INVESTIGATIONS MORE TOPICS V DATA & DOCS Stratch

Death By 1,000 Clicks: Where Electronic Health Records Went Wrong

BOTCHED OPERATION

The U.S. government claimed that turning American medical charts into electronic re make health care better, safer and cheaper. Ten years and \$36 billion later, the system mess. Inside a digital revolution that took a bad turn.

DHADMA

By Fred Schulte and Erika Fry, Fortune + MARCH 18, 2019



Docs struggle with EHR challenges

Lack of productivity, increased workload are among top complaints



Have you overcome EHR-related productivity challenges?

Opinion

The Business of Health Care Depends on Exploiting Doctors and Nurses

One resource seems infinite and free: the professionalism of caregivers.

By Danielle Ofri Dr. Ofri practices at Bellevue Hospital in New York.

June 8, 2019

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Digital Phenotyping

John Zulueta – Clinical Informatics Fellow, UIC jzulueta@uic.edu





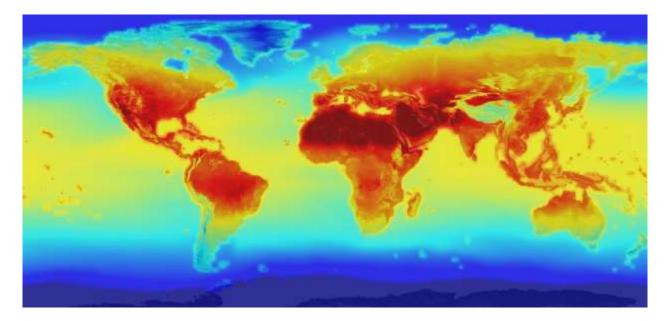




Photo by <u>chuttersnap</u> on <u>Unsplash</u>

Photo by <u>Max LaRochelle</u> on <u>Unsplash</u>





NASA





Photo by <u>Joshua Forbes</u> on <u>Unsplash</u>







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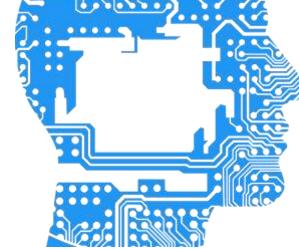
Photo by Martha Dominguez de Gouveia on Unsplash



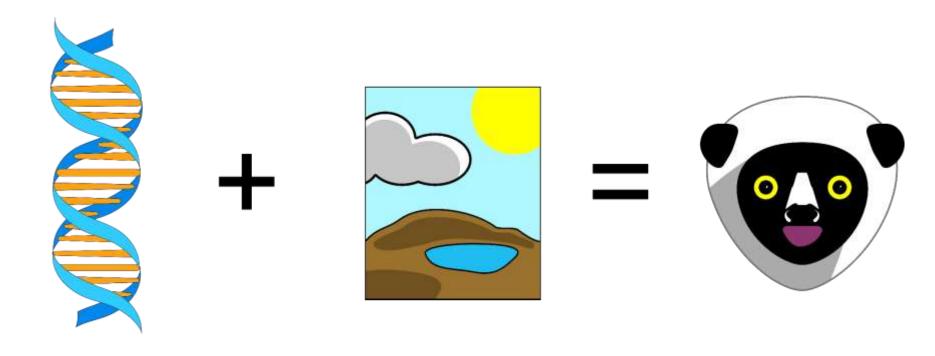


Photo by Eric Rothermel on Unsplash





PHENOTYPE



Genotype

Environment

Phenotype

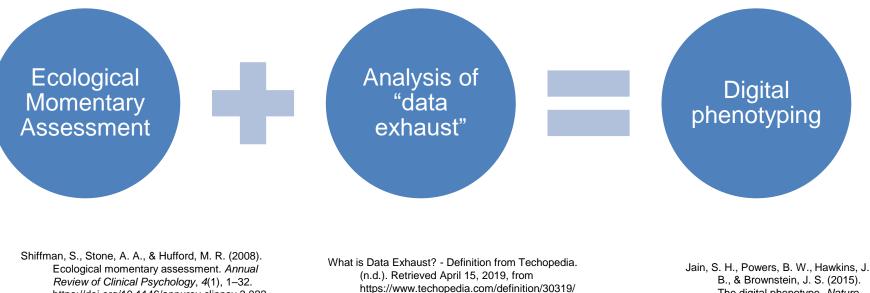
Keith Chan (https://commons.wikimedia.org/wiki/File:Genotype_Plus_Environment .svg), Resized and animated by J Zulueta, https://creativecommons.org/licenses/by-sa/4.0/legalcode



HOW DO YOU CREATE A DIGITAL PHENOTYPE?

https://doi.org/10.1146/annurev.clinpsy.3.022

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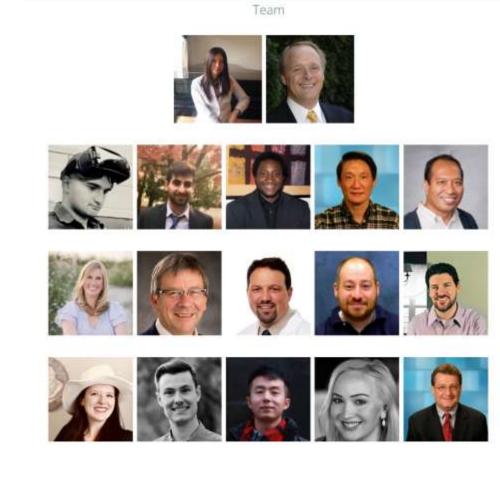
B., & Brownstein, J. S. (2015). The digital phenotype. *Nature Biotechnology*, *33*(5), 462–463. https://doi.org/10.1038/nbt.3223



CAN WE USE THE DIGITAL EXHAUST FROM MOBILE PHONES TO CREATE PHENOTYPES OF PSYCHIATRIC DISEASES?

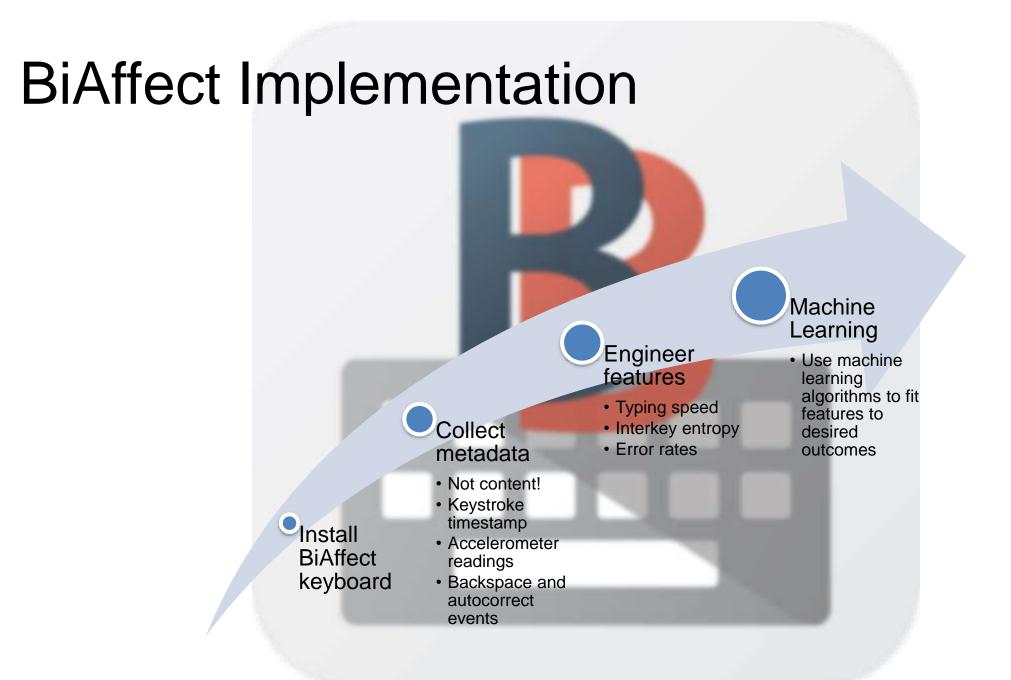


INTRODUCING BiAffect











PILOT RESULTS

 Completed a pilot study using an early version of BiAffect in 2017 with 40 subjects

ICCURSAL OF SERVICE INCOMENT BUSINESS.

Original Papel

Predicting Mood Disturbance Severity with Mobile Phone Keystroke Metadata: A BiAflect Digital Phenotyping Study

Inter Juliana", MD, Anders Precimile", MR, Walter Rana", BA, Rebecce Finite", BA, Pollavi Rubel, BA, Rott A Langanetter', Pub Melver McImiel, MD Olasola Agrany', MD JMD: Pater C Nebuol, PDD: Kells Rysel, PDD Alex Lucer, MD, Phile

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Abstract

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WILEY PERMIT

Let your fingers do the talking: Passive typing instability predicts future mood outcomes

Jonathan P. Stange¹ | John Zuluata¹ | Scott A. Langenecker¹ | Kelly A. Byan¹ Andrea Piscitelle¹ Janua Duttecy¹ Mehin G. Mcinnis² Pete Nelson¹ | Olusola Alilore²

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DeepMood: Modeling Mobile Phone Typing Dynamics for Mood Detection

Bokai Cao⁷, Lei Zheng¹, Chenwei Zhang¹, Philip S. Yu^{1,2}, Andrea Piachello⁷, John Zalaeta⁴ Ohi Ajilow¹, Kelly Pyin⁴, and Alex D. Leow^{1,3,3} ¹Department of Computer America, University of Binors at Chaogar ¹Institute for Data Internet, Tainglata University "Department of Psychiatry, University of Binom at Charage "Department of Provisities, Dravestics of Michigan Toyouttainen of Binorgizzoring, University of Binois at Chingscurbolias. Meng21. cohang94. provis opine11 grain esha joudurin, regident alsowetperch air, eds Report and another de-

ABSTRACT

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KEYWURDS.

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1 INTRODUCTION

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Figure 1: A sample of the collocied data in time sector.

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become the financial impact of the diates [21]. We study the methic phone typing dynamics metadata on a services level. A assesser is defined as hepstating with a heppersy-which occurs after 3 or more seconds have shaped sizes the last heypers and contrining and 5 or more scould claps between keypenset¹. The distribute of a sensitive in typically less than one screate in this manner, each participant woodl instribute many complex, our per phone mage assume, which readd breefs data such its and mashed training. Each penalise to contendard of fastment that are represented to realight them to modulities (e.g., signare more there does not describe a statement without the statement of the state of the chick has different transformer and discriments a domestic Figure Muchdong the multi-view item across data on multi-a line-grammer encodered himping several damatable dialogue

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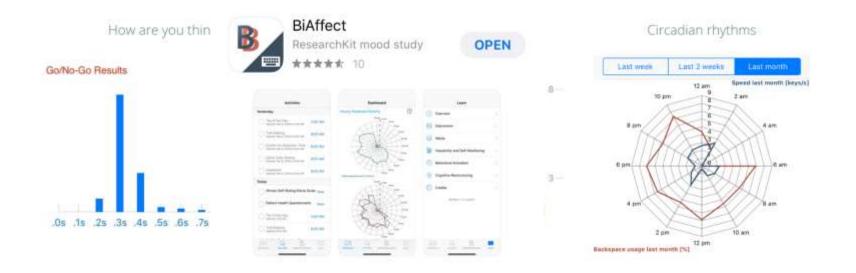
KEY FINDINGS

- 63% of the variance in depressive symptoms and 34% of the variance in mania symptoms is explained by our models
- Using deep learning methods subjects can be classified as depressed or not depressed with 90% accuracy
- Instability of daily typing metrics is 70% correlated with future depressive symptoms



CURRENT STEPS

- Study currently underway via Apple's Research Kit platform open to adults in the U.S.
- Includes self-reported measures and tests of cognitive function





2019

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2	13	14	15	16	17	18		9	10	11	12	13	14	15	14	15	16	17	18	19	20	11	12	13	14	15	16	17
9	20	21	22	23	24	25		16	17	18	19	20	21	22	21	22	23	24	25	26	27	18	19	20	21	22	23	24
6	27	28	29	30	31		1	23	24	25	26	27	28	29	28	29	30	31				25	26	27	28	29	30	31
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Photo by <u>Chad</u> <u>Madden</u> on <u>Unsplash</u>

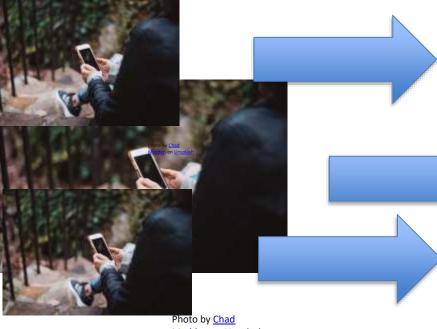


Photo by <u>Chad</u> Photo Madden on <u>Unsplash</u>

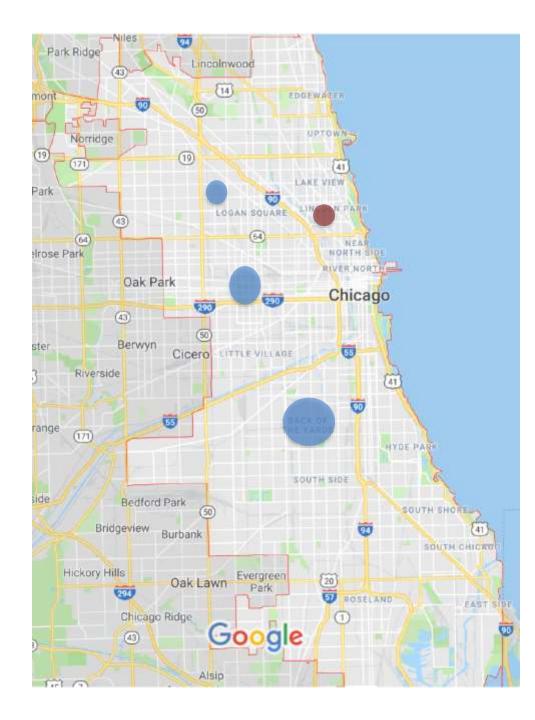








Photo by <u>Chad</u> <u>Madden</u> on <u>Unsplash</u>









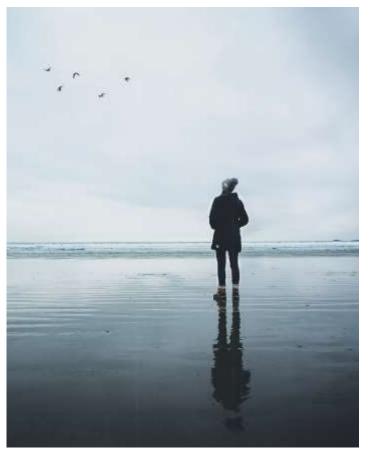






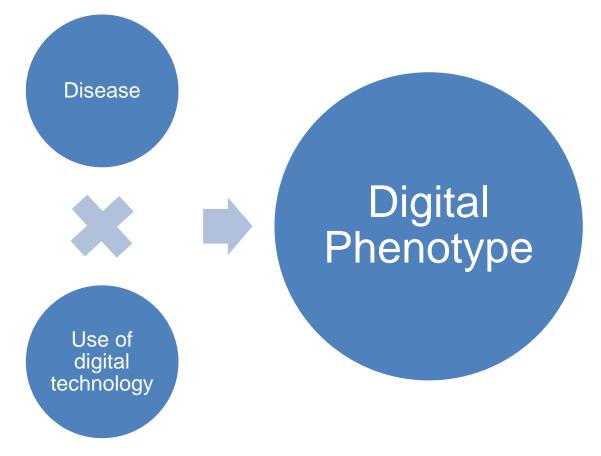


Photo by <u>Chiara Pinna</u> on <u>Unsplash</u>



Photo by <u>ben</u> <u>o'bro</u> on <u>Unsplash</u>

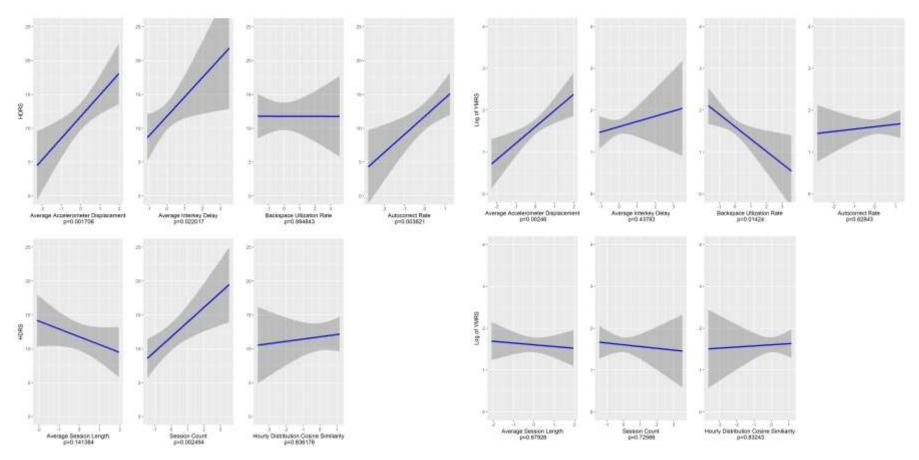
DIGITAL PHENOTYPE



Jain, S. H., Powers, B. W., Hawkins, J. B., & Brownstein, J. S. (2015). The digital phenotype. *Nature Biotechnology*, 33(5), 462–463. https://doi.org/10.1038/nbt.3223



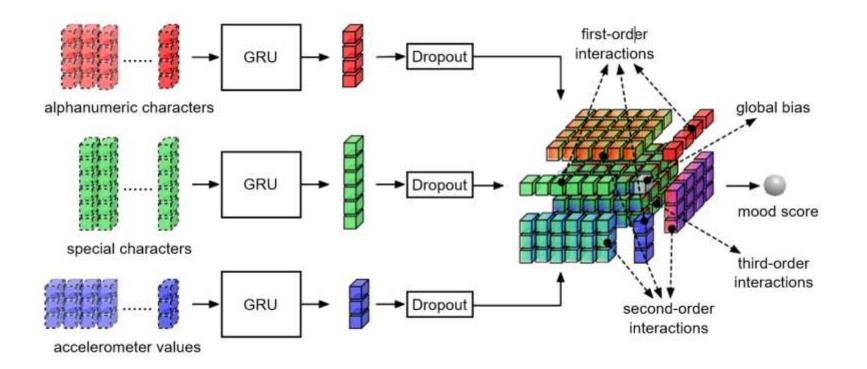
63% of the variance in depressive symptoms and 34% of the variance in mania symptoms is explained by our models



Zulueta, J., Piscitello, A., Rasic, M., Easter, R., Babu, P., Langenecker, S. A., ... Leow, A. (2018). Predicting Mood Disturbance Severity with Mobile Phone Keystroke Metadata: A BiAffect Digital Phenotyping Study. *Journal of Medical Internet Research*, 20(7), e241. https://doi.org/10.2196/jmir.9775



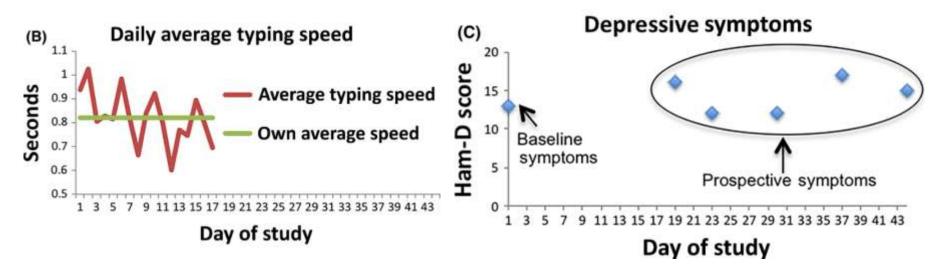
Using deep learning methods subjects can be classified as depressed or not depressed with 90% accuracy

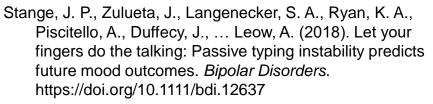


Cao B, Zheng L, Zhang C, Yu PS, Piscitello A, Zulueta J, Ajilore O, Ryan K, Leow AD. DeepMood: Modeling Mobile Phone Typing Dynamics for Mood Detection. Proc 23rd ACM SIGKDD Int Conf Knowl Discov Data Min - KDD '17 [Internet]. 2017;(August):747–755.



Instability of daily typing metrics is 70% correlated with future depressive symptoms







LAST TALK

HIJJAWI

