COMPUTATIONAL METHODS AND TECHNOLOGY-DELIVERED INTERVENTIONS FOR SEXUAL AND GENDER MINORITY HEALTH

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Health Disparities among Sexual and Gender Minorities (SGM)
Workshop, National Institute on Minority Health and Health Disparities

Technology-delivered interventions (TDIs) = preventative or remedial digital health tools that target mental, behavioral, or sexual health problems

Computational methods = artificial intelligence; i.e., machine learning, deep learning, natural language processing

MOTIVATION

TDIS FOR SGM HEALTH ARE PROMISING[8,15,18,19], BUT GAPS REMAIN THAT CAN BE ADDRESSED WITH COMPUTATION

- Concerns about feasibility and scalability[17]
- Lack of personalization[20,21] = tailoring TDIs to individual experiences
- Lack of engagement[20,21] = low motivation to use TDIs

Computationally enhanced TDIs have potential to be highly personalized, engaging, and scalable solutions to SGM mental, behavioral, and sexual health problems

What needs to happen to realize the potential of computationally enhanced TDIs for SGM health?

EVIDENCE, GAPS, & CHALLENGES IN COMPUTATIONALLY ENHANCED TDIS FOR SGM HEALTH

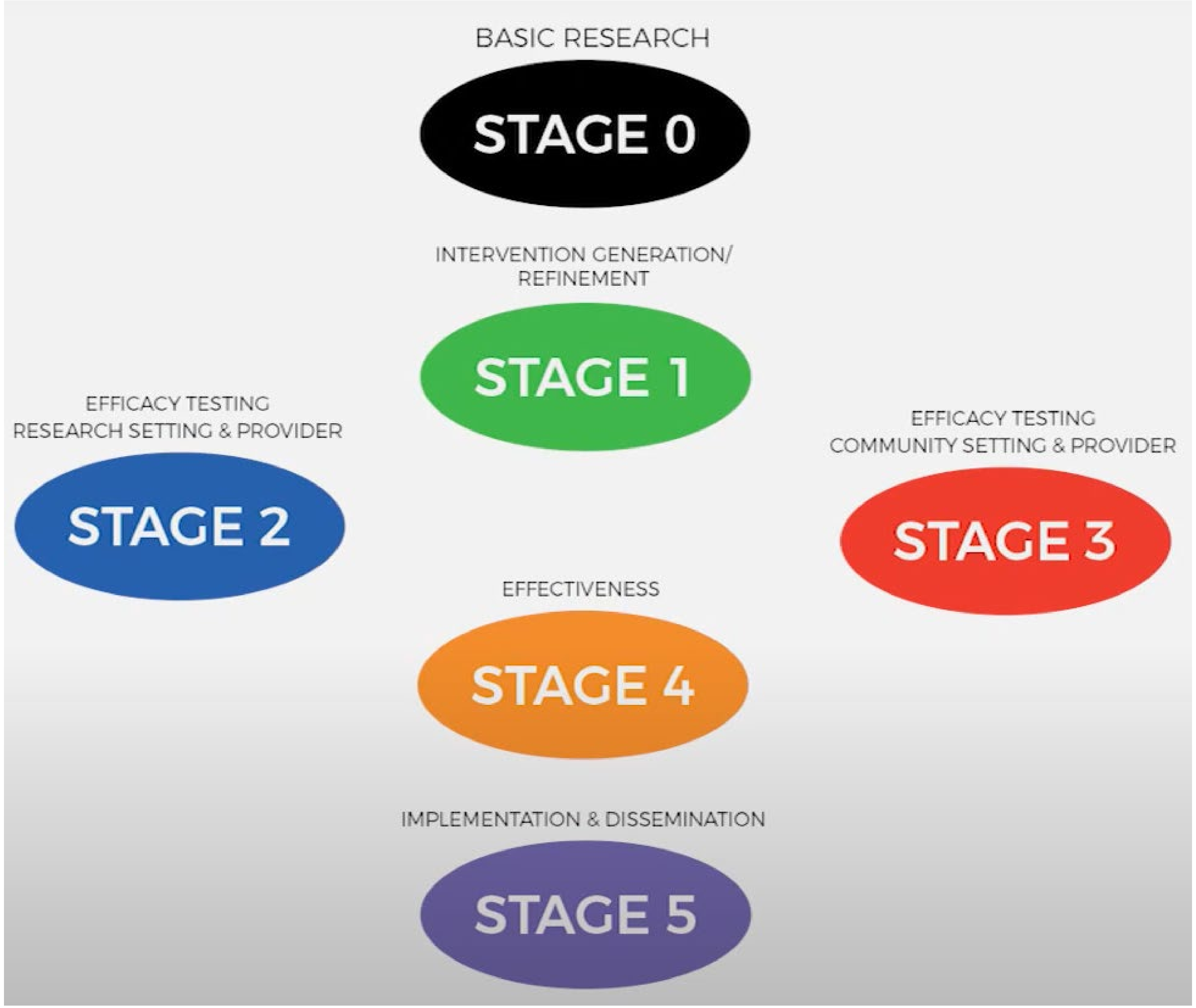


Image: National Institute on Aging

At each stage, specific challenges and gaps need to be addressed to realize the potential of computationally enhanced TDIs.

BASIC RESEARCH

STAGE 0

ONE BASIC CHALLENGE IS ESTABLISHING COMPUTATIONAL CONSTRUCT VALIDITY

Big Data

Statistical

Relationship

Psychometric surveys

Qualitative codes

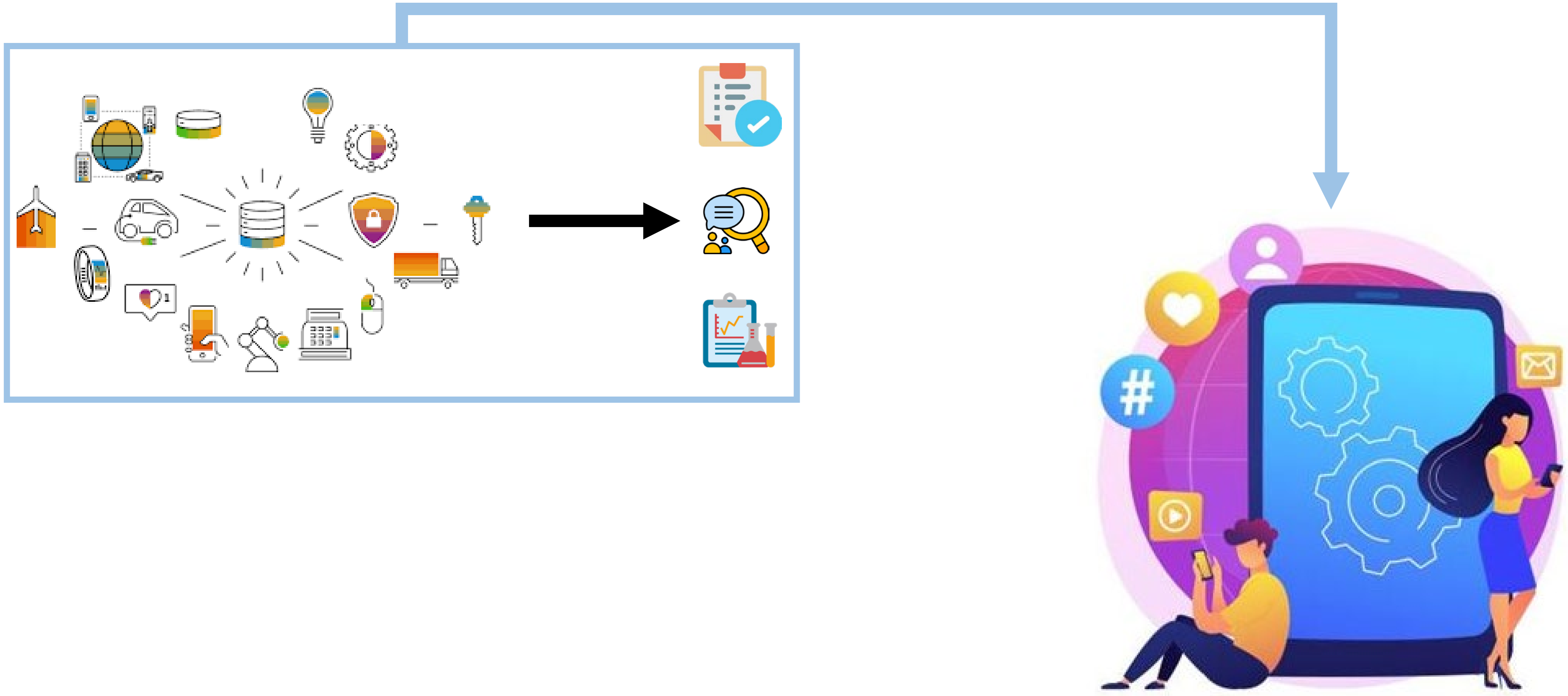
Physiological measures

Images: SAP and Flaticon

BASIC RESEARCH

STAGE 0

ONCE COMPUTATIONAL MODELING IS VALID, WE CAN INTEGRATE BIG DATA INTO TDIS



Images: SAP, Flaticon, *Frontiers in Psychology*

BASIC RESEARCH
STAGE 0

EVIDENCE OF COMPUTATIONAL CONSTRUCT VALIDITY

- Determinants
  - Psychosocial stressors among multiple groups[22–25]

- Mental health
  - Probable PTSD among SGM women[26]
  - Hazardous drinking among SGM women[26]
  - Gender dysphoria among TNB people[29]

- Behavioral health
  - Drug use among multiple groups[30,31]

- Sexual health
  - HIV risk among GBMSM[27,28]
  - PrEP use among GBMSM[30]
  - Candidates for PrEP among GBMSM[32]

MAIN GAPS = TOO FEW CLINICAL OUTCOMES AND CONTENT-BASED COMPUTATIONAL CONSTRUCT VALIDITY

BASIC RESEARCH

STAGE 0

- More clinical outcomes for specific populations
- Multimodal computation[33-36]
  - Combine data from wearable sensors, text data, GPS, images, etc.

MOST COMPUTATIONALLY ENHANCED TDIS ARE FOR SEXUAL HEALTH

- Just-in-time intervention for HIV risk[31]
- Public health interventions for youth at risk for HIV → used machine learning to target information dissemination[38]
- AI diary for PrEP adherence[39]
- Chat bots to promote HIV testing[40]
- Virtual reality to support HIV disclosure skills[41]

GAPS = MOST TDIS AT INDIVIDUAL LEVEL AND FEW FOR MENTAL / BEHAVIORAL HEALTH

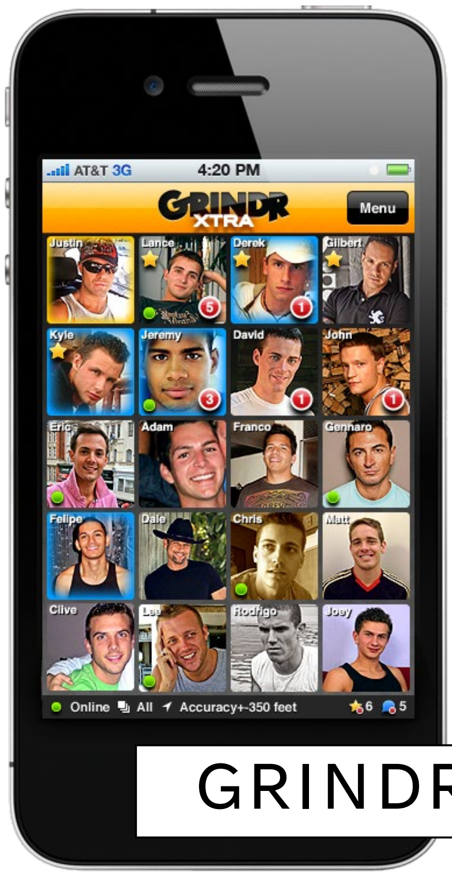
- Computationally enhanced TDIs for systems-level interventions
  - E.g., targeting sources of psychosocial stress

- Adapt SGM-tailored interventions (e.g., AFFIRM[43], ESTEEM[7]) for computation and digital delivery

CHALLENGE = INTERVENTION SCIENTISTS MAY LACK COMPUTATIONAL SKILLS

- What computational experts offer:
  - Software architecture[21]
  - Making apps appealing, user-friendly, and immersive[42,45]
  - Gamification[45]

COMPUTATIONAL EXPERTS ALSO OFFER DESIGN THAT WORKS



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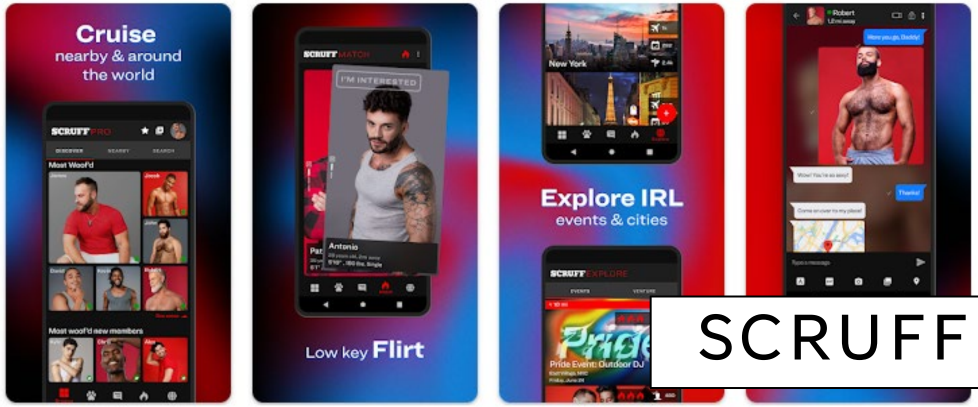


SCRUFF

Images: Google Play, Apple App Store

Efficacy & effectiveness = very underdeveloped areas

ONE MAJOR CHALLENGE IS THAT RIGOROUS RESEARCH MOVES SLOW, TECHNOLOGY MOVES FAST[45,46]

- Greater academic–industry partnerships to balance effectiveness and efficiency[47]
  - Start early, maintain throughout

- Help to prevent outdated computationally enhanced TDIs (i.e., shown to be efficacious/effective but no longer be cutting edge/usable)

ANOTHER MAJOR CHALLENGE IS THE REGULATION OF AI IN HEALTH[49]

- **Example of why**: most TDIs receive minimal premarket clinical testing due to FDA classification[50]
  - Substantially sparse evidence on computationally enhanced TDIs
- **Impact of problem**: who protects SGM people using these technologies?
  - Burden of determining effectiveness on individual providers[45]
- **Need** policy related to computationally enhanced TDIs

IMPLEMENTATION & DISSEMINATION

STAGE 5

Implementation & dissemination = very underdeveloped areas

IMPLEMENTATION & DISSEMINATION
STAGE 5

ONE CHALLENGE IS DELIVERING AI IN FRONTLINE CARE-DELIVERY SYSTEMS WITHOUT EXACERBATING INEQUALITY[52]

- Possible solutions:
  - Community-tailored algorithms
  - Algorithmic auditing
  - Systems-level solutions

IMPLEMENTATION & DISSEMINATION

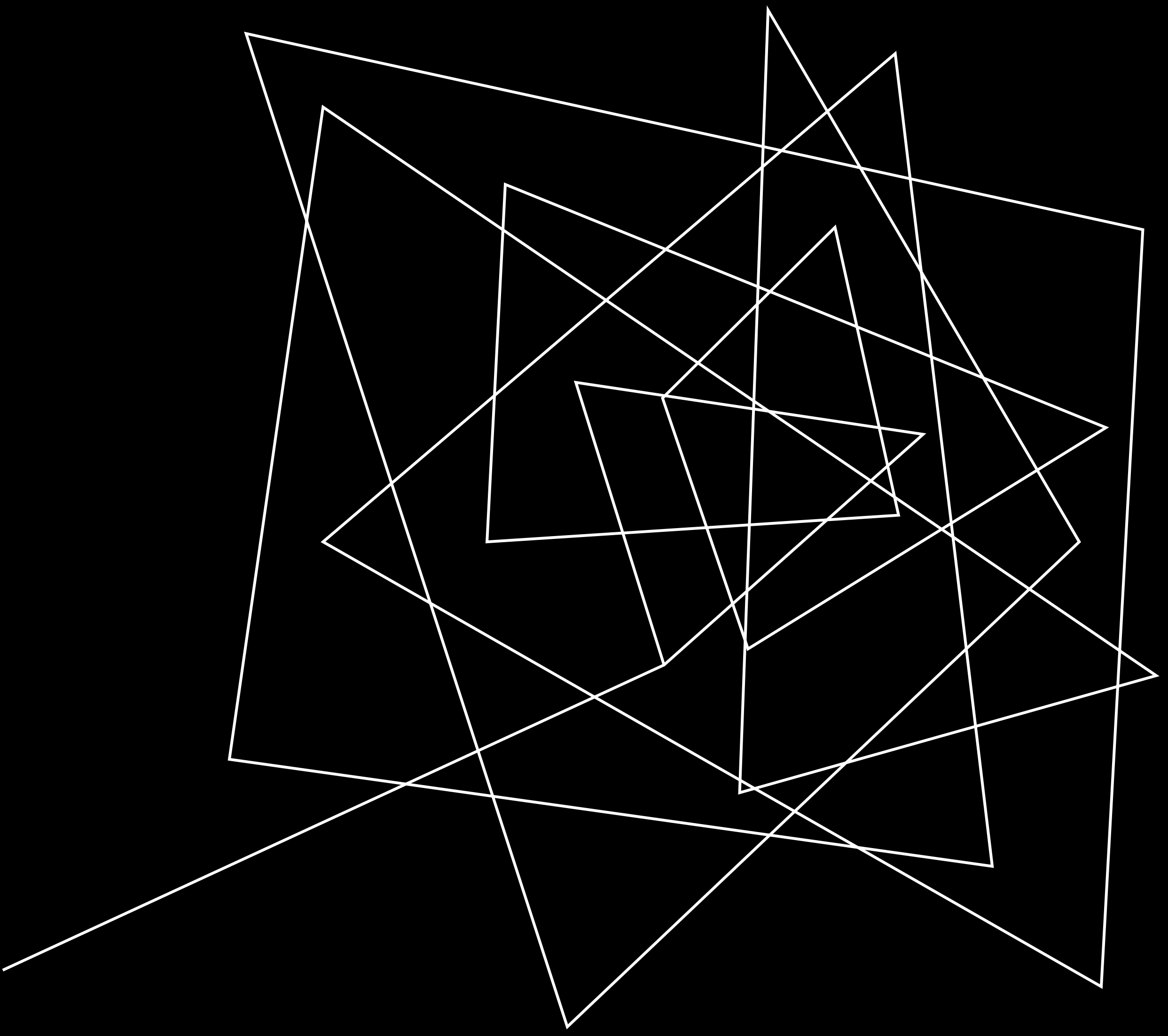
STAGE 5

ANOTHER CHALLENGE IS FUNDING[45,51]

- **<u>Problems</u>**:
  - Limitations of venture capitalism[51], such as overselling the app's ability to help[45]
  - Who can afford computationally enhanced TDIs if insurance companies do not offer reimbursement?[51]
- Solutions?

ETHICAL CONSIDERATIONS

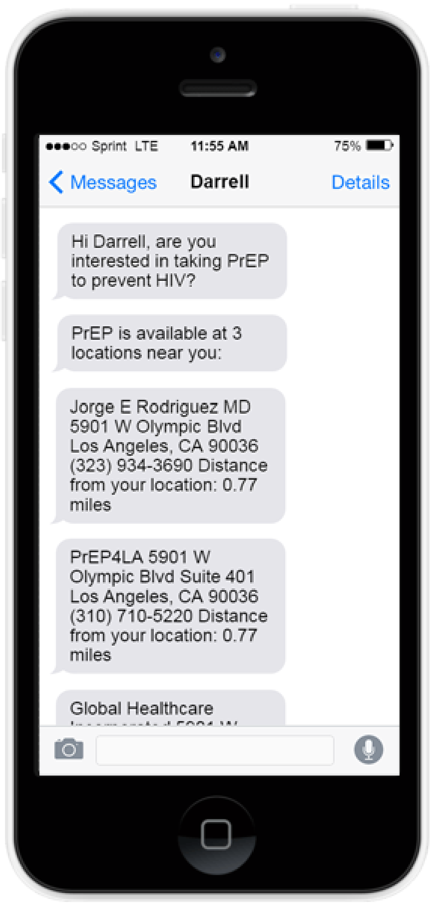
- Consent, privacy, and access
  - Informed consent
  - Public data is available, access allowed—but should we still obtain consent?
  - Unintentional outing of SGM people
  - Targeting of SGM people in high-stigma areas
  - Who has access to these very sensitive data?[45]
  - On the cloud or on the edge?[56,57]
- Bias baked into computational models[37]
- Insufficient acceptability evidence: do SGM people want this kind of research?
- Who is ethically and legally responsible for high-risk behavior, such as suicidal disclosure detected by the TDI? [58,59]



UTECH: A CASE STUDY

PROJECT OBJECTIVE

Overarching goal is to develop and test a data mining and machine learning algorithm to be used in personalized, technology-based HIV prevention.



PRIORITY POPULATION

- Gay, bisexual and other people who have sex with men (including trans and other identified people who have sex with men)
- Between the ages of 18-29
- Based in the United States
- Smart phone users (Android or iOS)
- History of substance use within the past 6 months
- History of substance use during sex within the past 6 months
- Use of dating apps and social networking apps for substance and partner-seeking online

PROJECT OVERVIEW

Phase 1: Formative

- Community engagement on the feasibility, acceptability, and appropriateness of technology-based data mining & machine learning
- Qualitative interviews with potential participants
- Development of culturally tailored text mining library

Phase 2: Algorithm Development & Testing

- Automated data collection from mobile smart phones and social networking app paradata
- Machine learning to identify patterns, predict substance use, and HIV risk and protective behaviors
- Personalized text messages to identify geolocation-based resources

MULTIMODAL DATA SOURCES FOR MACHINE LEARNING

Text

- Substance use related terms and emojis
- Sexual behavior related terms and emojis

Paradata

- Time spent on individual apps and websites for partner-seeking
- Specific apps used for partner-seeking

Geolocation

- Home zip code
- Time spent away from home zip code
- Geographic variability in participant movement patterns

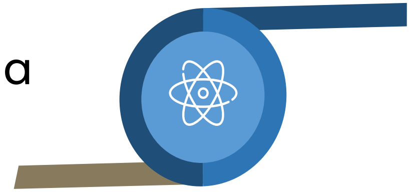
PRELIMINARY FINDINGS

- Initial findings indicate high willingness to install software (for Android users) and share data (for iOS users) on substance use and sexual behavior given appropriate safeguards for privacy and confidentiality
- Robust text mining library on terms and emojis used by the priority population for substance and partner-seeking online
- Machine learning algorithm can accurately predict methamphetamine use and PrEP use among the priority population based on self-reported data collected at 3-month intervals

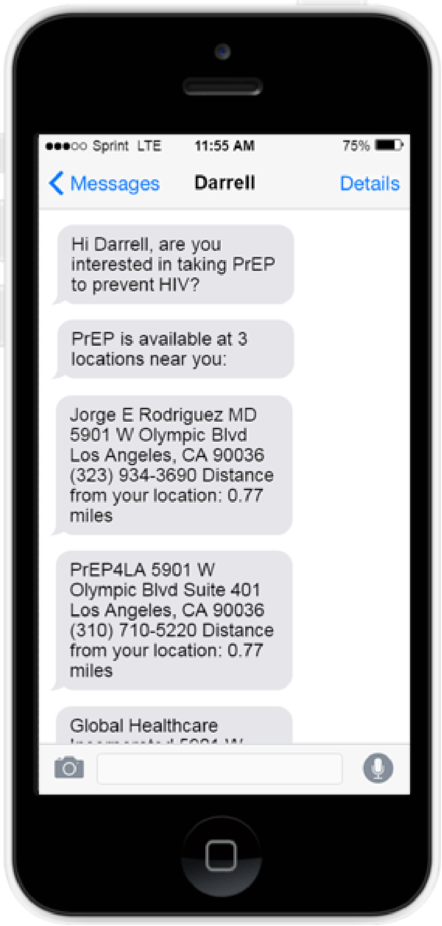
PERSONALIZED PREVENTION EXAMPLE

- 20-year-old, African American man
- Parties on the weekends
- Uses methamphetamine and GHB
- Often unable to successfully negotiate condom use

1. Machine detects he has or is approaching a risk event



2. Machine pushes a tailored prevention message



THANK YOU!

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