Value Propositions of Mobile Health Data Collection Systems

Nathaniel Osgood

University of Saskatchewan

Measuring and Modeling Health Behavior with Smartphone Mediated Data Collection

August 8, 2016

Agenda

- Context setting & motivations
- Hallmarks of big data in health
- Examples of delivered value
- Concluding remarks

Context:
Ever More Complex Health Challenges

- **Blowback (e.g., Antibiotic resistance organisms)**
- **“Syndemics”: mutually interacting conditions [Singer]**
  - **Chronic & communicable illness (e.g. obesity & H1N1)**
  - **Substance abuse, crime, poverty, suicide**
  - **Association with inequities & powerlessness**
- **Aging population, co-morbidities**
- **“One World, One Health”: Zoonoses & emerging IDs**
- **Big implications of Small worlds (Global travel)**
- **Intergenerational & epigenetic effects**
- **Critical periods, effects of early life insults**
- **Lowered risk perception (e.g. vaccination)**
- **Multiple-outcome, multiple-complic.conditions**
- **Counteracting ever more nimble corporate actors**

Complex Treatments & Interventions: Notable Needs

- Longitudinal perspective
  - Lifecourse effects
  - Differential treatment based on prior history
- Shaping and exploiting networks
- Tailored & targeted focus: Importance of heterogeneity
- Importance of
  - *Context*
  - *Relationships*
- Flexibility in level of detail incorporated
- Anticipating and incentivizing behavioral responses
- Rapidly learning from interventions and natural experience

Our Context: Increasingly Rich Simulation Models to Enhance Decision Making

- Many uses of computational models involving human health & behavior require copious data
- Such models help us understand the implications of such data for decision making
- Stratified aggregate models: Detailed cross-sectional views of a population's health
- Individual based models: Detailed longitudinal & cross-sectional views of a population's health
  - Strong motivations: Capturing history, network position, spatial dynamics, rich heterogeneity
    - Individual trajectories
    - Interventions design
    - Calibration
- Modeling as theory building: Broader & more detailed models typically involve more articulated theories

Common Challenge: Reliable Data on Key Health Behaviors are Often Hard to Secure

- Location (access to care, access to resources, barriers to activity, environmental risks)
- Physical activity (obesity, T2DM & GDM, risk of falls)
- Spatial proximity (transmission of pathogens and norms, imitative behavior, communication)
- Social context (norms, communication, perception of safety, risk perception)
- Communication: Personal & mass media (risk perception, norms, beliefs, social cues)
- Decision-making rules & heuristics

A Key Challenge: Reliable Data on Key Health Behaviors are Often Hard to Secure

- Location (access to care, access to resources, barriers to activity, environmental risks)
- Physical activity (obesity, T2DM & GDM, risk of falls)
- Spatial proximity (transmission of pathogens and norms, imitative behavior, communication)
- Social context (norms, communication, perception of safety, risk perception)
- Communication: Personal & mass media (risk perception, norms, beliefs, social cues)
- Decision-making rules & heuristics

Absent understanding of such behaviors, the potential to quantitatively evaluate policy tradeoffs is greatly limited

Traditionally Available Data is Becoming Harder to Secure

- Random digit dialing is becoming increasingly expensive per respondent
- Proliferation of content channels complicates monitoring
- Difficult to secure picture on certain demographic subgroups with evolving habits

Agenda

- ✓ Context setting & motivations
- Hallmarks of big data in health
- Examples of delivered value
- Concluding remarks

Reminder: Four “V’s” of “Big Data” (Google)

- **Volume**: Lots of evidence
- **Velocity**: High temporal resolution longitudinal data
- **Variety**: Cross-linked data sources support can “triangulation” of understanding
- **Veracity**: Physical measures are less subject to self-report, on-device self-reporting is more temporally proximate to health event (exposures, symptoms,…)

Agenda

- ✓ Context setting & motivations
- ✓ Hallmarks of big data in health
- Examples of delivered value
- Concluding remarks

Levels of Insight from Digital Epidemiology Systems

- **Self-care & informal-care**: "A More Perfect Mirror"
- **Clinical mgmt**: e.g., Helping a clinician and allied health professionals understand patient challenges, self-care & informal care, symptoms & contexts
- **Health services delivery**: e.g., Detecting inefficiencies & bottlenecks, quantifying key delays, identifying coordination challenges
- **Operational decisions**: e.g., prioritizing testing, faster outbreak identifying and localization, evaluating control strategies
- **Strategic decision making**: e.g., identifying high-leverage intervention & restructuring strategies

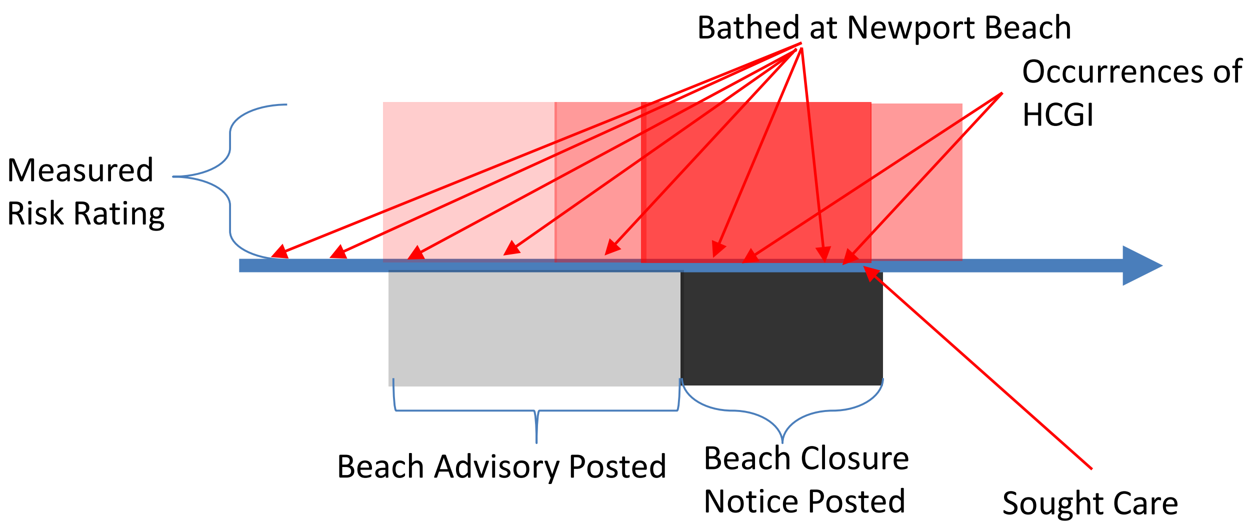
Key Use Cases for Mobile Data Collection Tools

- Assessing **symptoms** (both clinical & **subclinical**), cognitions and behaviors in relation to **risk factors & exposures**
- Enhancing the speed, reliability, and depth of learning from implemented interventions
- Clarifying choice contexts and mechanisms (including stated and revealed preferences) constructing options and changes in perceived and expected values over time
- Supporting broader understanding of the **texture of day-to-day life** for participants

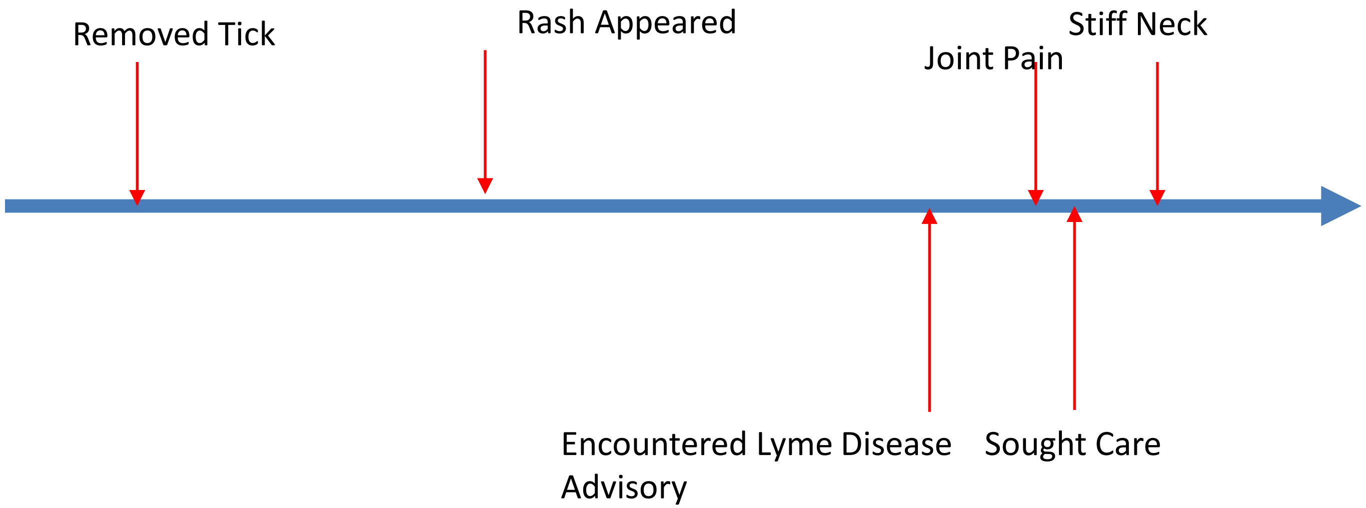
Key Use Cases for Mobile Data Collection Tools

- Assessing **symptoms** (both clinical & **subclinical**), cognitions and behaviors in relation to **risk factors (**including **exposures)**
- Enhancing the speed, reliability, and depth of learning from implemented interventions
- Clarifying choice contexts and mechanisms (including stated and revealed preferences) constructing options and changes in perceived and expected values over time
- Supporting broader understanding of the **texture of day-to-day life** for participants

Example Biography: Waterborne Illness

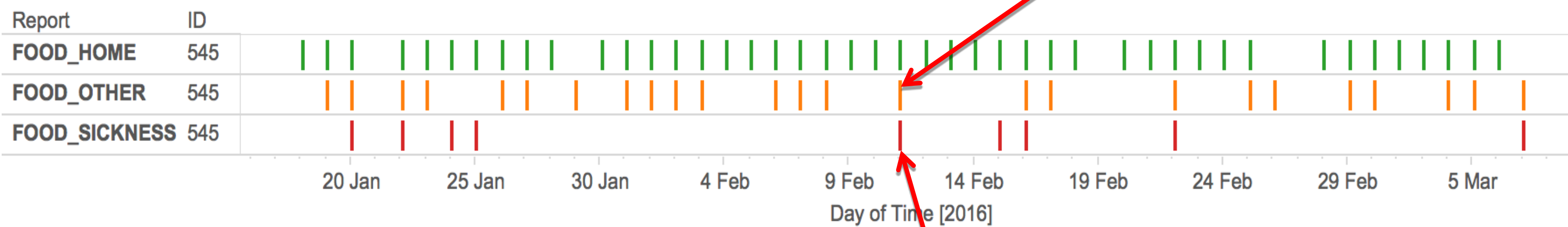


Example Biography: Lyme Disease



Individual Trajectories (ongoing)

To what degree is eating Non-home cooked meals

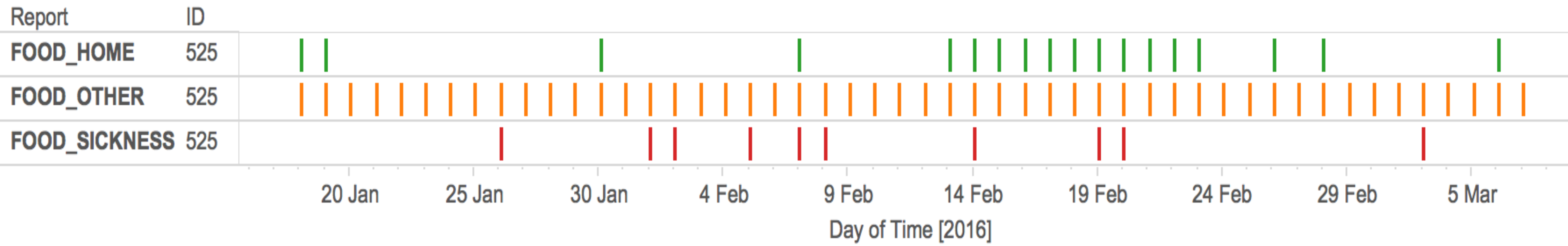


Time Day for each ID broken down by Report. Color shows details about Report. The view is filtered on ID, which keeps 545.

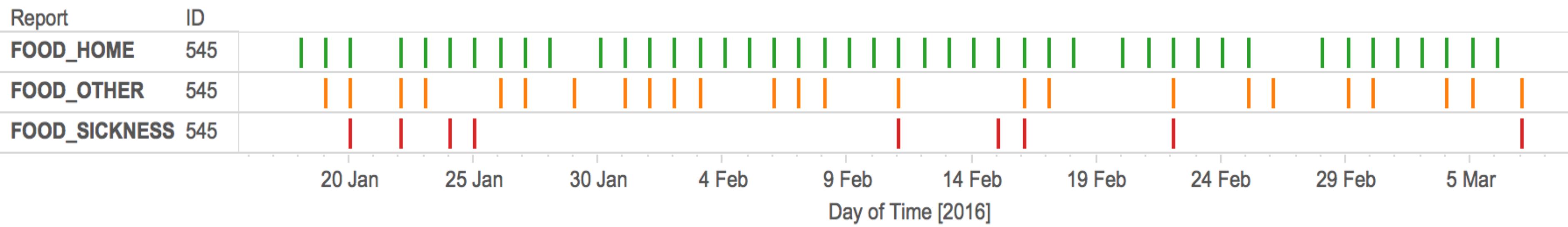
Associated with an elevated risk of Possible foodborne illness?

3 Individual Trajectories (ongoing)

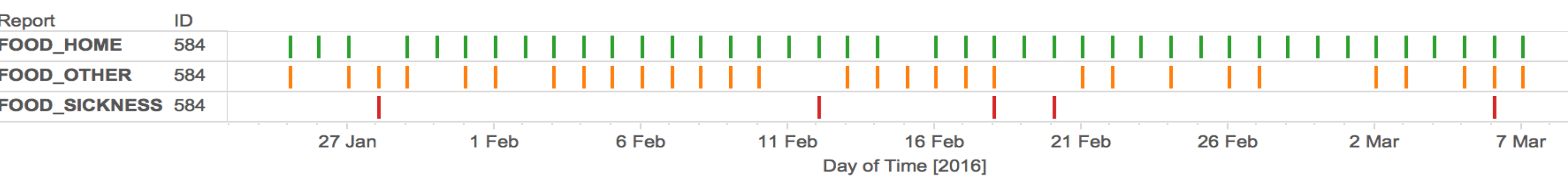
Event Plot



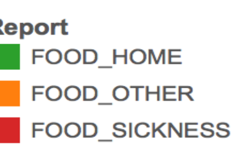
Time Day for each ID broken down by Report. Color shows details about Report. The view is filtered on ID, which keeps 525.



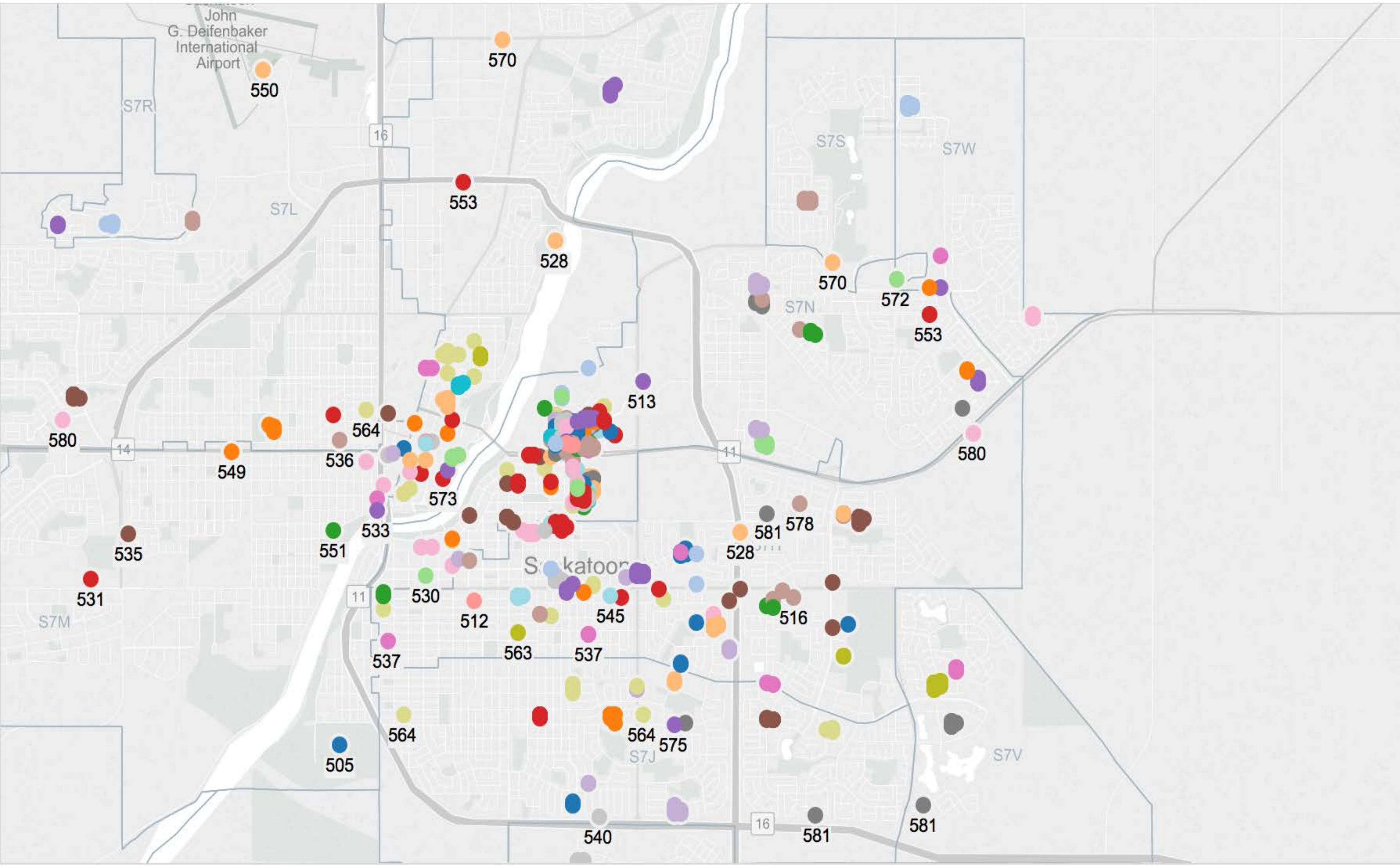
Time Day for each ID broken down by Report. Color shows details about Report. The view is filtered on ID, which keeps 545.



ime Day for each ID broken down by Report. Color shows details about Report. The view is filtered on ID, which keeps 584.

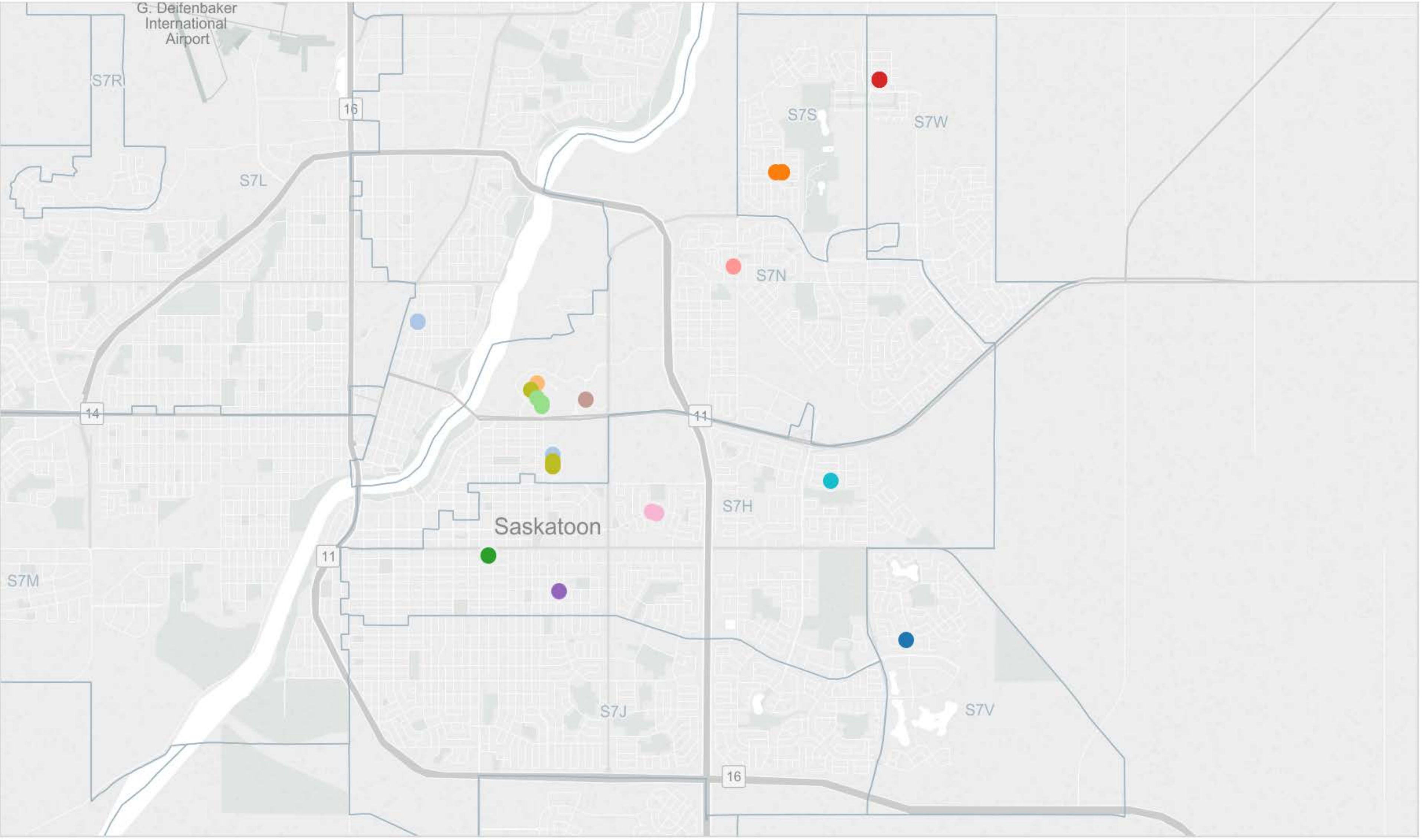


Eating Non-Homecooked Foods



Map based on Long and Lat. Color shows details about ID. The marks are labeled by ID. Details are shown for Time Hour. The view is filtered on ID, which keeps 80 of 80 members.

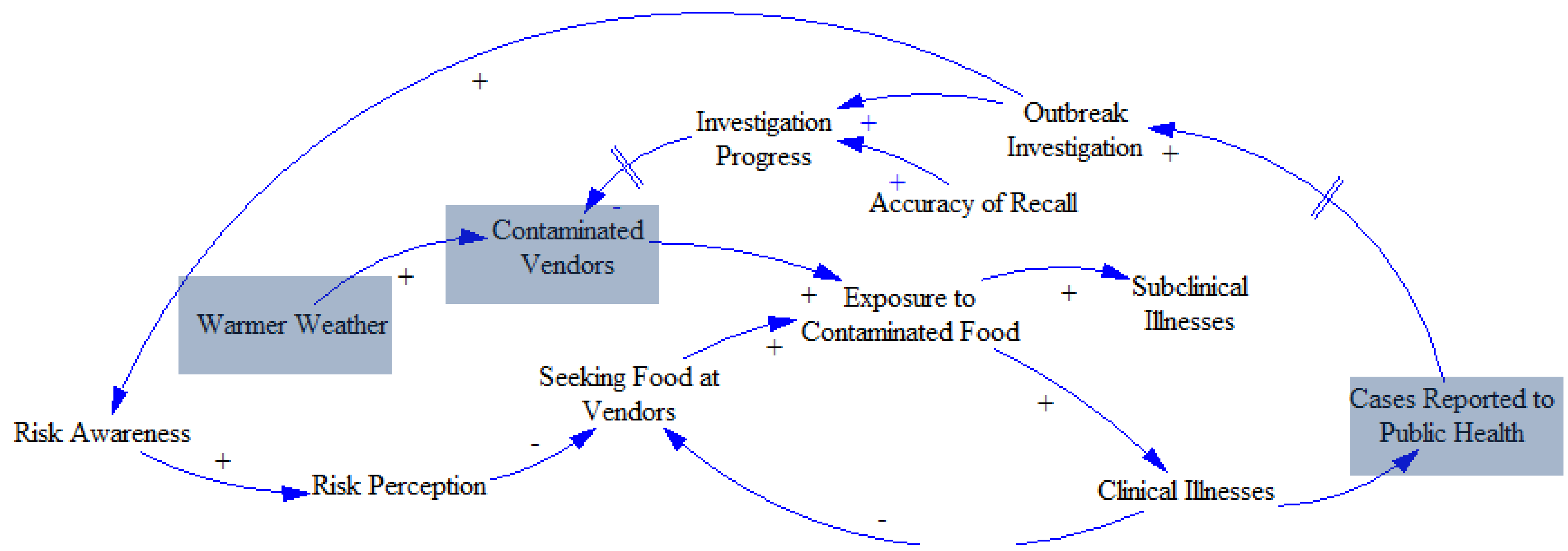
…within 24 Hours Before Illness



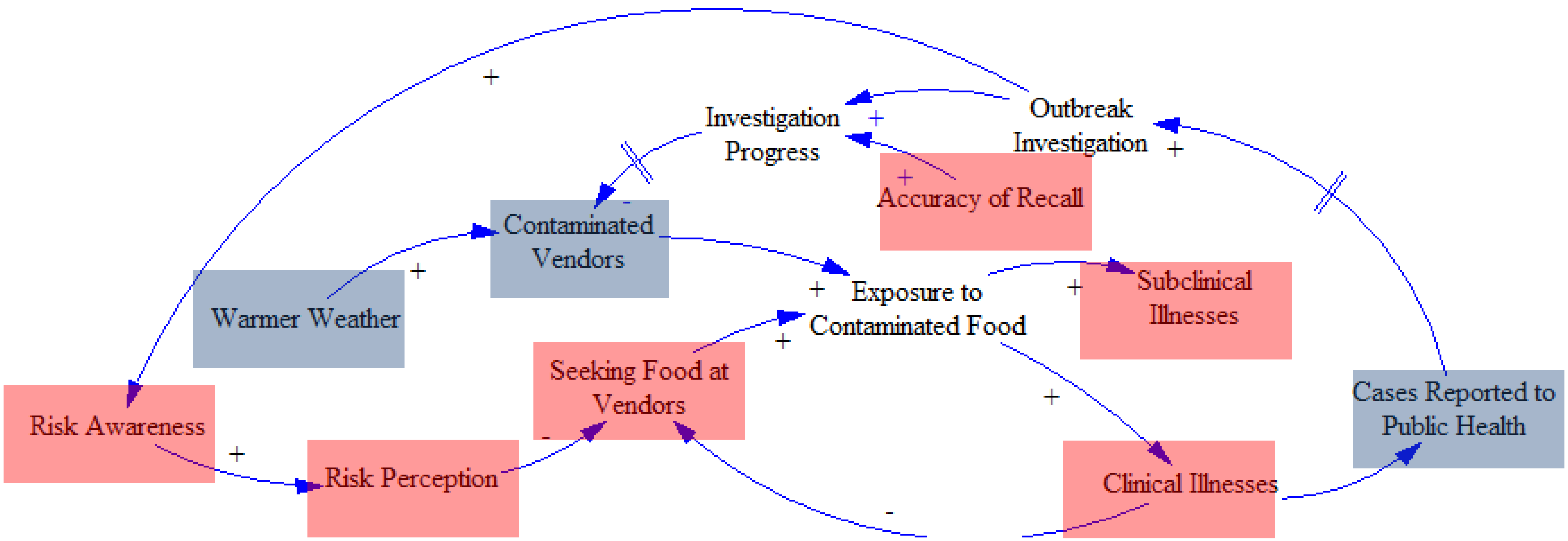
Map based on Long and Lat. Color shows details about ID. Details are shown for Time Hour and ID.

Filling in the Gaps: Areas Readily Addressed through Traditional Sources

Additions Being Considered **Currently in Model**



Filling in the Gaps: Areas addressed by “Big Data”



Application to Health Areas

- **Obesity**: 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) What exposures or ideations are likely associated with relapse?
- **Tobacco related disease**: To what degree is risk of relapse affected by interactions w/other smokers/vapers? by exposure to pro- or anti-tobacco messaging?
- **Environ. Epi**: To what degree does exposure to particular envs. explain occurrence of coughing/wheezing? Physical activity? Emotional stressors?
- **Communicable Illness**: How does risk behavior change throughout an outbreak? How does risk perception vary with exposure to infective individuals? How do contact duration and type (proximity, type of relation) contributing to transmission risk?
- **Mental Health:** How does individual reported stress, depressive symptoms or indicators of depressive symptoms vary with empirical physical activity, social contacts, medication use?
- **Health Service delivery**: Understanding how frequency, intensity and type of encountered symptoms & self-care affect care-seeking likelihood. Understanding the contribution of informal caregiving networks to quality self-care. Understanding the degree to which interprofessional consultations and coordinations contribute to length of stay.

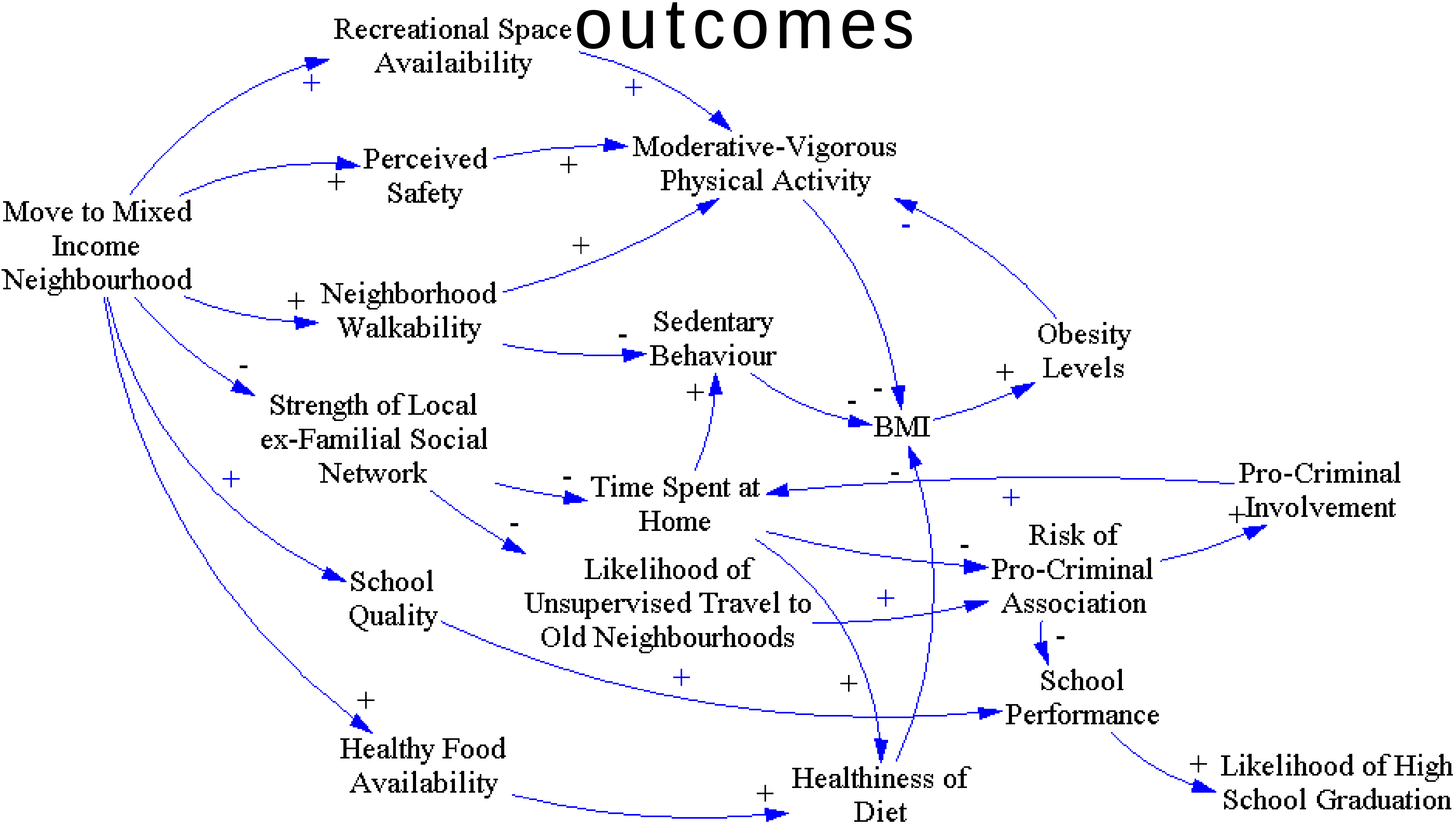
Key Use Cases for Mobile Data Collection Tools

- Assessing **symptoms** (both clinical & **subclinical**), cognitions and behaviors in relation to **risk factors (**including **exposures)**
- Enhancing the speed, reliability, and depth of learning from implemented interventions
- Clarifying choice contexts and mechanisms (including stated and revealed preferences) constructing options and changes in perceived and expected values over time
- Supporting broader understanding of the **texture of day-to-day life** for participants

Understanding Intervention Effects

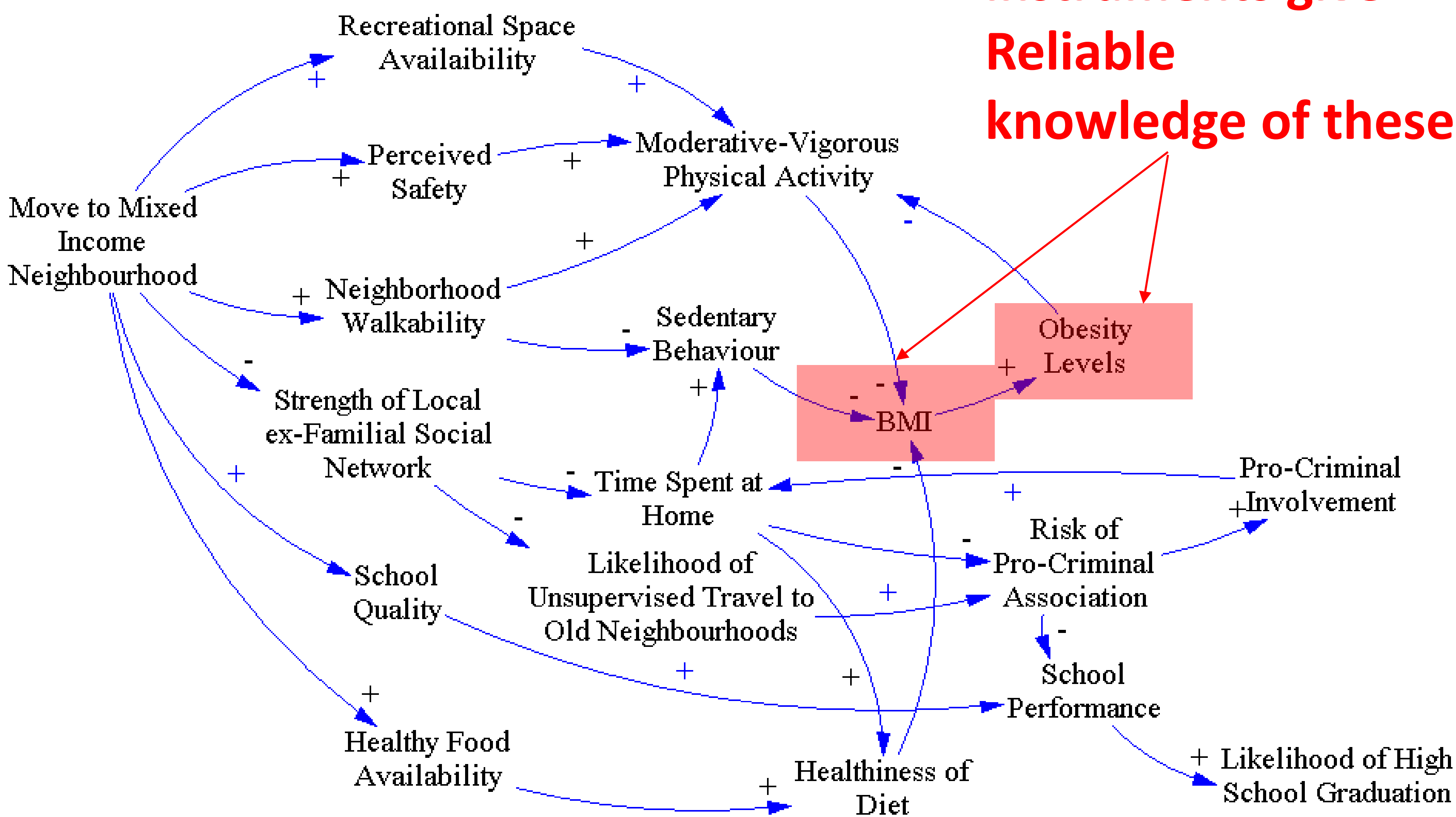
- By virtue of being able to examine which and by **how much and how soon different pathways were affected, learning is**
  - **Deeper**
  - **More reliable**
  - **Quicker**
- Learning is secured regardless of whether an intervention is successful or not in the end

A Key Motivating Challenge: Understanding pathways to learn more effectively from observed intervention outcomes

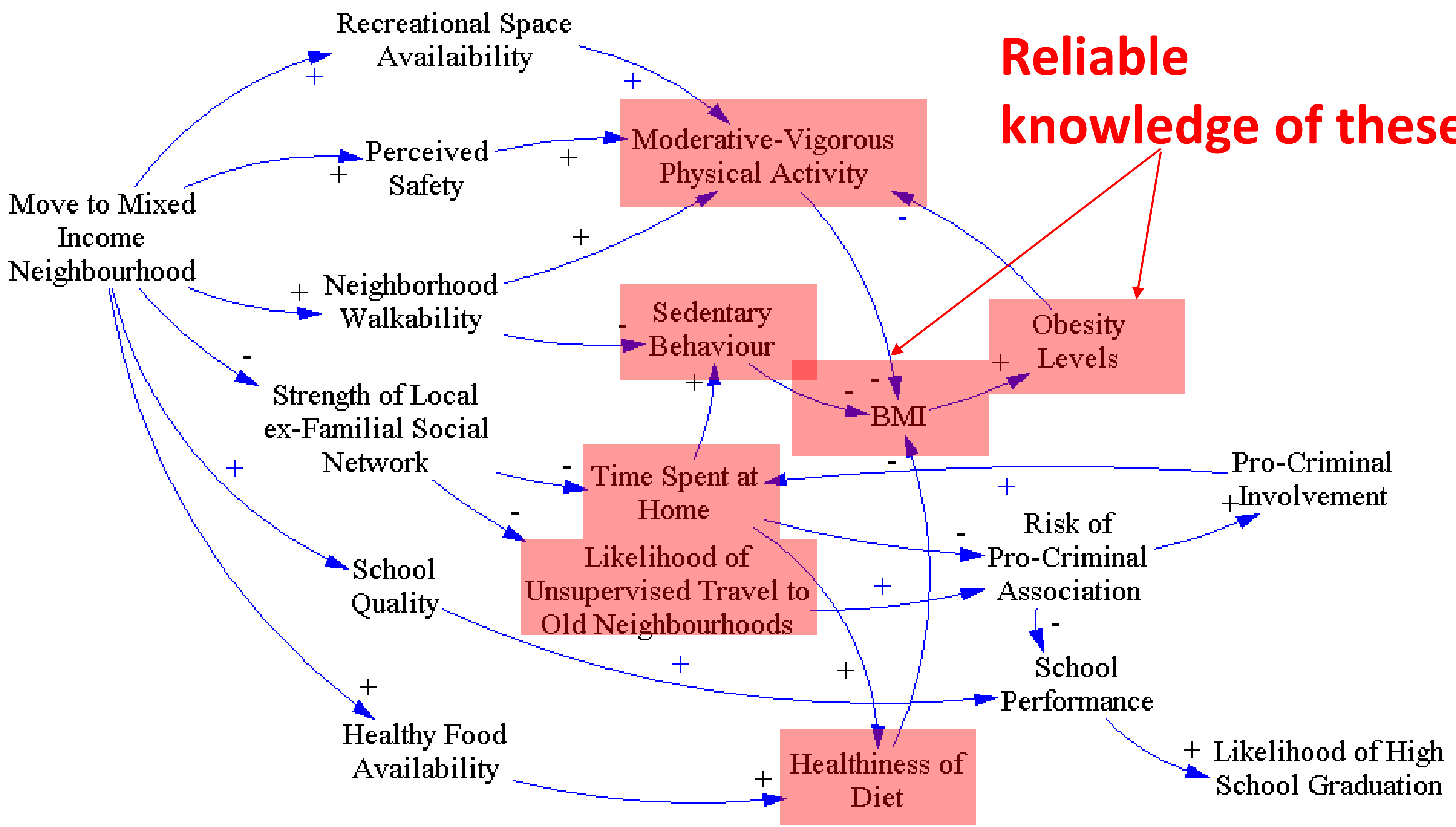


Understanding with Traditional Instruments

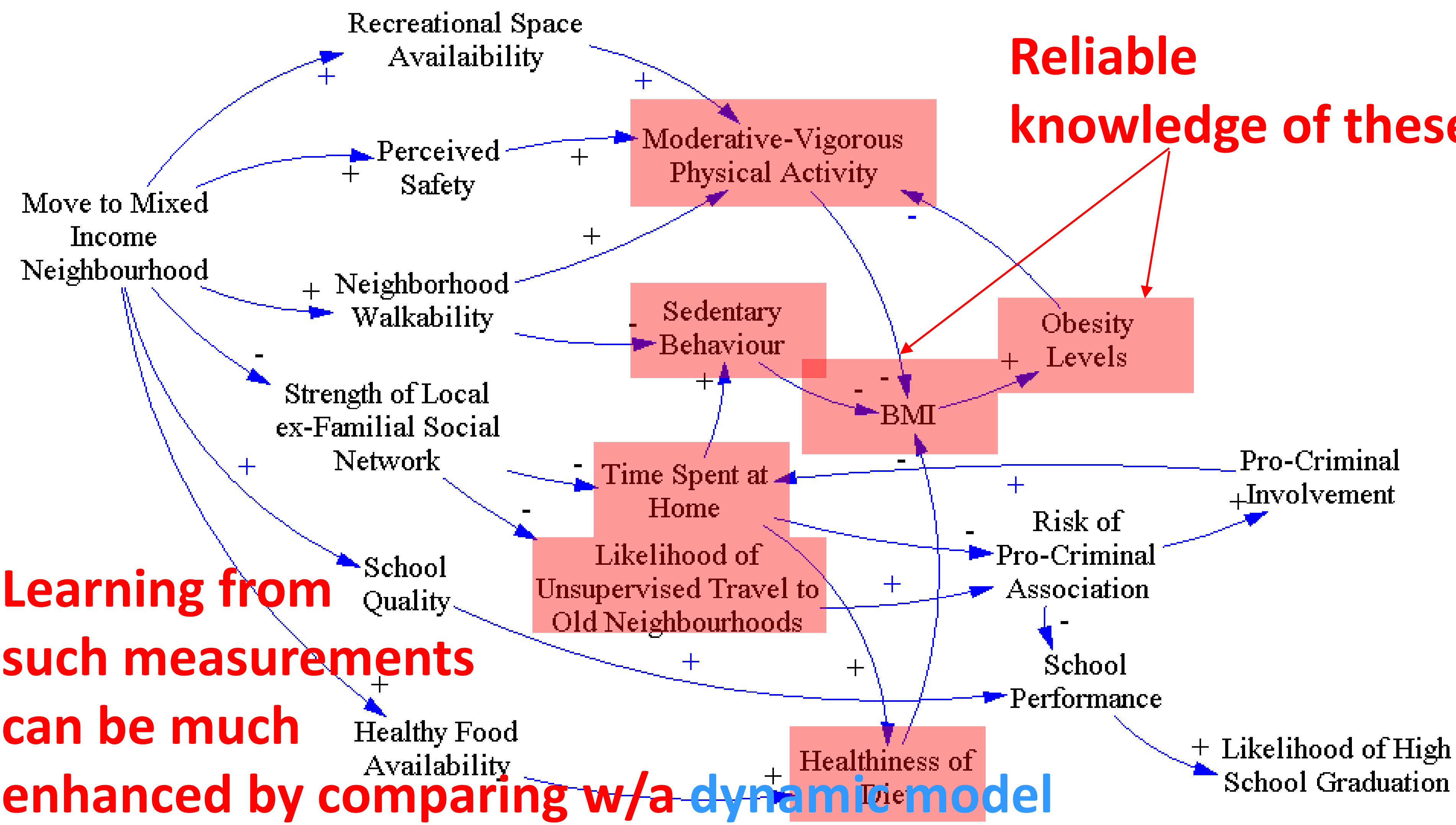
Traditional instruments give Reliable knowledge of these



Understanding With "Big Data"



Understanding With “Big Data”



Reliable knowledge of these

Learning from such measurements can be much enhanced by comparing w/a dynamic model

Key iEpi Uses

- Tease out effects across different pathways underlying intervention outcome
- Support subclinical reporting
- Connect exposures (e.g., to air pollution, fast food or tobacco promotion, other behaviours, etc.), with outcomes
- Understand effects of an intervention on an individual
- Resolve different pathways explaining observational variability
- Understand the impact of the social and physical environment
- Allow for crowdsourced reporting (e.g., of barriers to health, protective behaviours, risk behaviours)
- Tracing movement of individuals and inter-professional coordination with health care facilities
- Silently recording exposures that can be retrospectively examined in case of later development of adverse health conditions
- Secure more reliable information on risk factors and influences that are poorly reported by traditional self-report (e.g., transient contacts, exposures throughout activity spaces)
- Capture information on cognitions/affects just after exposures.

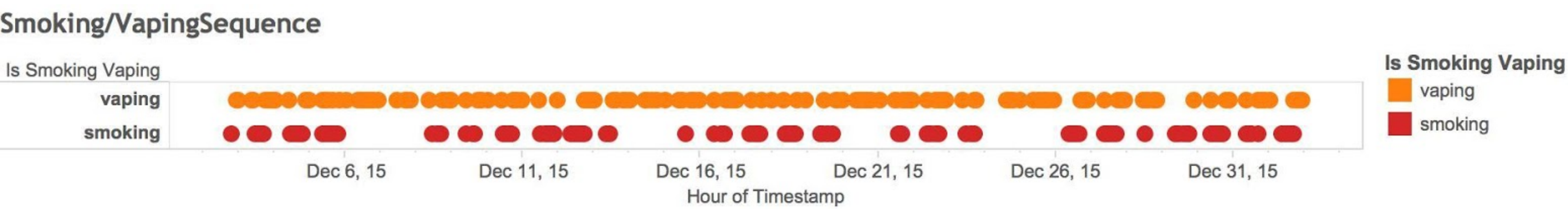
Application to Health Areas

- **Obesity**: To what degree has this lifestyle intervention budged sedentary behaviour/moderate-to-vigorous physical activity/dietary intake? In intervened upon groups? In non-intervened upon individuals within the social networks of those intervened upon?
- **Tobacco related disease**: 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?
- **Environ. Epi** : To what degree has improved ventilation changed occurrence of coughing & wheezing given different levels of exposure? Given PA?
- **Communicable Illness**: How has occurrence of vaccination changed mixing & associated risk behaviour? Reported risk perception? How much has social distancing changed empirical contact rates?
- **Mental Health:**? To what degree does the effect of a mental-health intervention reduce risk of suicidal ideation, stressors and adverse interventions between the patient and those around them?
- **Health Service delivery**: How has availability of an EHR altered waiting times at different stages of the process? Changed inter-prof. coordination?

Key Use Cases for Mobile Data Collection Tools

- Assessing **symptoms** (both clinical & **subclinical**), cognitions and behaviors in relation to **risk factors (**including **exposures)**
- Enhancing the speed, reliability, and depth of learning from implemented interventions
- Clarifying choice contexts and mechanisms (including stated and revealed preferences) constructing options and changes in perceived and expected values over time
- Supporting broader understanding of the **texture of day-to-day life** for participants

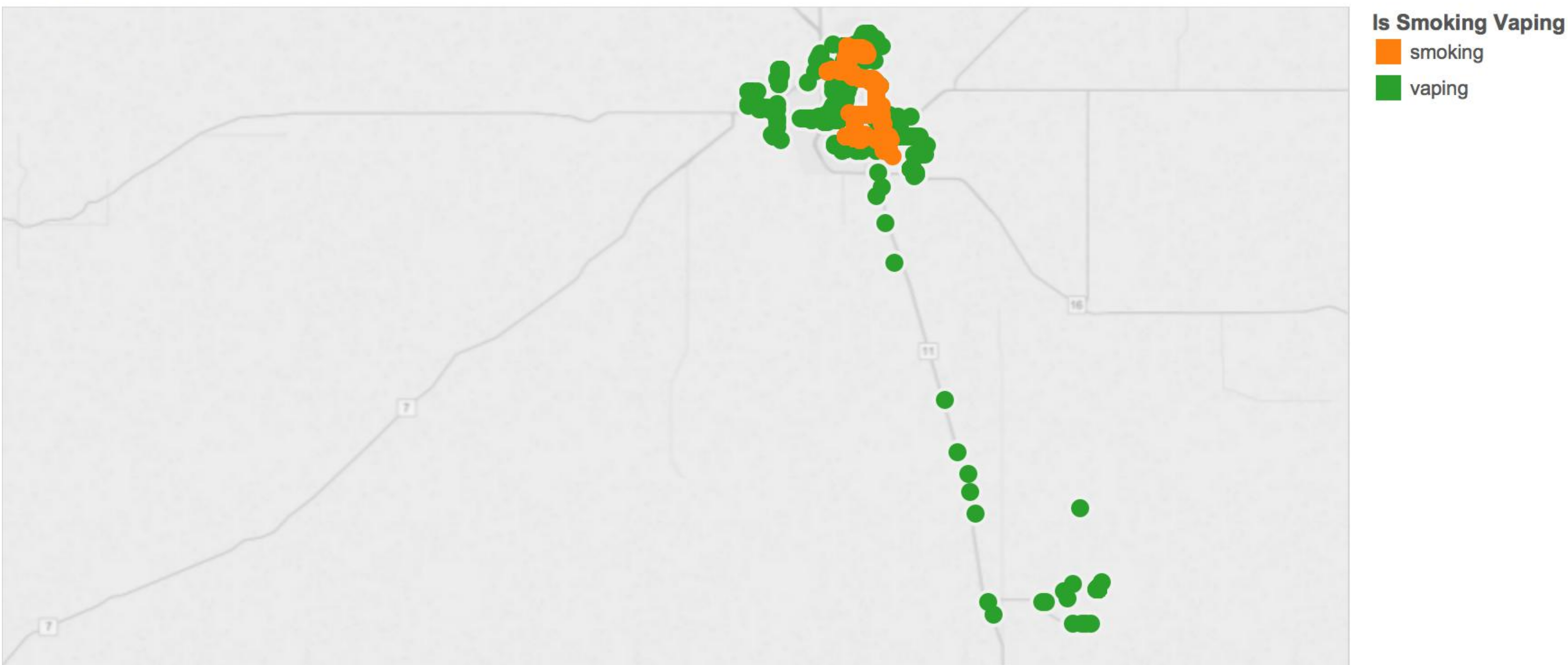
Smoking and Vaping Under Different Circumstances



Timestamp Hour for each Is Smoking Vaping. Color shows details about Is Smoking Vaping. The data is filtered on Creator Id, which excludes 4.>4(p!41<H<F2sDPMB!.]== and k1s%k10H6[ypy^F*bpB4//==. The view is filtered on Is Smoking Vaping, which excludes Null and neither smoking nor vaping.

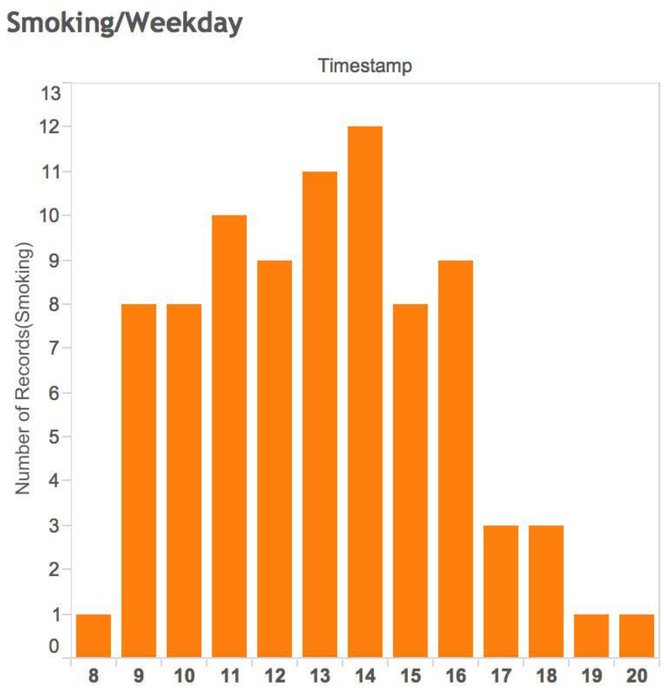
Geographic Context

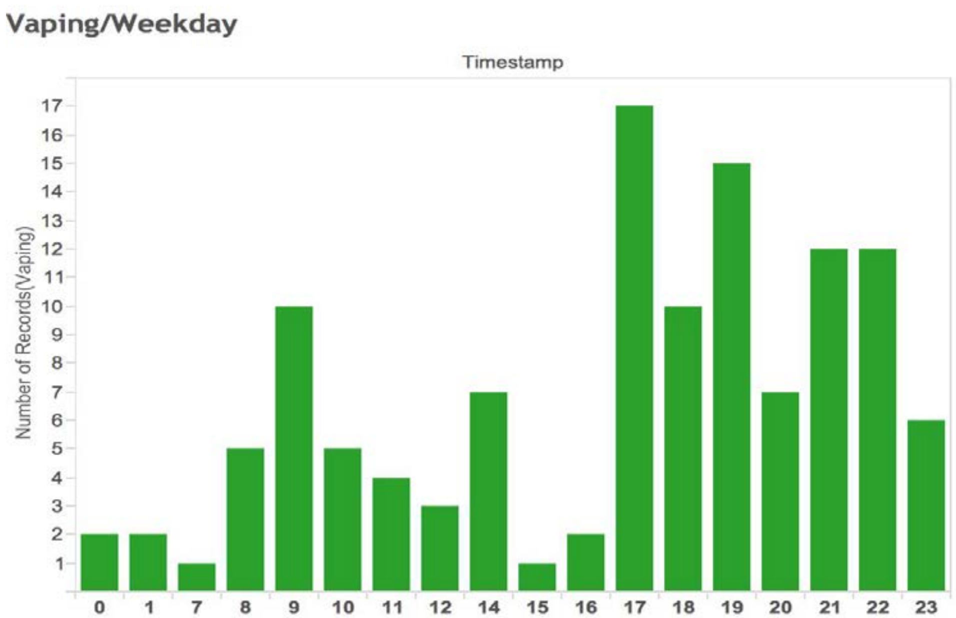
Where



Map based on Longitude and Latitude. Color shows details about Is Smoking Vaping. The data is filtered on Creator Id, which keeps bNSR-fw<sg9kx^bNB>4^ql]==. The view is filtered on Is Smoking Vaping, which excludes neither smoking nor vaping.

Temporal Context





Application to Health Areas

- **Obesity**: How does occurrence of physical activity vary with built environment? Food consumption with available food environment? How do choices vary in the context of distance, price and food type?
- **Tobacco related disease**: How do choices vary in the context of distance, price and food type? How does choice to smoke, vape, or neither depend on availability of each option?
- **Environ. Epi**: How does use of personal protective behavior vary with temperature and risk perception?   How does exposure vary in response to amenities?
- **Communicable Illness**: To what degree are contact behaviors reflective of transportation options?
- **Health Service delivery**: How does balking and presentation vary in light of perceived waiting times?

Key Use Cases for Mobile Data Collection Tools

- Assessing **symptoms** (both clinical & **subclinical**), cognitions and behaviors in relation to **risk factors (**including **exposures)**
- Enhancing the speed, reliability, and depth of learning from implemented interventions
- Clarifying choice contexts and mechanisms (including stated and revealed preferences) constructing options and changes in perceived and expected values over time
- Supporting broader understanding of the **texture of day-to-day life** for participants

Application to Health Areas

- **Obesity**: How does occurrence of physical activity vary in response to different levels of entropy? Breadth of activity spaces?
- **Tobacco related disease**: How do diverse exposures to tobacco use, e-cigarette use and tobacco-related advertising affect particular instances of tobacco use? To change in tobacco-related behaviours?
- **Environ. epi**: How does risk behavior/risk attribution vary as the extent of personal travel and environmental context rises?
- **Communicable illness**: How does regularity in taking medication reflect a tumultuous life? feasible to predict?How does occurrence of handwashing compliance vary w/work pressure & time of day? How does personal protective behavior vary w/extent of mixing?
- **Mental health**: How does the extent of personal activity vary with experience of stressors? With suicidal ideation?
- **Health Service delivery**: How does the likelihood of presenting for care, vaccination, etc. differ w/degrees of personal commitments?

Agenda

- ✓ Context setting & motivations
- ✓ Hallmarks of big data in health
- ✓ Examples of delivered value
- Concluding remarks

Conclusions

- Sensors are increasingly ubiquitous
- Commodity sensor-bearing devices can serve a dual use as versatile sensor, EMA & crowdsourcing platforms
- Diverse communication support deriving contexts
- Coupled with models, sensor data can offer significant and complementary health insights
- Cross-linked sensor-based & EMA data – as well as other components of "Big Data" – offer tremendous potential to complement & sharpen (not replace) traditional methods
- A key use of such data for social and health policy can benefit is to learn more quickly from interventions – "successful" or not