Key Needs Addressed by iEpi in Distinct Health Subdomains

General Comments

In what way could iEpi help advance health research objectives? There are diverse areas possible contribution, but several stand out in the below:

1) Assessing **symptoms** (both clinical and **subclinical**) on a 24x7 basis, and assessing its temporal relationship to **risk factors and exposures** recorded either by **sensors** (e.g., physical activity, pose, some social context, location), **EMAs** (medication compliance, self-reported stressors, second-hand smoke exposure, dietary intake, other aspects of social context), or “crowdsourced” active indications on the part of the participant.

2) Use of such monitoring to **enhance the speed, reliability, and depth of learning from implemented interventions**. More specifically, when an intervention succeeds or fails, because of limitations on traditional measurements instruments (e.g., their limited accuracy in measuring changes in medication compliance, physical activity, dietary behavior, socialization and mixing patterns, mobility, communicational behavior), there is often limited understanding of the specific pathways of effect by which such success was realized or thwarted. A tool such as iEpi is designed to inform an accurate understanding of the particular pathways by which an intervention affects important outcome measures (e.g., frequency and intensity of pain associated with osteoarthritis). **Regardless of whether an intervention is successful or not in the end, the learning from it can be much deeper, more reliable and quicker** by virtue of being able to examine which and by **how much and how soon different pathways were affected** (e.g., allowing observers to distinguish pathways that were successfully nudged vs. pathways that became a bottleneck and thereby stymied change in the outcomes of interest, or particular pathways that exerted disproportionate impact for interventions that did have effect.) Regardless of the success of the original intervention, securing such understanding from it can be of great value in devising more reliable interventions and implementation schemes.

The remainder of the document characterizes some of the advantages of application of iEpi in different health subdomains.

Obesity

Example Problems/questions that can be addressed:

To what degree has this lifestyle intervention budged sedentary behaviour/moderate-to-vigorous physical activity/dietary intake? In intervened upon groups? In their social networks/

To what degree is changing physical activity compensated by elevated dietary intake?

To what degree does changing physical activity also lead to a decrease in sedentary behaviour?

Identifying reliable early indicators of an impending incident of dietary lapse or lower physical activity

What fraction of meals are people likely eating at home?

What exposures or ideations are likely associated with relapse?

What exposures or ideations are likely associated with adverse weight measurements?

How do changes in a given person's target weight (if any) reflect weights of those around them?

To what degree are one individual's risk and protective factors likely to affect another person within their social network? (Physical activity, sedentary behaviour, diet)

With Interventions

How much and how soon does the intervention affect different pathways involving risk factors (e.g., diet, physical activity, sedentary behaviour, care seeking, etc.)

With dynamic modeling:

With a particle filtered dynamic model receiving a stream of accelerometer readings, weight measurements , possibly caloric consumption estimates, anticipating what lies ahead

Without intervention

With intervention

How would interventions to improve diet or physical activity on the part of one person be likely to affect their own trajectory, and that of their family and broader network?

Solution elements:

Automatic recording of certain risk and protective factors

Physical activity

Sedentary behaviour

Support for lightweight self-reporting of other risk and protective factors

Diet (e.g., with smartphone camera, potentially with barcode scanning)

Alcohol use

Support for automatic detection (sometimes possible) or lightweight self-reporting of weight outcomes

Support for lightweight self-reporting of

subclinical symptoms (e.g., Aches and pains)

Food cravings

Recording of certain biomedical measures (e.g., heart rate) that can support better estimation of caloric consumption

Recording of concern levels and motivational status

Tobacco Related Disease

Example Problems/questions that can be addressed:

To what degree has this intervention (anti-smoking messaging, elevated tobacco tax, couponing restrictions, etc.) budged initiation, cessation or relapse? Use of e-cigarettes? In intervened upon groups? In their social networks?

Identifying reliable predictors of an impending incident of smoking

Identifying reliable predictors of relapse

What are the sequences of use between e-cigarette use and use of traditional tobacco?

To what degree is one individual's smoking- or e-cigarette use uptake, cessation or relapse affecting others?

Does social network change (shifting to spend more time with non-smokers) serve as an effective predictor of success in avoiding relapse?

With dynamic modeling:

> How would interventions to reduce smoking on the part of one person be likely to affect their own trajectory, and that of their family and broader network?

Solution elements:

Likely, automatic detection of likely bouts of smoking/e-cigarette using

- Heart rate
- History of location
- Pose/orientation
- Physical activity level
- Timing
- Nearby individuals
- Bluetooth lighters?

Support for lightweight self-reporting of

- smoking/e-cigarette use
- use of quit aids (nicotine patches, nicotine gums, etc.)

Automatic recording of certain risk and protective factors

- Physical activity
- Sedentary behaviour

Support for lightweight self-reporting of other risk and protective factors

- Alcohol use
- Stressors

Recording of concern levels and motivational status

Chronic Disease

Example Problems/questions that can be addressed:

To what degree is changing physical activity compensated by elevated dietary intake?

To what degree does changing physical activity also lead to a decrease in sedentary behaviour?

To what degree is compliance in self-testing or self-administration of followed by taking medication?

To what degree is compliance in self-testing or self-administration of medication associated with improved chronic disease outcomes?

How critical are supports from social networks (e.g., reminders) in supporting compliance with self-testing or self-administration of medication?

Identifying reliable early indicators of an impending incident of smoking?

What exposures or ideations are likely associated with relapse?

To what degree is one individual's risk and protective factors likely to affect another person?

With Interventions

How much and how soon does the intervention affect different pathways involving risk factors (e.g., diet, physical activity, sedentary behaviour, care seeking, etc.)

With dynamic modeling:

- How would enhanced reminders for self-testing on the part of one person be likely to affect the patient’s own health trajectory?
- How would enhanced education involving the link between test result and medication self-administration on the part of the patient or informal caregivers affect the patient’s health trajectory?

Solution elements:

Automatic recording of certain risk and protective factors

- Physical activity
- Sedentary behaviour
- Smoking

Support for lightweight self-reporting of

- other risk and protective factors
    - Diet (e.g., with smartphone camera, potentially with barcode scanning)
    - Alcohol use
    - Smoking
- subclinical symptoms
- reminders from informal care network?

Support for automatic detection (sometimes possible) or lightweight self-reporting of self-care

Results of biomedical tests (e.g., blood glucose tests or blood pressure cuff readings, which could in theory be automatically detected with bluetooth enabled systems)

self-administration of pharmaceuticals (e.g., insulin, which could in theory be automatically detected with bluetooth enabled systems)

Recording of certain biomedical measures (e.g., heart rate)

Recording of concern levels and motivational status

Communicable Disease Epidemiology

Example Problems/questions that can be addressed:

Assessing how a given intervention would be likely to lower the transmission ofthe infection in the population

Understanding how self-reported risk attitude changes during an outbreak

Understanding how automatically measured risk behaviour changes during an outbreak

Identifying the role that contact duration and type (proximity, type of relation) plays in contributing to the spread of infection

Identifying likely individuals who may be carriers or who could be asymptomatically infected

Identifying likely reservoirs of pathogen on surfaces

To what degree do variations in humidity or temperature account for risk of infection?

Understanding the association between pathogen burden and handwashing

With Interventions

How much and how soon does the intervention affect different pathways involving risk factors (e.g., contact diversity, frequency and duration; etc.) and protective factors (hygeine; vaccination; use of personal protective equipment; cleaning and disinfection), etc.

With dynamic modeling:

How would various interventions (enhancing handwashing compliance, upon-admission patient testing and potential isolation, patient or clinical cohorting) be likely to change the spread of infection within the facility population?

Solution elements:

For some pathogens (e.g., droplet or airborne pathogens), automatic detection of contact networks

For other pathogens (e.g., sexually transmitted or fluid-borne pathogens),

automatic detection of places where exposure may take place (often an indication of contact)

support for manually recording such contacts automatic detection of exposure to locations associated with surfaces that many carry pathogen

Recording of subclinical symptomology (which may be important to better judge timing of infection, initiation of (nearly) asymtomatic shedding, etc.)

Support for easy self-reporting of level of risk concern

Support for easy self-reporting of level of risk and protective behaviours (e.g., condom use, washing of hands)

Mental Health

Example Problems/questions that can be addressed:
Identifying early predictors of aggressive or disruptive behaviour by dementia or other mental health patients

To what degree does the effect of a mental-health intervention reduce risk of stressors and adverse interventions between the patient and those around them?

What sensor-based measurements can serve as reliable predictors of depression?

What sensor-based measurements can serve as reliable proxies for depression?

Identifying individuals likely to be suffering from depression

Identifying dynamics of stress at an individual or dyadic fashion

Identifying antecedents of depressive episodes

Understanding transmission of depressive tendencies or other adverse aspects of mental health (e.g., within family, maternal-infant)

Contacting family members when an individual appears likely to be suffering from depression

Understanding the relationship between physical activity and depressive episodes

With dynamic modeling:

> Assessing the impact of an intervention that could allow much earlier detection of -- and coordinated response to -- incipient aggression in a ward

Solution elements:
From sensor data, automatically detecting changes in behaviour that might be indicative of emerging depression

> change in physical activity and sedentary behaviour
>
> change in physical socialization pattern
>
> change in communicational behaviour
>
> changes in mobility patterns in general
>
> changes in level of visits associated with adverse exposures, influences or risk behaviours (e.g., visits to liquor stores, bars, known places associated with narcotic use)

Detecting stress levels with appropriate analyses or additions (e.g., voice tone, galvanic skin response sensors, heart rate, utterances even when alone)

In addition to above, permitting self-reporting of stress levels

Recording occurrence of stressors in situ

Understanding history of exposures (in addition to self-reports above, using automatically recorded trajectories of where a person has traveled, with whom they have been, etc.)

Recording adverse cognitions (e.g., thought of self-harm)

Detecting or allowing reporting of risk behaviors or markers (smoking, alcohol use, self-cutting)

Recording of self-administration of pharmaceuticals

Environmental Epidemiology

Example Problems/questions that can be addressed:
To what degree does variability in exposure explain variability in outcomes within the population?

How proximate is the impact of exposure on symptomology in different subgroups?

To what degree do other stressors or risk or protective factors (e.g., physical activity) mediate the strength of symptoms seen from a given exposure?

With dynamic modeling:

> How much would an intervention (removal of point source X, use of personal protective gear, enhanced ventilation, etc.) help reduce the burden of infection in the population?

Solution elements:
Detecting exposure to environmental risks (e.g., poor air quality [e.g., diesel fumes], mosquitoes, pro-tobacco promotion or messaging)

Auto detecting some risk status (e.g., being in a feed barn, being outside, swimming in the ocean). Typically the severity of this risk status is detected by cross-linking with other database (e.g,. UV information, reports of pollutant levels from environmental sensors)

Allowing manual reporting of certain risk status that cannot be automatically detected (e.g., wearing short sleeves, wearing mosquito repellent)

Experience of subclinical symptoms that would otherwise go unreported (e.g., wheezing and coughing, stomach ache, headaches)

Through sensors (location, time, bluetooth): More reliable information on context of exposures: where, when, with whom

Health Services Research

Example Problems/questions that can be addressed:

Understanding how frequency, intensity and type of encountered symptoms affect care-seeking likelihood

Understanding the contribution of informal caregiving networks to quality self-care

Understanding how effects of informal caregiving affect care-seeking behaviour

Understanding how dynamics of informal caregiving networks affect attempts of institutionalization

Understanding the degree to which self-care or informal-caregiving is supportive of effective compliance

Understanding the degree to which interprofessional consultations and coordinations contribute to length of stay

How much time are individuals spending traveling back and forth to certain resources?

To understand antecedents and consequents of formal care-seeking, recording of self-care: self-administration of pharmaceuticals, testing of blood sugar, etc.

Understanding what temporally proximate factors lead to presentation (including experience of subclinical symptoms, affect and attitudes towards care seeking)

Understanding the amount of time required in each stage of a patient flow process more accurately than via the officially reported data (often batched, or recorded later, or not recorded because not billed to government)

With dynamic modeling:

> To what degree would throughput be enhanced by elevating the numbers of a different classes of professionals, or their hours of availability?
>
> To what degree would providing respite care to the informal caregivers enhance the health of patients, and affect the number of visits and admissions?

Solution elements:

Detecting interprofessional consultations and coordinations

Enquiring with patients about their status before and immediately after professional contacts

Detecting episodes of care or (e.g., complementary and alternative medicine) providers not compensated by the payer, and thus not included in available administrative data

Picking up extra cues that could aid in automatic classification mechanisms for patient status (e.g., ALC status)

Reducing the burden of recording "spaghetti diagrams", etc.

Recording of dynamics of informal caregiving

More accurate measurement of time-to-disposition-decision data