



LHSCollaboratory
Putting Data, Knowledge, and Practice into Motion at the University of Michigan

Fall Kickoff and Poster Session

September 18, 2018

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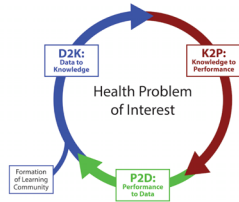
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The Ethical, Legal, and Social Implications of Learning Health Systems: An ELSI-LHS approach to moving from knowledge to practice

(adapted from a poster presented at the Mobilizing Computable Biomedical Knowledge Conference, July 11-12, 2018, which was prepared by: Jodynn Platt, PhD, MPH¹; Elizabeth Cope, PhD, MPH¹; Melissa Creary, PhD, MPH²; Emily Dibble¹; Frank Manion, PhD³; Dorene Markel, MS, MHSA¹; Paige Nong¹; Minakshi Raj, MPH²; Kayte Spector-Bagdady, JD, MBE¹; M. Grace Trinidad, MPH¹; Joshua Rubin, JD, MBA, MPP, MPH¹
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Background



In a learning health system cycle, **data and experience are used to generate new knowledge, to generate new data**. Learning occurs throughout this cycle to improve health.

Addressing ethical, legal, and social implications of learning health systems (ELSI-LHS) is a core aspect of ensuring learning health systems achieve their potential to improve health, deliver higher quality care, and health delivery organizations are better places to work.

The ELSI-LHS Team in the Department of Learning Health Sciences at the University of Michigan aims to tackle important questions in this area in order to advance LHS policy, practices, and interdisciplinary research. Programmatically, the team is dedicated to: (1) identifying and promoting research on key issues in need of theoretical and empirical exploration; (2) providing service and informing practice in local, state, national, and global initiatives; (3) cultivating support for students, faculty, staff, and communities with educational and collegial opportunities related to the impact of learning health systems on science, practice, and society; and (4) translating research findings for greatest impact and meaning to practice and policy.

To foster responsible research and innovation, ELSI-LHS adopts the imperative that diverse stakeholders work together throughout the learning cycle to better inform decisions affecting health and align process and outcomes with social values, needs, and expectations.

This poster considers what an ELSI-LHS approach might look like as learning health systems take new knowledge into practice

The LHS Knowledge to Practice ecosystem

The generation and implementation of knowledge spans a number of roles, each held by individuals within organizations and systems.

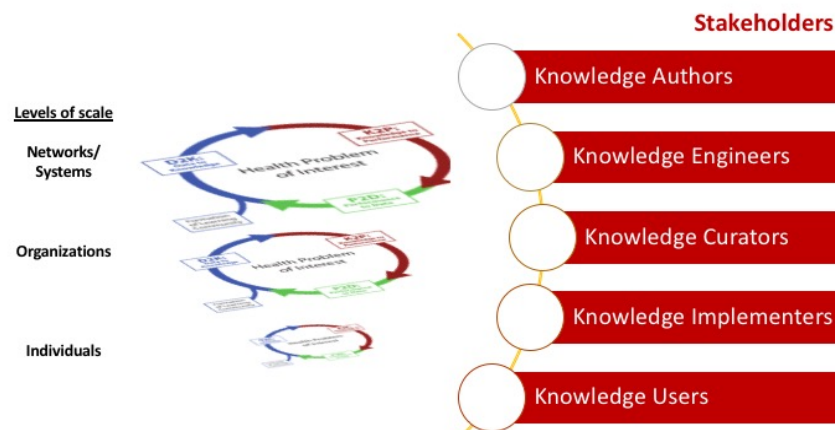


Figure. The learning cycle and the K2P ecosystem. Adapted from: Friedman CP, Rubin JC, Sullivan KJ. Toward an information infrastructure for Global Health Improvement. Yearbook of medical informatics. 2017 Aug;26(01):16-23.

The ELSI Approach

Principle	Definition	Conventional Approach	The ELSI Approach
Construction of Knowledge	Knowledge production is dependent on the social circumstances of its creation.	The belief that empirical research carried out properly is impermeable to social or cultural influences	Stakeholders critically engage with majority and minority sources in literature review or R&D processes to consider implications for equity and inclusion on an individual artifact and systems
Structural Determinism	The fundamental role of macro-level forces in driving and sustaining inequities	Emphasizing individual or interpersonal factors	Work considers policy and system-level factors that may promote inequities
Social Reflexivity	Deep awareness of one's social position; awareness of social stratification processes operating in ostensibly objective contexts	Believing in the irrelevance of discrimination, often by misattributing causal factors (e.g., conflating socioeconomic status and race)	Individuals clarify biases before beginning work
Voice	Prioritizing the perspectives of marginalized persons; Privileging the experiential knowledge of outsiders within	Routine privileging of majority perspectives	Stakeholders intentionally pursue feedback from affected communities not represented by majority perspectives
Critical Approaches	To dig beneath the surface and develop a comprehensive understanding of one's biases	To accept phenomena or explanations at face value	Stakeholders consider alternative explanations for findings than those previously posited; review policies and operating procedures with diverse stakeholders and frameworks.
Disciplinary Self-Critique	The systematic examination by members of a discipline of its conventions and impacts on the broader society	Limited critical examination of how a discipline's norms might influence knowledge on a topic	Stakeholders examine the implications of the words they use to describe their work, and consider and report unintended consequences and unequal outcomes that may result from the use of their tool

Table. Principles of an ELSI approach to moving knowledge into practice in a LHS. Adapted from: Ford CL, Airhihenbuwa CO. The public health critical race methodology: praxis for antiracism research. *Social Science & Medicine*. 2010 Oct 1;71(8):1390-8.

Ensuring FAIRness^a is fair, **the ELSI approach** is based on principles adapted from Chandra Ford's anti-racism praxis framework and theories of **epistemic privilege^b**, (social positions of power are likely to generate and propagate perspectives that are different than others'), **epistemology of ignorance^c**, (recognizing that one cannot fully understand the complex practices of knowledge production and the variety of features that account for why something is known, without also understanding the

practices that account for *not knowing*), and **situated/partial knowledge^d**, (knowledge specific to a particular situation are often embedded in language, culture, or traditions). Most problems have to be solved by taking advantage of a partial understanding of the problem context and problem data.

Implications going forward

Generating new knowledge and putting it into practice will advance an important part of what we know can have a lasting and meaningful impact on health and healthcare. Attention to the ethical, legal, and social implications of what is and is not encoded in knowledge artifacts will be a critical factor in ensuring LHS-generated knowledge realizes its full potential and in its future development and sustainability. An ELSI requires prioritization of research and practice that examines perspectives of multiple stakeholders engaged in the design, development, and clinical and policy implementation and is self-critical in its capacity for inclusion.



The Knowledge Grid for Health

A technical platform for managing and deploying computable biomedical knowledge at scale

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What is the Knowledge Grid?

In short, the Knowledge Grid is technical infrastructure to support curating, managing, and utilizing computable biomedical knowledge. These functions are enabled through the interaction of three main components when they form a grid:

Component 1. KNOWLEDGE OBJECTS

Packages for computable biomedical knowledge (CBK) which enable a variety of services to make CBK findable, accessible, interoperable, and reusable

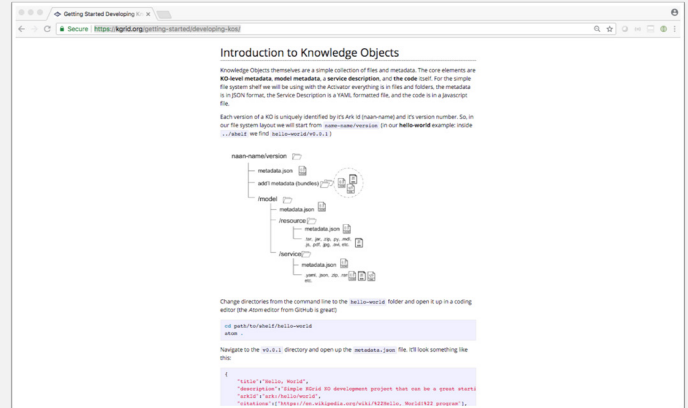
Component 2. ONLINE LIBRARY

An online, open-source library system purpose-built for curating and managing large collections of Knowledge Objects that hold CBK resources.

Component 3. ACTIVATOR

The technical system and framework which allows the CBK within Knowledge Objects to be accessed through Application Programming Interface (API) services.

More Online at www.kgrid.org



The Printing Press gives way to Server Clusters that in turn make the Knowledge Grid possible

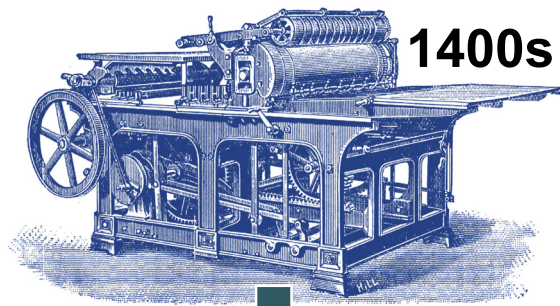
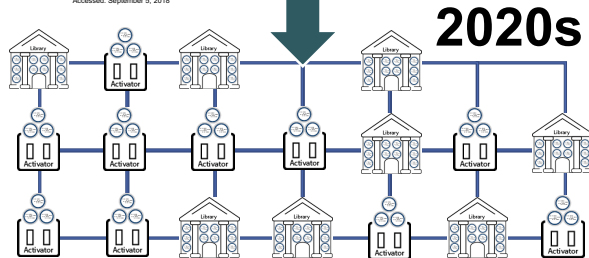


Image from: Changing the World – The Printing Press
 Manchester Historian, June 12, 2016



Image from: <http://www.cnet.com/tech/server/78463/>
 Accessed: September 5, 2018



Some Example Use Cases for the Knowledge Grid are

Use Case 1: Calculating and Using Reliable Risk Prediction Scores in Clinical Practice

The era of "Big Data" is upon us and a wide variety of statistical techniques can now be used to create risk prediction models to inform complex health decisions.

As one example of this, it is now possible to predict someone's risk of being **diagnosed with lung cancer** over the next 5 to 10 years with good accuracy. Such predictions can be used to support clinician-patient **shared decision making about lung cancer screening**. The Knowledge Grid facilitates the adoption and use of predictive models.

Use Case 2: Widely Sharing Complex Knowledge about Medications and Genetics

Precision medicine, whereby genetic information is used to tailor treatments to individual persons, depends on complex knowledge about genetic relationships.

Knowing **how genes determine an individual's capacity to metabolize various medications** can lead to **safer prescribing** and better health outcomes. Because this knowledge is complex, it can be curated and managed in the Knowledge Grid once and shared with those who need it around the globe.

Use Case 3: Using Social Determinants of Health Data to Highlight Needful Services

It turns out that, in addition to clinical factors, many social factors also influence our health and well-being in ways that can be enhanced, if they are good, or mitigated, if they are bad.

By systematically using computable models that are curated, versioned, and managed in the Knowledge Grid, it is possible to highlight for individuals a range of social services from which they could benefit, including housing, transportation, food pantries, and other services.

Flynn, A.J., Boisvert, P., Gittlen, N., Gross, C., Iott, B., Lagoze, C., Meng, G. and Friedman, C.P., 2018. *Architecture and Initial Development of a Knowledge-as-a-Service Activator for Computable Knowledge Objects for Health*. *Studies in health technology and informatics*, 247, pp.401-405.

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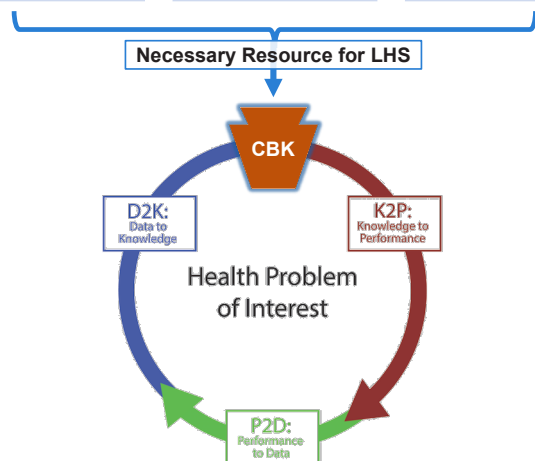
Mobilizing Computable Biomedical Knowledge

A Growing Community to Transform Health

Matthew Fiorillo¹, Charles Friedman¹, Rachel Richesson², Peter Boisvert¹, Lisa Ferguson¹, Allen Flynn¹, Jodyn Platt¹, Josh Rubin¹

¹ University of Michigan Medical School, Department of Learning Health Sciences; ² Duke University School of Nursing

Computable	Biomedical	Knowledge
<ul style="list-style-type: none"> Machine-executable and systematically applicable using calculation or logical operation 	<ul style="list-style-type: none"> Related to human health 	<ul style="list-style-type: none"> Result of an analytic or deliberative process undertaken by a community



Excerpt: A Manifesto for Mobilizing CBK

In order to improve health care, population health, and individual health, every decision affecting health should be informed by the best available knowledge in computable forms.

We will:

- Sustain the CBK ecosystem
- Establish participatory governance
- Enable the ecosystem with open standards
- Make the ecosystem diverse and inclusive
- Build and uphold trust in CBK
- Ensure the safe and effective use of CBK
- Explore the sciences of CBK collaboratively
- Generate value for CBK creators, users, and the general public
- Be agile to reflect rapid changes in knowledge
- Engender equity in health and in knowledge accessibility
- Ensure methods to support transparency for CBK
- Implement the highest standards of privacy and security
- Enable staged transitions of knowledge from human-readable to fully computable forms

Why Mobilize CBK? To effectively organize knowledge so that CBK is properly encoded, versioned and curated, shared rapidly and widely, and used repeatedly, by stakeholders including researchers, informaticians, librarians, health IT vendors, clinicians, patients, and health system administrators

Community Building

- MCBK conference: Oct 18 & 19, 2017, Ann Arbor, MI
- **MCBK meeting: July 10 & 11, 2018, National Library of Medicine, Bethesda, MD**
- Upcoming webinars
- Future MCBK meeting: July 2019
- **Ongoing activity of 4 workgroups**



Standards Workgroup

Establish requirements for data, knowledge representation, exchange, function, and metadata, for CBK developers and consumers

Next steps: Develop set of CBK artifact metadata exemplars, with rationale for each element; Identify metadata models to use

Technical Infrastructure Workgroup

Identify framework components necessary to move knowledge from generation into practice by facilitating dissemination, testing, versioning, use, evaluation, scalability, and interoperability of CBK

Next steps: Learn from other industries; Define metadata; Describe use cases to solidify CBK requirements; Establish governance structure; Identify candidate platforms and CBK representations

Sustainability for Mobilization and Inclusion Workgroup

Identify and engage diverse stakeholders of CBK to accelerate and sustain adoption; Leverage existing networks, communities, and resources; Identify communication needs; Mitigate bias and discrimination

Next steps: Identify and engage champions in stakeholder groups such as professional societies, patient advocacy groups, clinical guideline orgs, libraries, and industry vendors

Policy and Coordination to Ensure Quality and Trust Workgroup

Determine process to ensure high quality and trustworthy knowledge in a CBK ecosystem

Next steps: Explore current practices; Compare metadata schema to identify gaps; Evaluate transparency in CBK systems; Map regulatory space; Extend FAIR principles (Findability, Accessibility, Interoperability, Reusability) with TLC (Traceability, Licensure, Connectedness)

Select organizations developing platforms to mobilize CBK:

Knowledge Grid (kgrid.org)	Apervita (apervita.com)	IBM Watson Health (truvenhealth.com)
CDS Connect (cds.ahrq.gov)	Semedy (semedy.com)	MAGIC – GRADE (magicproject.org)

For more information visit: dlhs-umi.ch/mcbk

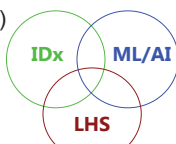
Merging 3 Communities in an LHS for Diagnostic Excellence

Leveraging Disciplinary Differences

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The Grand Challenge of Diagnostic Improvement

- Errors in medical diagnosis vary widely, frequently lack data that might define their causes, and are often obscured by the culture of medical practice
- 3 foundational concepts of the LHS can be applied to achieving timely, efficient, and accurate diagnoses:
 - I. Learning from every health event;
 - II. Engendering a system solution to a system problem;
 - III. Significantly shortening the latency between knowledge generation and its application to practice.
- Doing so requires stakeholders from 3 academic communities
 - Improve diagnosis (IDx)
 - machine learning & artificial intelligence (ML/AI)
 - LHS



A Novel Demonstration

- LHS efforts have typically sought better health outcomes through improving treatments, under the assumption a correct diagnosis has been made
- Many participating community members were known to each other, but had never collaborated directly with a shared goal to reduce diagnostic error



Community-Building Methods

- Following key-informant interviews with experts from all 3 communities, we shared a white paper envisioning the collaboration, then hosted 34 participants in a working meeting:
 - 17 from IDx, 7 from ML/AI, and 11 from LHS
- Participants joined interdisciplinary small-groups focused on conditions disproportionately affected by diagnostic error
 - sepsis, stroke, lung cancer, and melanoma
- Small-groups designed a “prototypical” learning cycle for their assigned condition and discussed potential infrastructure

Results from this Initial Convening

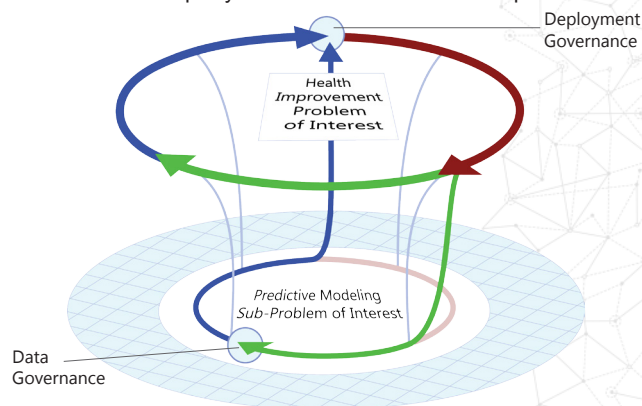
- Reiterated that current barriers to defining, measuring, and monitoring diagnostic error impede progress
- Demonstrated that the communities could find consensus using LHS concept as overarching framework
- Learned that each community brings unique, deep expertise to the aim **AND**
- Inferred that directly leveraging different approaches and methodologies might strengthen collaborative processes

Generously funded by the



A Modified, Collaborative Framework

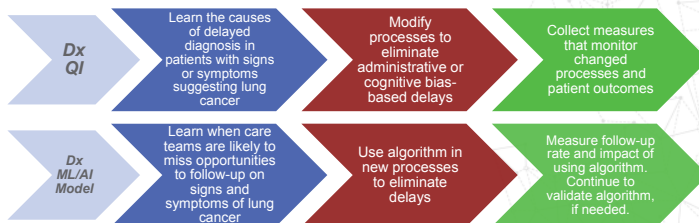
- Affirms and integrates different facets of Dx problems of interest:
 - *Health Improvement*—surveillance and implementation of changes in clinical processes and resulting outcomes
 - *Predictive Modeling*—generation, revision, and deployment of predictive models
- Unified K2P emphasizes that outcomes are the interaction of interventions from complementary learning processes
- All stakeholders equally invested and involved in all phases



- *Governance nodes* facilitate reciprocal needs concerning the development and deployment of potential predictive models
- Through these governance structures, the learning community can ensure the models are:
 - clinically meaningful, clinician-interpretable, and responsive to the needs of care teams
 - applied with consistency and validity to the model’s capabilities
 - protected from negative feedback, if necessary

Simplified Example Learning Cycle— End Delays Diagnosing Lung Cancer*

Note: all learning cycles must first begin with an initial P2D phase for improved data collection



Next Steps

- Validate example learning cycles and conceptual framework with broader group of participants
- These learning cycles require robust data, which require supporting infrastructure: we’ll host a second, smaller convening to design and propose these components

***Thank You** to Kathryn McDonald, PhD MBA and Hardeep Singh, MD MPH for continued input building the lung cancer example





Identification of High Risk Characteristics Through Implementation of the Comprehensive Diabetic Retinopathy Program

Modifications to Clinic Workflow and Data Infrastructure to Support a LHS

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Background

- Diabetic retinopathy (DR) is the most common complication of diabetes mellitus¹ and is the leading cause of blindness in working-age adults in the world.²
- Longer duration of diabetes mellitus, poorer glycemic control as measured by hemoglobin A1c (A1c), and higher blood pressures are associated with increased incidence and prevalence of DR.³⁻⁷
- Aggressive control of both blood glucose and blood pressure significantly reduces the risk for development and progression of DR.⁸⁻¹⁰
- Despite the clear importance of parameters such as A1c, blood pressure, and duration of diabetes in the prevention and treatment of DR, many ophthalmologists are often unaware of patients' overall diabetes management status.

Purpose

- We implemented a Comprehensive Diabetic Retinopathy Program to collect and store structured data in the EHR on patients with diabetes presenting to the Kellogg Eye Center retina clinic. The program created infrastructure to support an efficient LHS by making the longitudinal data more easily accessible on an ongoing basis and thereby will allow for more frequent future data analyses.
- We propose that obtaining comprehensive data on patients with diabetes will allow ophthalmologists to better risk stratify and tailor patient care.

Methods

- Changes to the clinic workflow included beginning to collect blood pressure and POC HbA1c and utilizing a newly created EHR form that captured structured data assessing high risk. The newly acquired data being stored in the EHR was combined with pre-existing data in the EHR as well as responses from survey questions.
- Demographics, body-mass index (BMI), blood pressure (BP), A1c, smoking history, diabetes type, DR diagnosis, diabetes duration, number of retina clinic visits, and kidney disease history based on both self-report and microalbuminuria ($\geq 30 \mu\text{g}$ albumin/mg creatinine) were collected on all patients with diabetes presenting to the Kellogg Eye Center retina clinic for both new patient visits and return visits from 7/1/16 to 6/30/17.
- A subgroup of patients with 2 or more of the following factors, determined "high risk" for complications by endocrinologists, was targeted for additional data collection and analysis: A1c > 9% in the last 6 months, BP > 140/90 in the last 6 months, history of kidney disease, and diabetes duration > 10 years.
- Technicians trained in diabetes education administered a three-question multiple choice survey to patients in this subgroup to assess knowledge of diabetes management goals.

Results

Table 1. Survey Results

Survey Questions and Responses	Within the Subsample: risk score ≥ 2 n=418 (patients who answered)	
	n	%
HbA1c goal:		
<7.0 (correct)	366	87.56
7.0-9.0	32	7.66
>9.0	0	0
No recommendation	3	0.72
No/unclear answer	17	4.07
Blood Pressure goal:		
<140/90 (correct)	192	45.93
<120/80	201	48.09
<160/100	8	1.91
No recommendation	2	0.48
No/unclear answer	15	3.59

Grant Support

- Research to Prevent Blindness
- A. Alfred Taubman Medical Research Institute, University of Michigan
- National Eye Institute Travel Grant

Results continued

Table 2. Baseline Characteristics

	Entire cohort N=2378				Subsample: risk score ≥ 2 N=826			
	N or Mean	% or SD	Min	Max	N or Mean	% or SD	Min	Max
Patient age Mean (SD)	63.1	14.34	12	100	61.58	14.02	16	97
Race N(%)								
Asian	110	4.63			33	4.00		
Black, African American	351	14.76			158	19.13		
White or Caucasian	1783	74.98			589	71.31		
Unknown/other/mixed	134	5.63			46	5.57		
Sex N(%)								
Female	1112	46.76			379	45.88		
Male	1266	53.24			447	54.12		
Ever smoked N (%)								
Yes	1045	43.94			347	42.01		
No/unknown	1333	56.06			479	57.99		
Diabetic retinopathy N (%)								
Yes	1369	57.57			650	78.69		
No	1009	42.43			176	21.31		
Diabetes type N(%)								
Type 1	306	12.87			124	15.01		
Type 2	1518	63.84			592	71.67		
Type 1 or Type 2	75	3.15			48	5.81		
Not recorded	479	20.14			62	7.51		
Max microalbumin N(%)								
<30	183	7.70			74	8.96		
≥ 30	131	5.51			113	13.68		
Unknown	2064	86.8			639	77.36		
History of kidney diagnosis N (%)								
Yes	408	17.16			353	42.74		
No/unknown	1970	82.84			473	57.26		
Duration of diabetes ≥ 10 years								
Yes	1168	49.12			731	88.50		
No	1210	50.88			95	11.50		
Max patient's BMI Mean (SD)	33.40	8.02	17	81	33.98	8.34	17	81
Max systolic blood pressure Mean (SD)	140.06	22.61	80	237	150.52	22.48	87	237
Max diastolic blood pressure Mean (SD)	72.75	11.57	40	123	75.90	12.03	42	116
Patient's number of visits Mean (SD)	2.34	2.31	1	19	3.01	2.71	1	18
Max patient's A1C Mean (SD)	7.94	1.76	4.30	15.20	8.58	2.00	4.70	15.20

Conclusions

- Implementation of this program supports an efficient LHS through the creation of a longitudinal dataset on patients with diabetes presenting to a retina clinic.
- Despite low mean A1c and number of visits, the large range of A1c values (4.3%-15.2%) and number of visits over 1 year (1-19) suggest that significant health resources are being devoted to a small number of patients.
- 87.56% of subgroup patients know their A1c goals, suggesting that knowledge of care goals is not a primary cause for poor control of their diabetes.
- Further data collection and analysis will lead to better understanding of which patients with diabetes are most at risk for vision loss, and how to best address their needs.

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Disclosures

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Infrastructuring for D2K in Network-Based Research

An Example of a Node on PCORnet

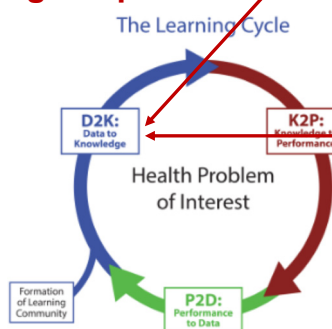
Marcelline Harris, PhD, RN^{1,2}; Airong Luo, PhD^{(previously)1,3}; PhD, Lisa Ferguson, MS^{1,3}

¹University of Michigan, ²School of Nursing, ³School of Medicine

Learning Health System

A system in which “science, informatics, incentives, and culture are aligned for continuous improvement and innovation, with best practices seamlessly embedded in the delivery process and new knowledge captured as an integral by-product of the delivery experience.”
(Institute of Medicine, 2015)

Learning Loop Framework



medicine.umich.edu/dept/lhs (retrieved 9/15/2018)

PCORnet: the National Patient-Centered Clinical Research Network

- A "network of networks" that brings together patients, clinicians, researchers, and healthcare systems to share information and participate in research.
- A platform for making patient-centered research more efficient.

• Independent, nonprofit authorized by Congress in 2010.
(pcori.org, last updated March 2018)

People-Centered Research Foundation

- Builds on the success of PCORnet
- Receives support from government, foundations, and industry
- Integrates people into all phases of research and the learning health system
(pcrfoundation.org (retrieved 9/15/2018))

Infrastructuring for Network-Based Research

Research Networks, Each with Specific Infrastructures, n1...nx

n1: PCORnet – PCRF

- Governance
- People-centered engagement
- Network leadership and management
- PCORnet data
- Network clinical research infrastructure
- Severability

nx: How many networks?

- What infrastructure is specific to each network in which an institution is a node?

Network makes decision to confer node status

- Node meets network requirements for governance, management, resources and services

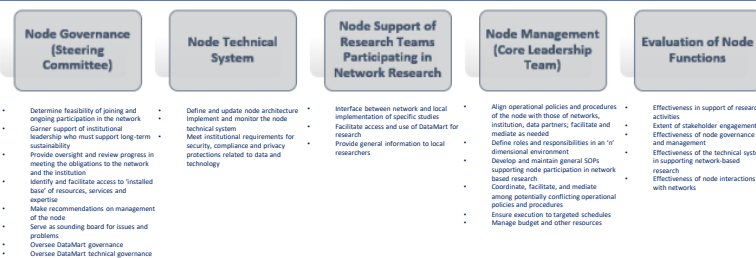
Challenge: scalable and interoperable socio-technical infrastructures for re-use across networks and institutions



Institution makes decision to seek node status:

- Alignment of network requirements with institutional strategic goals, governance, and operational priorities
- Capacity & capability to meet network requirements

For Each Network The infrastructuring work of the institution is collaboration and coordination across institutional units to 1) assemble existing resources and services, 2) develop new resources and services as needed, and 3) align node governance, management, technical systems, informatics, research support, and evaluation with network(s) requirements.



Developing and Implementing Large-Scale Community-Driven Integrated Care

Buyuktur, A.G.,^{1,2,3} • Ackerman, M.S.,^{1,5} • Rubinstein, E.B.,⁴ • Platt, J.⁵ • Spiroff, M.,² • Klinkman, M.S.^{2,4}

(1) School of Information; (2) Michigan Institute for Clinical & Health Research; (3) Center for Healthcare Research & Transformation; (4) Department of Family Medicine; (5) Department of Learning Health Sciences
UNIVERSITY OF MICHIGAN, Ann Arbor, MI.

1. Background

Two community-driven projects are currently underway in southeast Michigan to develop and test the effectiveness of enhanced linkages between medical, behavioral / mental health, and social service providers to better identify and manage unmet social needs and improve clinical outcomes. Both efforts include developing new intra- and inter-organizational workflows and information technology (IT) capabilities to support care coordination or social services navigation. We describe the results of an ancillary study that qualitatively explores the processes for developing and implementing novel integrated care models in these two communities.

2. Methods

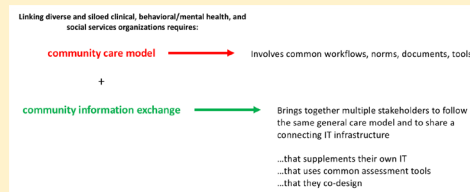
- (1) Participant observation
 - Planning and implementation committees, site visits, IT design, quality improvement processes
- (2) In-depth semi-structured interviews with project leaders, providers, and managerial staff
 - Existing linkages, practices for information exchange, current IT capabilities, and perceived opportunities and barriers for improving care integration.

Inductive methods were used for data analysis.

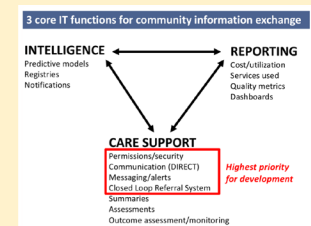
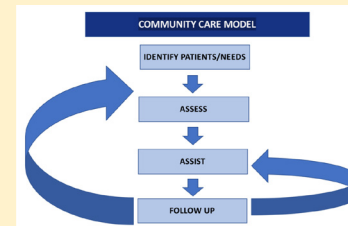
3. Preliminary Findings

- (1) Workflows, norms, and IT design are slowly negotiated by the community and may require facilitation.
- (2) Cross-agency IT systems are necessary for integrating care, but also cause disruptions to local workflows.
- (3) Trust between stakeholders is paramount to the success of SDOH screening and effective care integration.
- (4) Care managers primarily want to know who else is involved in the care of the patient/client. They rarely need detailed clinical information.

4. Common Elements of Community-Driven Integrated Care Models



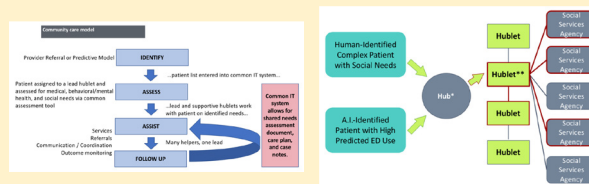
“Boundary objects” collaboratively designed in both communities to guide work



5. Community Approaches

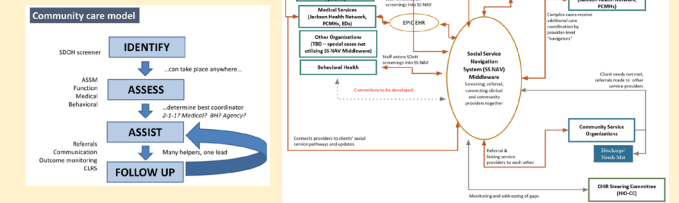
Livingston / Washtenaw State Innovation Model

Focus: Patients with frequent ER utilization. Care coordination involves a team-based approach among community providers that is managed by an administrative hub and facilitated by an IT platform called *MiCareConnect* ©PCE Systems. Twelve provider agencies (“hublets”) are participating in this intervention.



Jackson State Innovation Model

Focus: Improving coordination of care for persons with medical, social and behavioral health needs by linking SDOH screening and assessment to a scalable community-wide navigation, referral, and communication IT infrastructure (RiverStar Software and Epic). All community service providers are participating.



6. Conclusion

Developing and implementing community-driven integrated care models is a slow and iterative process but necessary for effective action. Our preliminary findings highlight implications for inter-organizational partnerships and suggest long-term challenges such as the sharing and governance of patient data.

Support for this poster is provided by: UL1TR002240 and CMS-1G1-14-001

Poster not available for publication.

Harnessing Data to Unveil Discoveries & Transform Health: Michigan Integrated Center for Health Analytics & Medical Prediction (MiCHAMP)

Joan Kellenberg, Akbar K. Waljee, Ji Zhu, Jenna Wiens, Michael Sjoding, Marcy Harris, Brahmajee K. Nallamothu

MiCHAMP Overarching Goal

To create a new health research “ecosystem” for deep collaborative work in data science with multidisciplinary method, clinical & informatics experts



M MICHIGAN INTEGRATED CENTER FOR HEALTH ANALYTICS & MEDICAL PREDICTION
UNIVERSITY OF MICHIGAN
Harnessing Data to Unveil Discoveries and Transform Health

MIDAS Health Sciences Challenge Grant (March 2017)

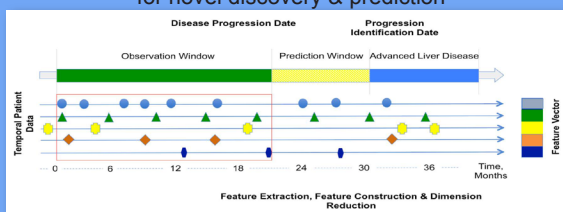
Aim 1 - Improve accuracy & timeliness of diagnosing Acute Respiratory Distress Syndrome (ARDS) onset.

Aim 2 - Advance abilities to predict progression of chronic HCV Infection.

Underlying Infrastructure (i.e., Aim 3) - Create a research platform that addresses key informatics challenges (e.g., meta-data, data provenance, reproducibility, scalability).

Methodological Thrust

Exploit temporal patterns in longitudinal data for novel discovery & prediction



Key Deliverables

- Research Clinically-Relevant Problems
- Develop Research Ecosystem for Machine Learning/Artificial Intelligence in Health
- Work with Trainees toward Career Development
- Aggressive & Early Extramural Funding Schedule
- Develop External Partnerships

Research Ecosystem

- Schools/Colleges - 5
- Research Faculty - 42
- Trainees - 20
- Staff - 7

Biweekly Seminar Series

- Internal & External Speakers
Andrew Gelman & John Ioannidis
- Proposals Under Development
- Work-In-Progress

Partnerships

- IHPI
- MIDAS
- MCIRCC
- VA CCMR

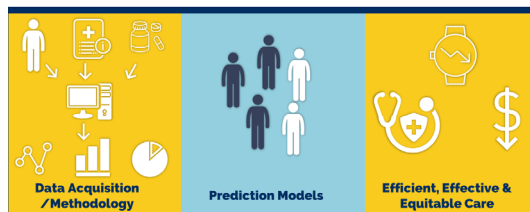


MiCHAMP will host the annual Machine Learning in Healthcare Conference August 8-10, 2019

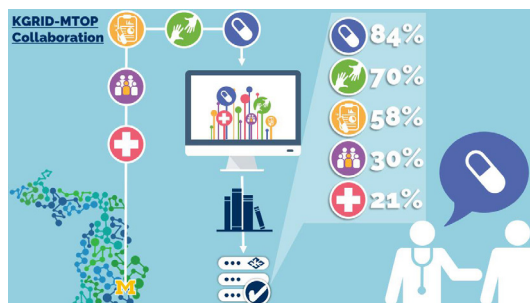
Collaboration With Learning Health Systems

Apply prediction models to Michigan Medicaid population with HCV infection at greatest risk for progression to advanced liver disease to guide treatment in the Knowledge-to-Treatment Optimization Program (K-TOP). M-TOP will be conducted in partnership with K-GRID, an initiative of DLHS.

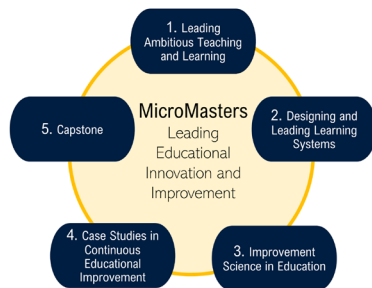
Michigan Treatment Optimization Program (M-TOP)



M IHPI INSTITUTE FOR HEALTHCARE POLICY & INNOVATION
UNIVERSITY OF MICHIGAN

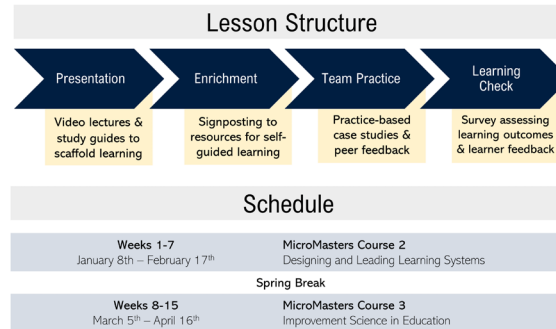


MicroMasters Overview

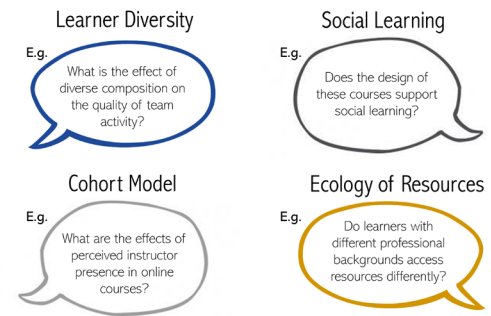


Blended MA	
MicroMasters	12 Credits
+	
Residential Study	18 Credits
=	
MA Educational Studies	30 Credits

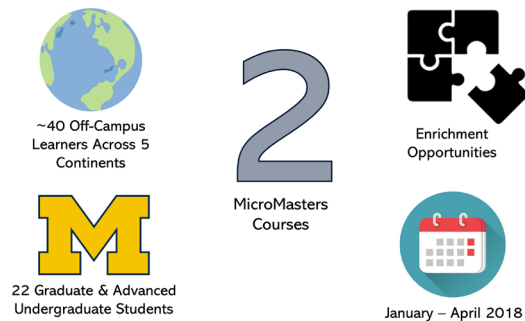
Structure & Schedule



Research



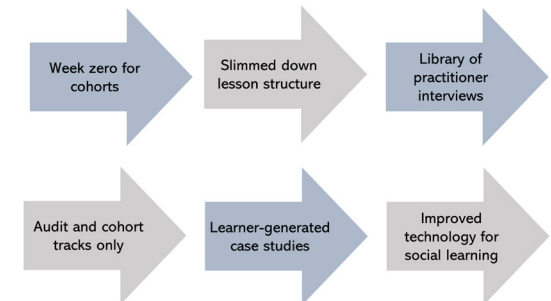
Curated Cohort Design



Enrichment Opportunities



Future Iterations





CENTER FOR HEALTHCARE ENGINEERING & PATIENT SAFETY UNIVERSITY OF MICHIGAN

cheps-contact@umich.edu

Our mission at the University of Michigan Center for Healthcare Engineering and Patient Safety (CHEPS) is to improve the safety and quality of healthcare delivery through a multi-disciplinary, systems engineering-based approach through collaboration, implementation, innovation, education, and dissemination.



Collaboration

The University of Michigan has nationally-recognized strengths in engineering, medicine, nursing, public health, business, and more. We work to identify, foster, and promote collaborative projects across these units.

Collaboration with LHS

The CHEPS SCOPES team collaborated with the Gastroenterology Learning Community within the Department of Learning Health Sciences (LHS) to work on quality/process improvement initiatives in the Michigan Medicine Medical Procedure Unit. In collaboration with the Health Systems Data Warehouse, they were able to translate a simple tool created in CHEPS to the first GI data warehouse in Michigan Medicine, providing a better understanding of the workings of the GI Department. CHEPS continues to work with LHS on analyzing the data gathered.



Implementation

Our research is grounded in real problems that affect real patients. We conduct hands-on projects both inside and outside of the University, locally, nationally, and globally. Because of this geographic diversity, research at the Center has an immediate and measurable impact.

Education

A key part of our mission is to train future generations, helping engineering students to understand the challenges and opportunities found in healthcare delivery as well as educating healthcare providers about the benefits that engineering tools can yield on real-world problems.

Innovation

Hands-on projects form the foundation for longer-term, cutting-edge research projects that advance the state-of-the-art in both medicine and engineering.

Dissemination

We serve as a source of information for the broader community about new advances in healthcare engineering and patient safety through our web site, white papers, seminar series, symposia, and outreach activities.



LHSCollaboratory
Putting Data, Knowledge, and Practice into Motion at the University of Michigan

Targeting failed appointments in an LHS cycle in order to improve access, education, revenues and resource utilization

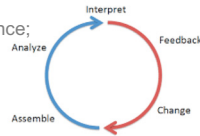
Exploratory data analysis

Weber K, Dault J, DaSilva AF, Eber R, Huner K, Jones D, Ramaswamy V, Snyder M, Ward B, Nalliah RP.

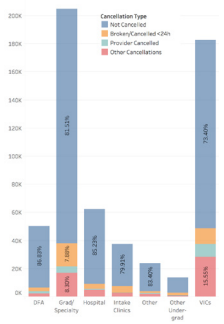
BACKGROUND

The University of Michigan School of Dentistry (UMSOD) is a major care provider with over 200,000 patient encounters per year. Unfortunately, over 20% of appointments are cancelled, 7% by the patient within 24 hours of the appointment. Cancelled and failed appointments disrupt care delivery and have broad impacts including:

1. Lost opportunities for the patient to receive care;
2. Lost opportunities for students to gain clinical experience;
3. Unnecessary delays for other patients seeking care;
4. Lost revenue for the school; and
5. Wasted resources



UMSOD seeks to reduce the rate of failures to attend appointments. We have undertaken exploratory data analysis of our electronic health records together with public census data to better understand where and why patients fail to attend, so we can consider interventions that may result in improved patient attendance.

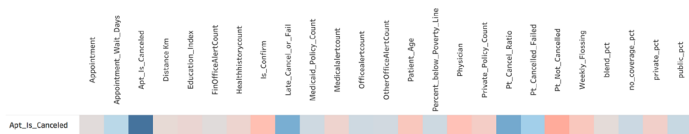


ASSEMBLE

We extracted three years of appointments from our Electronic Health Record, including patient demographic information, clinic and provider, appointment confirmation tools and responses, reported patient health status, and attitudes toward dental treatment. We merged this with US Census bureau data at the ZIP code level and with travel time via car and transit between a geo-masked patient address and the UMSOD.

We normalized continuous features and built a correlation matrix between them and cancellation status. Blue is a positive correlation, red is negative.

Correlation Matrix

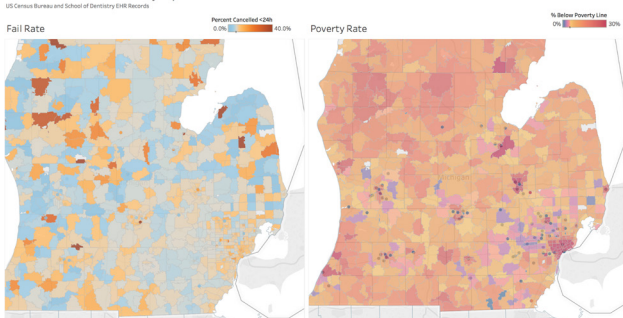


ANALYZE/INTERPRET

First findings were unremarkable:

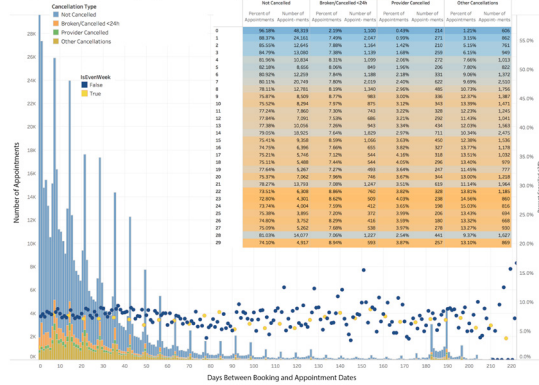
1. Patients who cancel appointments cancel appointments
2. Patients without private insurance cancel appointments
3. Patients with longer medical histories don't cancel as frequently

Patient Characteristics by Zip Code



Some findings were interesting surprises:

Appointment Wait Days by Cancellation Type



An overwhelming majority of appointments are booked for exactly n weeks from 'today.' These appointments are kept at significantly higher rates than the rest.

Tabular Time Series by Patient Contact Type

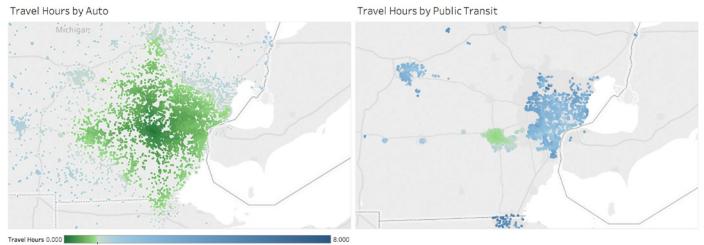
Month of Appointment Date	Null			Call			Email			Text		
	% of Total Appointments	Number of Appointments	Percent Cancelled	% of Total Appointments	Number of Appointments	Percent Cancelled	% of Total Appointments	Number of Appointments	Percent Cancelled	% of Total Appointments	Number of Appointments	Percent Cancelled
April 2018	51.63%	9,280	8.4%	44.21%	7,435	13.7%	231	5.7%	113	1.1%	325	2.6%
May 2018	36.46%	7,045	8.7%	52.48%	11,880	4.3%	74	5.4%	1,096	1.9%	345	2.6%
June 2018	30.70%	6,027	8.8%	60.86%	10,956	5.4%	1,590	7.7%	1,936	3.6%	545	2.8%
July 2018	27.85%	5,511	8.3%	60.46%	10,256	6.7%	1,505	9.4%	2,171	5.1%	770	3.5%

FEEDBACK

We found superior attendance rates when confirmed via email/text and are moving toward this method of confirmation (which was only utilized by 3 of 9 clinics)

Analysis of Travel Times to UMSoD

Source: Google Directions



Some of our patients face major transportation barriers if they are unable to drive to an appointment

Next Steps - CHANGE

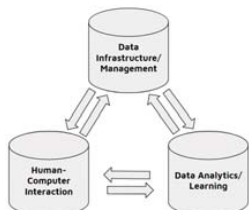
1. Increase clinic adoption of text messaging reminders
2. Look at ways to customize patient reminders to meet the needs of different populations
3. Assess whether encouraging clinic staff to book on even week intervals makes a difference to attendance rates
4. Assess the impact of transportation challenges and possibilities for addressing them
5. Better distinguish between attributes of patients who are associated with cancellations and the attributes of the appointments themselves (clinic, procedure, etc.)
6. Apply clustering algorithms to the data set to better target interventions to groups of patients
7. Establish a regular cycle of data refreshes and reporting to support follow-up on each of these interventions

Pharmacy INformatics Group (PING) A LHS and College of Pharmacy Collaboration

Corey A Lester, PharmD, PhD · Michael P Dorsch, MS, PharmD · Karen B Farris, PhD
Antoinette B Coe, PharmD, PhD · Allen J Flynn, PharmD, PhD

Mission

To be the internationally recognized leader in pharmacy systems research



Collaboration

- We bring together a range of expertise along the pharmacy informatics continuum, including data-driven analytics, software and technology development, data infrastructure, pharmacy practice, and implementation science.

Implementation

- PING will establish shared research programs that advance the state-of-the-art in pharmacy systems to enhance the quality, safety, and experience of medication use.

Innovation

- PING pioneers novel pharmacy systems research and bridges the gap between science and practice.

Education

- We will train the next generation of pharmacy researchers and pharmacists to leverage data and technology to improve the quality, safety, and experience of medication use.
- We will bring in experts to share their experiences and enhance the research of our members.

Dissemination

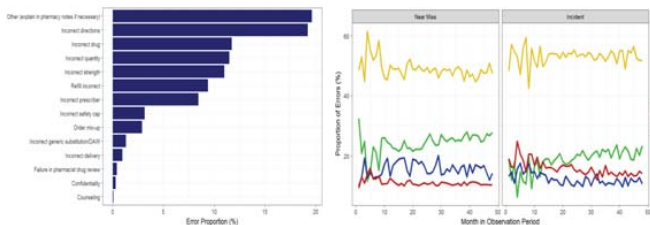
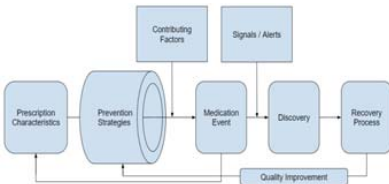
- We will disseminate findings through published research, implementation, open-source tools, and entrepreneurial activities.

Medication Errors in Community Retail Pharmacies

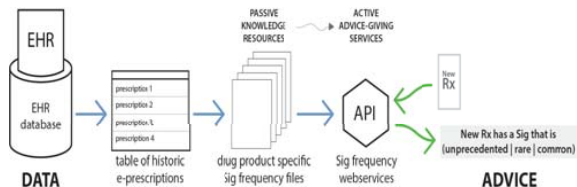
Background: Medication errors are costly and deadly. Patient safety organizations tasked with collecting QRE data to engage pharmacies in quality improvement strategies.

Objective: To describe the characteristics of self-reported quality-related events in US community pharmacies using a proposed conceptual framework

Method: Dataset of 531,555 QREs collected from 1,660 pharmacies between 2011-2014. Descriptive statistics of the data as well as the use of structural topic modeling to analyze the free-text narrative of QRE reports.



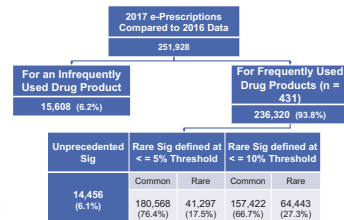
ScriptNumerate: Identifying the “typicality” of prescription directions



Background: Pharmacists review every medication prior to dispensing, however, their work is not supported by ready available, computable data.

Objective: To develop a computer-aided detection tool for identifying atypical electronic prescriptions

Method: Historical electronic prescription data was used to determine the frequency of medication, strength, form, and direction combinations. These data were applied to future prescriptions and built as a knowledge object and deployed into Kgrid infrastructure.

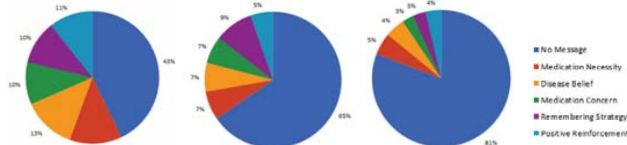
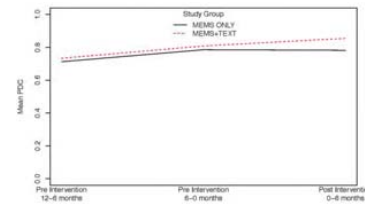


Reinforcement Learning Agent to Improve Medication Adherence

Background: Medication adherence continues to be problematic. Innovative solutions tailored to patient reasons for non-adherence need to be developed

Objective: To determine the effectiveness of tailored messaging using a reinforcement learning (RL) algorithm on medication adherence.

Method: Pre-post randomized controlled trial of 47 patients. RL agent adapted messaging by tailoring along several reasons for non-adherence. Adherence measured using proportion of days covered (PDC).

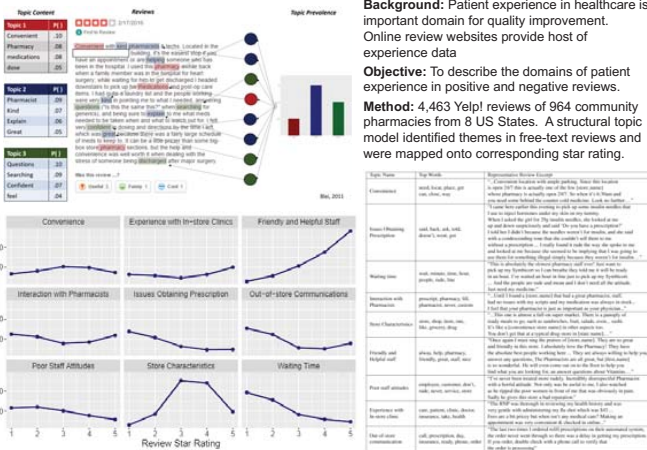


Pattern Exploration of Patient Experience in Community Pharmacies for CQI

Background: Patient experience in healthcare is important domain for quality improvement. Online review websites provide host of experience data

Objective: To describe the domains of patient experience in positive and negative reviews.

Method: 4,463 Yelp! reviews of 964 community pharmacies from 8 US States. A structural topic model identified themes in free-text reviews and were mapped onto corresponding star rating.

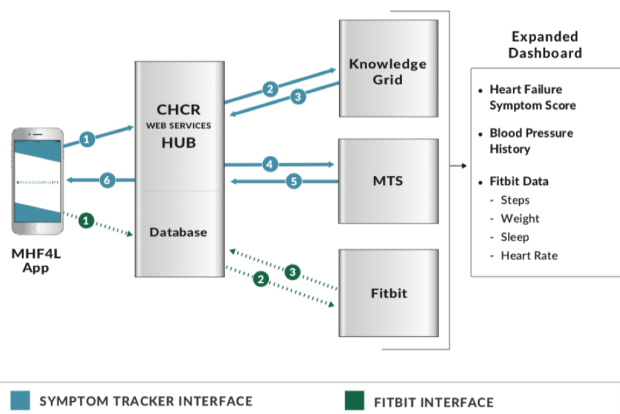


Linking the Knowledge Grid, Michigan Tailoring System and Fitbit data within a patient centered mobile application for heart failure

Dorsch MP, Arzac J, Hummel SL, Koelling TM
mdorsch@med.umich.edu



- In the United States, heart failure (HF) is the most common hospital discharge diagnosis among older adults.
- About 40 percent of patients are readmitted within 1-year following their first admission for HF and hospitalization accounts for approximately 70 percent of the costs of HF management.
- Previous research shows that patient education, case management and telephonic support are effective in reducing HF hospitalizations, but these strategies can be costly.
- As a result, the management of HF patients is evolving from the traditional model of face-to-face follow-up visits toward a proactive real-time technological model of assisting patients with monitoring and self-management while in a health system.
- This award to supplement existing funding by addressing the following:
 - Integrating motivational messages for heart failure patients that will evoke a behavior health change into a mobile application based on the Michigan Tailoring System,
 - Integrating remote monitoring sensors data into the mobile application to enhance the use of the data within an algorithm.
 - Creating an algorithm, using machine learning, that predicts clinical worsening of heart failure using remote monitoring.
 - Develop knowledge objects to hold, manage, and facilitate deployment of the clinical worsening of heart failure predictive algorithm using the Knowledge Grid platform under development in the Department of Learning Health Sciences.



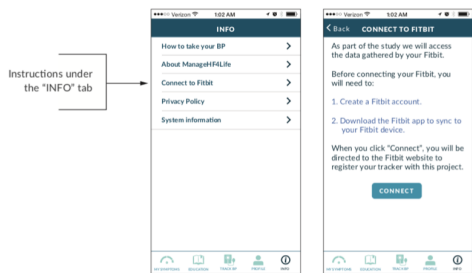
Symptom Tracker Interface

- MHF4Life App sends Heart Failure Symptoms to HUB that talks to Database
- HUB asks KnowledgeGrid to calculate Heart Failure Score
- KnowledgeGrid returns Heart Failure Score to HUB
- HUB asks MTS to tailor a Results Message based on Heart Failure Score
- MTS creates a Results Message and returns to HUB.
- HUB forwards Results Message to MHF4Life App.

Fitbit Interface

- & 2. MHF4Life App authorizes access to Fitbit App to see results data for Steps, Weight, Sleep and Heart Rate.
- HUB regularly collects and stores Fitbit data.

Authorize connection to Fitbit App

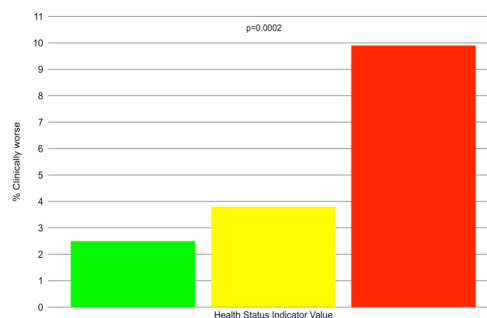


Annotations:

- KnowledgeGrid returns Heart Failure Score
- MTS creates tailored Results message from KnowledgeGrid Heart Failure Score
- Link to Fitbit allows user to see data collected for Steps, Weight, Sleep and Heart Rate

- The results screen presents a health status indicator graphic and the ability for the patient to view the results.
- The health status indicator is a speedometer-like graphic that goes from green (good health status) to yellow (fair health status) to red (poor health status).
- The movement from green to yellow to red is based on the answers to each daily questionnaire.
- A score of 0-16 is green, 16-26 is yellow and 26 or greater is red.
- The score is calculated based on the sum of answers to questions with an add-on to the score based on weight change.
 - The add-on for weight only occurs if the weight is higher than the dry weight.
 - The add-on is the change in weight (dry weight - current weight) multiplied by 3.

Question score	0	1	2	3	4
Sense of fullness during a meal earlier than usual	Never	Rarely	Sometimes	Most of the time	Always
Loss of appetite	Never	Rarely	Sometimes	Most of the time	Always
Pain or discomfort in abdomen	Never	Rarely	Sometimes	Most of the time	Always
Shortness of breath	None	Walking up a flight of stairs	Walking 100 yards	Showering or bathing	When sitting down
Energy level	Very good	Good	Fair	Poor	Very poor
Level of swelling	None	Ankles and feet	Up to the level of the shins	Up to the level of the thighs	Up to the level of the abdomen or back
Shortness of breath while laying down flat	Never	Rarely	Sometimes	Most of the time	Always
Shortness of breath when bending over at the waist	Never	Rarely	Sometimes	Most of the time	Always



The Michigan Surgical Quality Collaborative Learning Health System: Changing Practice and Reducing Surgical Site Infection for Elective Colon Surgery

Joceline V. Vu, MD¹; Elizabeth Seese, MS²; Stacey D. Collins, MA²; Samantha Hendren, MD, MPH¹; Michael J. Englesbe, MD^{1,2}; Darrell A. Campbell, MD^{1,2}; Greta L. Krapohl, PhD, RN²

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Introduction

Surgical site infection (SSI) is the second most common type of hospital-acquired infection and is associated with significant morbidity and health care use.

The emphasis on SSI after colectomy has increased with the institution of financial penalty for this outcome in 2017, as part of the Centers for Medicare and Medicaid Services Hospital-Acquired Condition Reduction Program.

Starting in 2012, MSQC hospitals promoted a "bundle" of the following three actionable process measures:

-  Decontamination bundle prophylactic intravenous antibiotics
-  Oral antibiotic with mechanical bowel preparation
-  Postoperative day-1 glucose < 140 mg/dL

Methods

Setting: The Michigan Surgical Collaborative Patient Safety Organization

Study design: Prospective cohort study of elective colectomy patients from 2012 – 2016.

Intervention: The MSQC actively promoted the SSI bundle with an data auditing system to provide feedback on implementation and SSI rates, conference presentations at face-to-face meetings, site visits, analytic reports and support for local SSI quality improvement projects.

Outcomes Measured



Bundle Element Use






SSI Rates



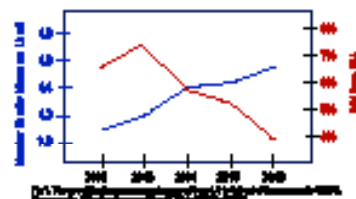
Readmissions/
Health Utilization

Results

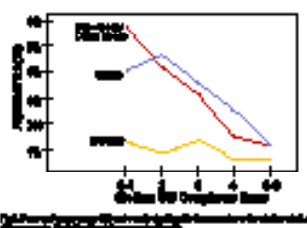
5742 patients were included. When stratified into groups by compliance score (0 – 6), the low compliance group (0 – 1) had higher proportions of older patients, black patients, and patients with comorbid conditions (obesity, diabetes, ASA class 3 – 4). We used a hierarchical logistic regression model to examine the association of bundle score and SSI, adjusting for patient and hospital factors.

-  18.6% → 32.3% of patients (p<0.001)
-  42.9% → 62% (p<0.001)
-  No significant change (49% → 53%)

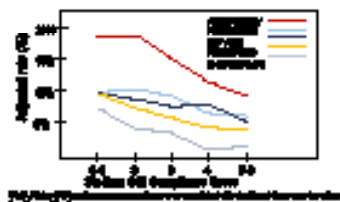
Three-Year Bundle Use and SSI Rate Over Time



Mortality/Morbidity Over Time



Lower Healthcare Utilization is Associated with Higher Bundle Use



Conclusions

Our findings show a significant increase in bundle measure use after implementation of a quality improvement initiative by MSQC hospitals.

Lower SSI rates, as well as lower rates of other morbidity and postoperative healthcare utilization, were associated with higher bundle use compliance.

Although the adoption of published evidence in clinical practice can be slow, the Learning Health System approach to providing continuous and systematic data, audit, and feedback has the potential to accelerate practice change.

PRECISION HEALTH AT THE UNIVERSITY OF MICHIGAN

Making Connections, Discovering Solutions for Healthier Lives

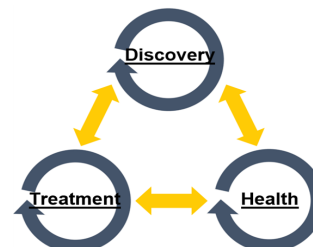
precisiohealth.umich.edu



PRECISION HEALTH
UNIVERSITY OF MICHIGAN

What is Precision Health at U-M?

A population-based strategy that uses advanced tools and technology to discover how genetic, lifestyle, and environmental factors influence a population's health



Mission

Research

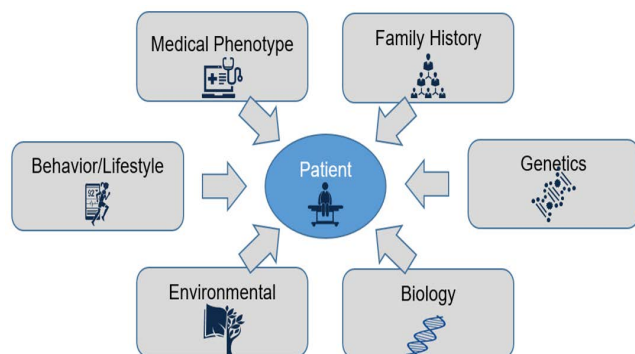
Create, test, and publish new knowledge that advances precision health science. Fund projects through our Investigators and Scholars Award programs.

Education

Establish Precision Health certificate program. Train and enable researchers/clinicians to incorporate new techniques and evidence into daily work.

Service

Develop tools to enable the integration of research at the point of care, and evaluate the impact on the health of Michigan residents.



The Precision Health approach looks at many factors, and how they impact each other.

Objectives

- Develop a diverse **patient cohort**, integrating novel datastreams and sources
- Establish a secure **analytics platform** with leading-edge software stack and computing hardware
- Enable **secure access** to real-world clinical and health data while adhering to expectations of consented participants
- Build a **collaborative research community** bridging the breadth of expertise at U-M
- Sponsor a **competitive grants program** to provide funding to advance PH research
- Devise processes that **integrate discoveries into patient care**
- Tackle important health issues through **use cases** ranging from opioid misuse to mental health, metabolic disease, and cancer

Services

Research Data and Access for Faculty

- Research Data Warehouse and DataDirect
- Michigan Genomics Initiative
- Central Biorepository
- Faculty-generated data sources

Data Analytics/IT Support

- Secure data enclaves
- HIPAA/PHI/CUI compliant platforms
- Cloud computing
- Scientific facilitators

Education and Training Programs

- Seminar series
- Symposia
- Certificate program
- Patient education
- Health professional training

Research Output Implementation

- Processes/policies to take discovery to implementation at Michigan Medicine
- Use of curated decision support visualizations at point of care



LHSCollaboratory
Putting Data, Knowledge, and Practice into Motion at the University of Michigan

State Innovation Model:

Towards a Learning Health System to Reduce Emergency Department Visits in Livingston and Washtenaw County

On behalf of the State Innovation Model Workgroup in the Center for Healthcare Research and Transformation

Problem

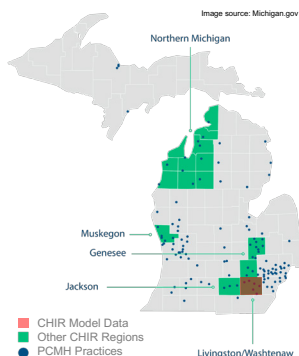
High utilizers of the Emergency Department (ED) often have complex needs that require coordination of care between multiple organizations.

Approach

We describe a Learning Health Systems (LHS) approach to reducing ED visits, in which an intervention is delivered to a cohort of high utilizers identified using population-level data and predictive modeling.

What is the State Innovation Model?

Michigan received a State Innovation Model (SIM) grant from the Center for Medicare and Medicaid Innovation (CMMI) to test delivery and payment system changes.



5 Community Health Innovation Regions (CHIRs)

Each CHIR has a "regional backbone." Ours is the Center for Healthcare Research & Transformation (CHRT).

How often do individuals use the emergency department?

ED visits in 6 months	N	Proportion
0	270,748	89.20%
1	24,799	8.17%
2	5,174	1.70%
3	1,591	0.52%
4	566	0.19%
5+	636	0.21%
Total	303,514	100.00%

High utilizers (4, 5+)

A predictive model is used to identify the highest risk individuals. The process is repeated every two months.

Model version 1

- MM data only
- Created 11 predictors
- Trained on 185,597 patients
- Run on 188,089 patients
- Results shared on: 11/1/2017

Model version 2

- MM, SJM & IHA data
- Created 58 predictors
- Trained on 303,514 patients
- Run on 311,962 patients
- Results shared on: 1/25/2017

Model version 3

- Added latitude & longitude using geocoded addresses
- 58 predictors

Model version 4

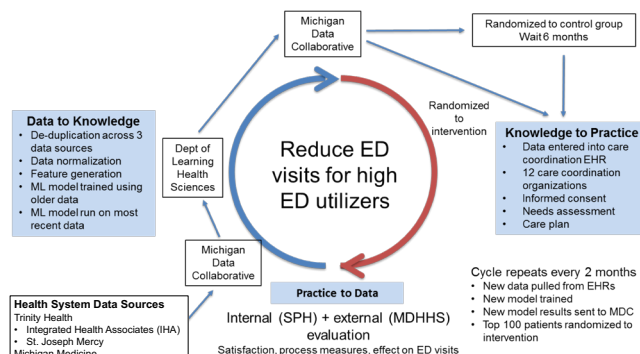
- Added ICD-10 codes highly correlated with ED visits
- 150 predictors

Model version 5

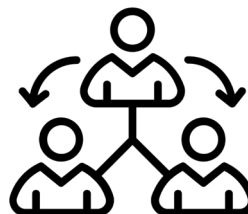
- Refined and validated additional billing codes
- 441 predictors

For context:
Total population of 2 counties = **538,683 people**

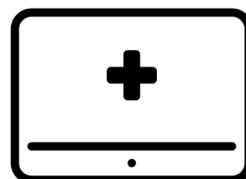
The learning cycle



How are we aiming to reduce ED visits?



Assign patients to a "hublet," which serves as the primary point of contact for care coordination



Use a web-based portal to track referrals and share case notes and care plans among hublets



Improve communication between the health system and the community

Have we reduced ED visits?

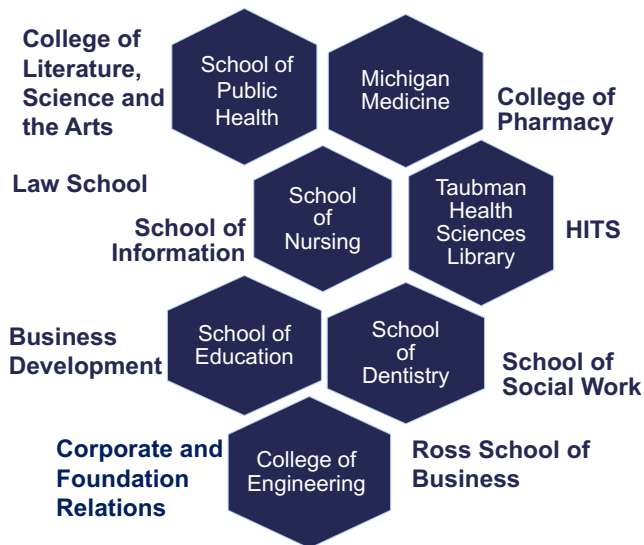
Once we enroll a sample size to achieve sufficient power, an analysis of the efficacy will be forthcoming.

The Learning Health System (LHS) Collaboratory

Advancing interdisciplinary research and development of learning health systems

Charles Friedman, Douglas Van Houweling, Lisa Ferguson, Cindy Diakow
University of Michigan Medical School, Department of Learning Health Sciences

LHS Collaboratory: A University of Michigan Community Focused on Improving Individual and Population Health



Goal: Build a community that enables UM to lead the national and international movements to achieve learning health systems.

Components of the Collaboratory

Seminar Series

- Renowned LHS Speakers
- Interactive Audience Participation
- Networking Opportunities
- Monthly Cadence During Academic Year
- Luncheon

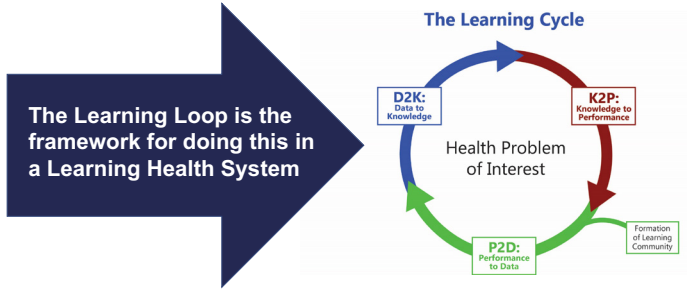


Learning Action Projects

- Focused on real-world challenges that put the Learning Cycle into action to prevent or treat specific health problems of interest
- Opportunity to collaborate with colleagues
- Ability to engage based on area of interest or expertise
 - Sociotechnical Infrastructure
 - Implementation and Process
 - Ethical, Legal, Social
 - Organizational Business Models

In a **Learning Health System (LHS)**, organizations or networks continuously self-study and adapt using data and analytics to generate knowledge, engage stakeholders, and implement behavior change to transform practice. The LHS concept, first expressed by the Institute of Medicine in 2007, is now being rapidly adopted across the country and around the world.

An efficient learning process, supported by infrastructure, is one that actually enables continuous improvement to be embedded into routine practice.



Data to Knowledge (D2K): Many improvement efforts focus on gathering data and gleaning knowledge from the data (D2K). Often the cycle stops there, however the Loop continues, harnessing the real power of data.

Knowledge to Performance (K2P): Effective learning health systems apply the knowledge to implement change and transform health care through individual training, team training, implementation of new processes, integration of new technologies, and changes to the process and environment of care.

Performance to Data (P2D): The lessons of improved performance are used to inform and refine the next cycle of gathering data.

The learning cycle repeats continuously.



Are you interested in exploring how your research work is relevant to Learning Health Systems?
Join the LHS Collaboratory Community!

Learn More: dlhs-umi.ch/lhs-collaboratory

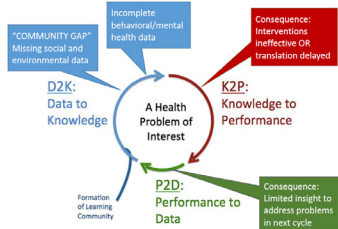
Using Participatory Design to Co-create a Community Health Information Hub in Jackson, MI

Michael Klinkman^{1,8}, Mark Ackerman^{2,3}, Ken Toll⁴, Joshua Williams⁵, Bob Fike⁶, Amy Sintes⁶, Marty Woodruff⁷, Aaron Wootton⁸, Richard Thoune⁹, Keven Mosely-Koehler⁵, Laurie Gustafson⁵, Amy Schultz^{8,10}

1-UM Department of Family Medicine; 2-UM School of Information; 3-UM Department of Learning Health Sciences; 4-Jackson United Way; 5- Jackson Collaborative Network; 6- RiverStar Software; 7- Michigan Health Information Network; 8- Henry Ford Allegiance Health; 9- Jackson County Health Department; 10- Jackson Health Improvement Organization

Context. In most communities, information related to individuals' health is distributed across multiple unconnected care silos created to support medical, behavioral, and community service providers. While progress has been made toward EHR interoperability for the medical enterprise, community-side information remains highly fragmented and sequestered..

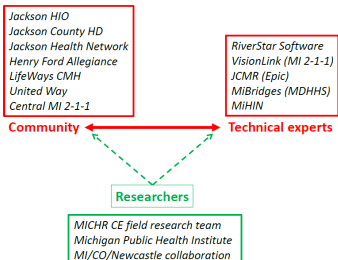
The result is that community care providers often work with incomplete information, cannot connect to the broader system of care, and unintentionally create complex pathways of care that fail to effectively address health disparities. This 'community data gap' also limits our ability to carry out meaningful learning health cycles in community settings.



Objective. To co-design a community health information hub that connects community service agencies (CSAs), behavioral health providers, and medical practices actively engaged in the care of an individual client/patient.



The community design team



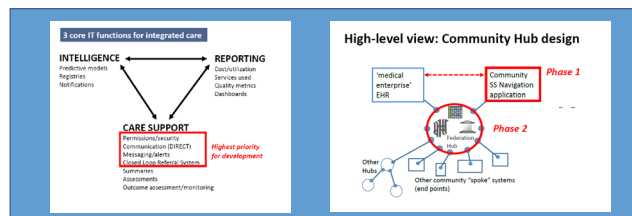
Actions. Under the guidance of the Jackson Collaborative Network community stakeholder coalition, over 40 CSAs and stakeholders entered into a participatory design process to co-create a local Community Information Exchange as part of the Michigan State Innovation Model demonstration in Jackson. Three organizations, United Way of Jackson County, Central Michigan 2-1-1, and LifeWays Community Mental Health, provided leadership in their role as local conveners.

Early stakeholder interviews identified information exchange as a core problem:

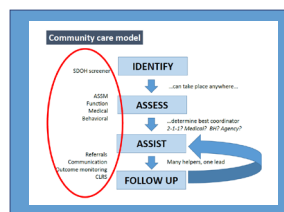
- Over 200 community service agencies (CSAs) provided overlapping and duplicative services
- The community 2-1-1 service was underutilized
- Most agencies worked from their own incomplete 'catalogs' of local CSAs
- Coordination between medical, behavioral, and social service providers was informal and infrequent.

Results. Over an 18-month period, a series of design tasks was completed by commissioned *ad hoc* working groups composed of CSA representatives and dedicated support staff.

1. Deciding upon overall approach to integration, scope of work for IT infrastructure build, and identifying a vendor partner for design and build



2. Co-developing a community care model to establish common steps in the care process.



3. Co-creating a single shared SDoH screening tool and common approach to client assessment.

Domain	Screening question (all topics)
Healthcare	In the past 12 months, did your provider or overall health keep you from doing your usual activities, like work, school or hobby?
Food	In the last 12 months, have you needed to use a dietary, but could not because there wasn't enough money to buy?
Housing	In the last 12 months, did you ever pay less than you felt you should because there wasn't enough money to pay?
Transportation	Do you need help with housing problems?
Children	In the past year, have you had a hard time paying your utility company bill?
Employment	Do you need help getting to work, school, or appointments?
Language	Do you ever need help reading important papers?
Insurance	Do you ever need help finding a job or other steady source of income?
Education	Do you think completing more education or training, like finishing a GED, going to college or learning a trade would be helpful for you?
Safety	Are you and your rights to live in your apartment building in jeopardy?
General	Would you like assistance with any of these needs? Are any of your needs urgent?

4. Co-designing (with IT vendor) the set of key functional requirements for the community hub.

Basic IT 'tools' used in CARE SUPPORT design

ID	Description	Purpose	Issues
H01	Health directory	Establish user connections	
Common Key	Unique patient identifier	Ensure data correctly linked to best client	Difficult process
ACS	Active Care Relationship Service	Confirm membership in care team and allow access to individual's record	Need extension to cover CAE, call, referral, services
ADT	Admit/Discharge/Transfer notification	Confirm that an 'event' occurred	Expanded to cover all interactions (calls, referrals, services)
CCDA	Consolidated Clinical Document Architecture	Specify encoding, structure and transmission of clinical documents for exchange between EHR and Hub	Need to create CCDs, operating CCDs, and referral data
SDOH	SDOH screening instrument	Screening instrument to determine needs by domain	Standardization, EPIC v2/Hub

IT components and vendors

Michigan 2-1-1 database (VisionLink)
 Indirect database of CAE, information using temporary terms

Community SS navigation platform (RiverStar)
 SDOH screening and assessment tool (integrations) linked to various SDOH/Sufficiency Matrix scoring, communications function, closed loop referral function, plus outcomes monitoring

Community IT Hub (RiverStar)
 Current: CCD data exchange between SS Hub and JCMR (Epic)
 Near future: FHIR based data exchange between SS Hub and JCMR
 Future: Data exchange with other local CAE IT platforms (LifeWays)

Indian Community Medical Record (Epic)
 RiverStar SDOH screening and assessment tool mirrored in Epic

MI Bridges (MDHHS)
 Data exchange across Hub in development

5. Launching the Jackson Care Hub – testing functionality, prototyping, and implementing.

The Jackson Care Hub provides a shared community platform to supplement but not replace the IT applications used by individual CSAs. It has 2 components. **Community Navigation** - enables any user to carry out screening (SDoH and behavioral), match needs to available local service resources using an enhanced 2-1-1 database, send referral 'tasks' to CSAs and track their status, identify and directly message other members of the client's active care team to coordinate care, and monitor outcomes. **Information Exchange** – enables data exchange between Hub and IT platforms used by community providers: for example, exporting results of SDOH screening completed in the community EHR (Epic) to the Hub, moving referral 'tasks' between Epic and Hub as status changes to enhance tracking and follow up.

The Hub went 'live' on June 18, 2018 with 14 participating CSAs. Additional CSAs are being added as rapidly as training can be completed. Hundreds of SDOH screens have been completed at CSAs and in participating medical practices, with hundreds of social service referral tasks created and actively tracked by CSA staff, 2-1-1 navigators, and SIM project staff.

