Use of Mobile Monitoring and Intervention (MMI) Technology for Adaptive Aging

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Definition of a Mobile Monitoring & Intervention (MMI) System

- An MMI system has two primary components
- **Monitoring** requires sensors, processors, and software/algorithms to interpret sensor data, transceivers (transmitters and receivers), and data storage capabilities.
- **Intervention** requires prediction of behavior, usually through data mining with AI, and actuator components that can alert or communicate with the recipient of the intervention, usually the older adult but also care providers
  - visual, auditory, and haptic output capabilities

- Example – Smartphone/Wearable Infrastructure

Some Assumptions about MMI

Question	Normative Response	Constraints
Why	Prevent harm, promote well-being	Ethical, legal, self-determination for lifestyle, societal resources
Who	Aging adult	Co-dependent dyads, caregiving teams
What	Physiological (e.g., blood pressure), psychological (e.g., cognition, well-being) indicators	Reactivity, lifestyle constraints
Where	Home, work, everywhere	Privacy, legal
When	Continuous, intermittent intervals, self-chosen intervals	Privacy, data transmission bandwidth, storage, data security
How	Sensors, probe questions (e.g., EMA) for person, for proxy	Power source, device, person and network capability and availability/reliability and security

Issues for MMI Systems: Privacy

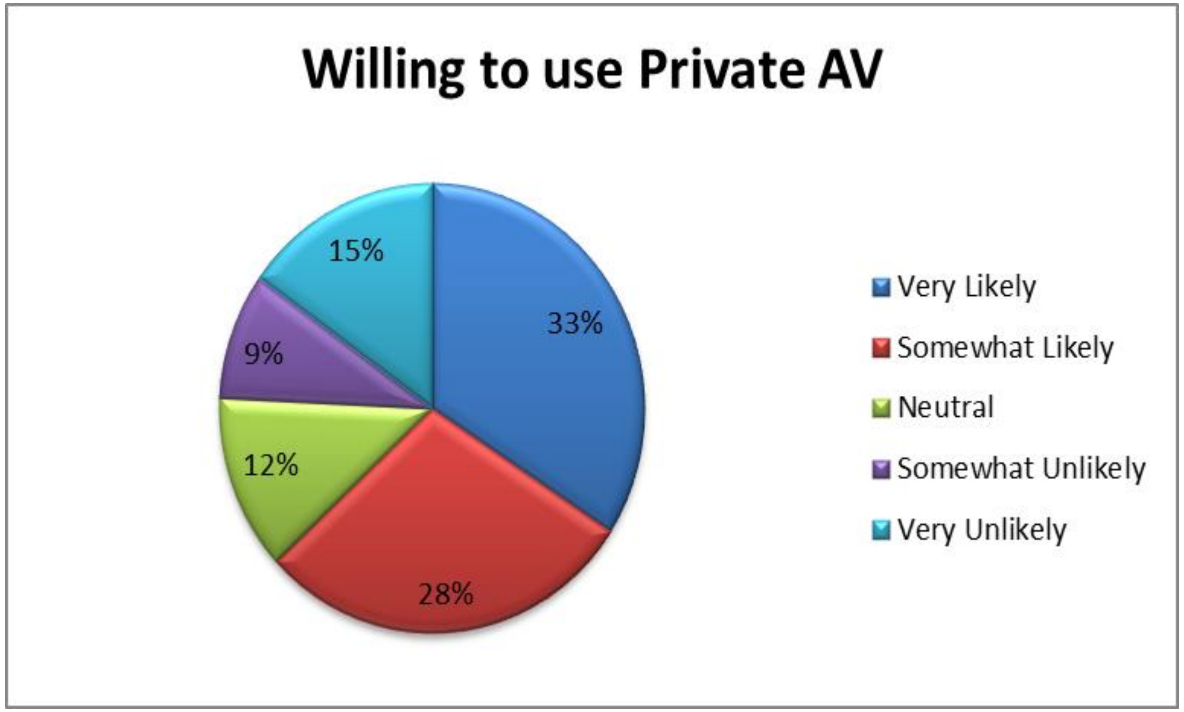
Nationally representative data from Pew show

- Older adult cohorts are more aware than younger cohorts about government monitoring
- They are less likely to view as "very sensitive" contents of email, text messages, and health information
- They are equivalently sensitive about their social security number
- A year following entry into a study of unobtrusive monitoring, normal older adults and those with MCI showed more concerns with privacy than at entry
  - However, 72% still showed acceptance of monitoring.
  - (Boise et al., 2013)

- A diverse sample of aging American adults (45+ yr), and particularly those with disabilities reported a willingness to trade off privacy in favor of maintaining independence even for rather intrusive monitoring options, such as cameras
- They were more willing to share monitored information with family members and health care providers than with researchers
  - least favorable about sharing information with insurance companies or government.
    - (Beach, Schulz, Downs, Matthews, Barron & Seelman, 2009).
- In a representative Swiss survey, 57% of those age 50+ who tracked health data (28% of the sample) were willing to share data with researchers
  - (Seifert, 2018)

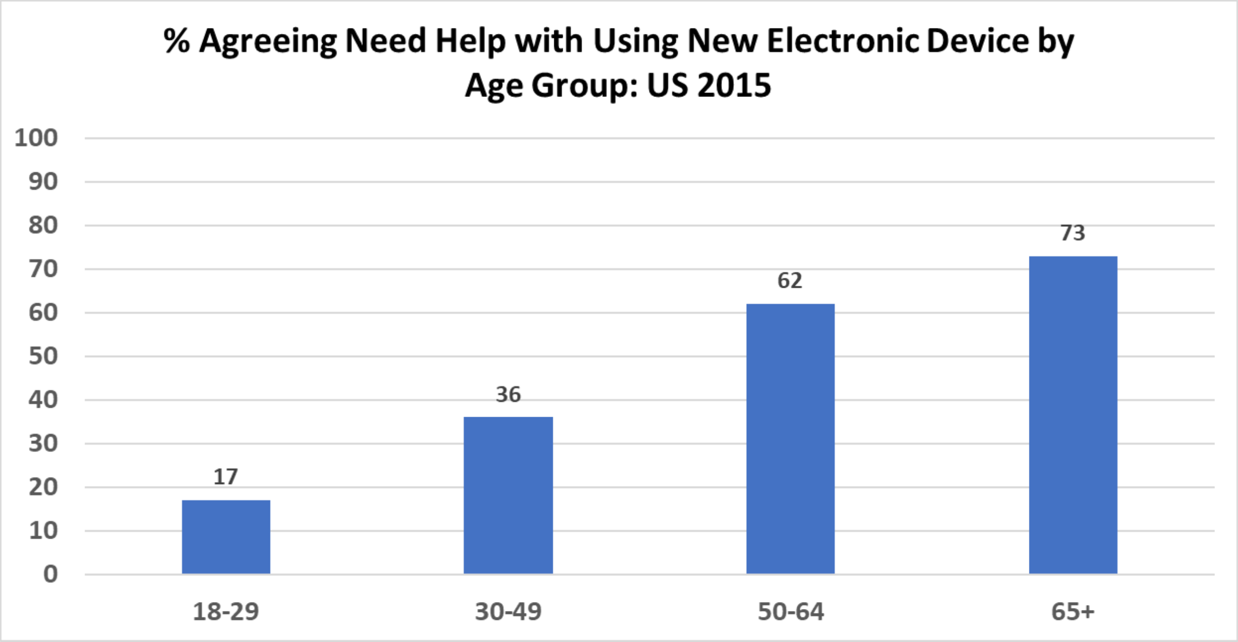
Issues for MMI Systems: Trust

- Older cohorts also have greater concerns related to trust in technology, e.g., willingness to use an autonomous vehicle
  - (Charness, Yoon, Souders, Stothart & Yehnert, 2018; Duncan et al., 2016).



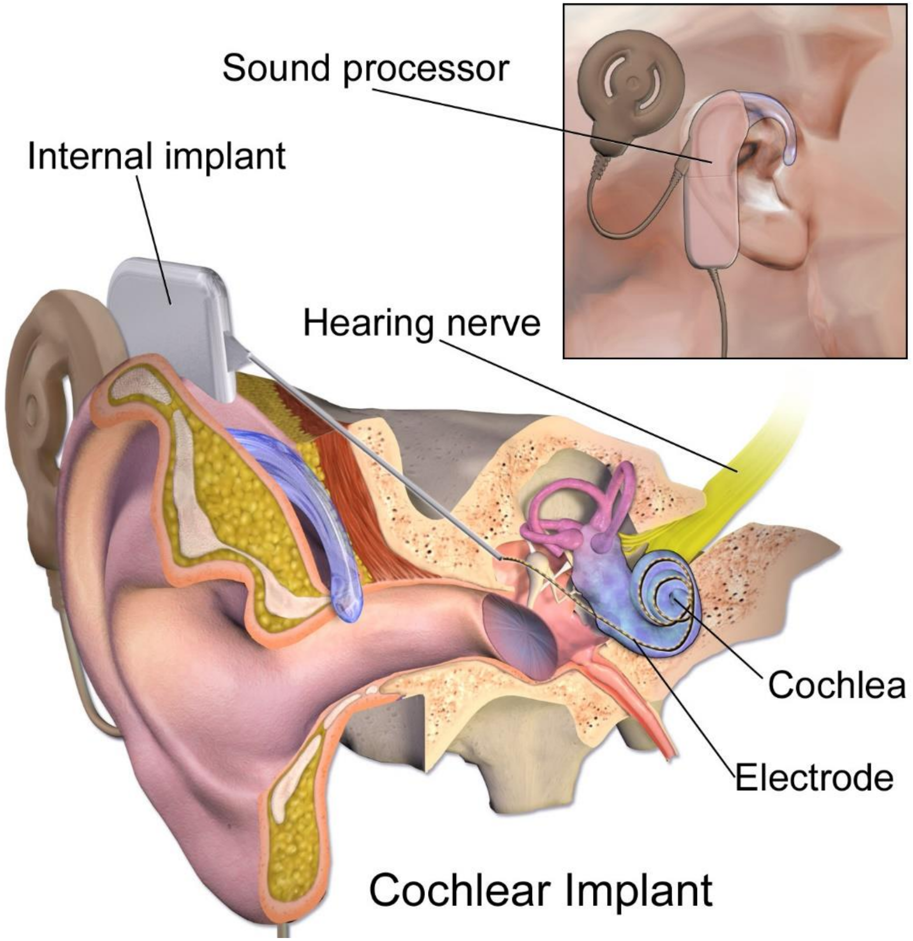
Issues for MMI Systems: Ability

- Older cohorts are less likely to take appropriate measures to protect their privacy online such as by asking to have information removed, or anonymizing postings, or to change their Facebook privacy settings
  - Madden (2014)
- 64% of those age 18-29 years having changed privacy settings compared to 33% of those age 65+
  - (Perrin, 2018)



Framework for Interventions: PRAS

- Prevent Impairments
  - Reach old age in best possible shape
- Rehabilitate – train person
  - If reach is impaired by a stroke, provide exercises to improve reach
- Augment – support a failing function
  - If hearing is failing, provide a hearing aid to increase sound volume
- Substitute – replace a failed function
  - Cochlear implant for destroyed hair cells in the cochlea



State of the Art for MMI for Older Adults: Monitoring

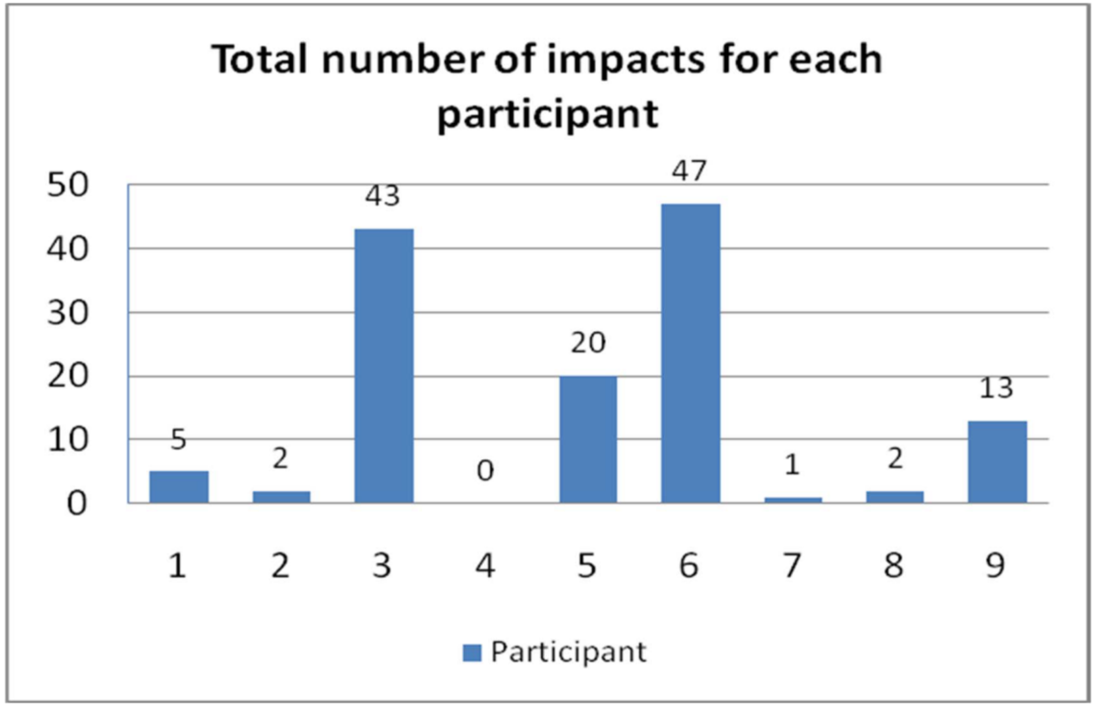
- Few or no studies exist that monitor, predict, and intervene
- Monitoring meta-analysis by Baig, Afifi, GholamHosseini & Mirza (2019) found 14 studies from 12 projects between 2015 and 2019
  - 7 fall detection
  - 1 depression detection
  - 1 dementia detection
  - Others passive monitoring for ADL, IADL

State of the Art for MMI: Prediction

- Suhara, Xu & Pentland (2017) monitored and forecasted depressive affect in young and middle-aged adults
- Sanchez, Martinez, Campos, Estrada & Pelechano (2015) predicted loneliness in older adults
  - Both used supervised machine learning, requiring a human in the loop to classify patterns
    - low scalability unless caregivers can be provided with a tool and trained to hand code cases

State of the Art for MMI: Intervention

- Commercial fall detection systems intervene to call designated parties for falls
- Facebook experimentally manipulated mood for 100s of thousands of its members by changing the information that a user saw in their news feed
  - (Kramer, Guillory & Hancock, 2014)
- Evans et al. (2016) monitored heart failure patients and used an SMS to alert home health nurses to contact people when an intelligent system determined that measures such as weight, blood pressure, questionnaires about HF, departed significantly from baseline.



Zero falls reported in diaries in Charness, Fox, Papadopoulos, & Crump (2013)

Is There an App for That?

- Google and Apple app stores contain 100,000+ apps for health including MI situations such as medication adherence, weight, nutrition, physical fitness, BP, diabetes, sleep, mood
  - Self-report, smartphone sensors for monitoring
  - External sensors such as smartwatches, fitness trackers, telehealth devices, webcams

- Apps are not regulated by the FDA unless a user can be harmed
- Efficacy is unknown for these apps
- Usability is poor for some aimed at supporting medication adherence, managing HF, pain management
  - Morey et al. (2019)
  - Bhattarai, Newton-John, Phillips (2017)
- Adherence to apps and platforms is a significant issue

Adherence Interventions

- Technology-based reminders for medication adherence included
  - Telephone, text-messaging, software-based reminders, remote monitoring, electronic drug monitoring
    - (Mistry et al., 2015)
- Cochrane report (2014) on technology-based interventions concluded

"Even the most effective interventions did not lead to large improvements in adherence or clinical outcomes"

"will need to improve if clinically important effects are to be realized"

Efficacy & Cost Effectiveness

- There are numerous examples of efficacy for technology-based interventions, particularly for telehealth interventions
- Cost-effectiveness was evaluated in the largest clinical trial (n=3230) for management of chronic conditions by the National Health Service in the UK
  - Diabetes, COPD, HF and compared telehealth intervention to usual treatment
    - Steventon et al. (2012); Henderson et al. (2013)

Cost Effectiveness of Telehealth Monitoring & Intervention?

- Conclusions: The QALY gain by patients using telehealth in addition to usual care was similar to that by patients receiving usual care only, and total costs associated with the telehealth intervention were higher.
  - Equipment costs dominated
- Telehealth does not seem to be a cost-effective addition to standard support and treatment.
- Trial registration ISRCTN43002091

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RESEARCH

Cost effectiveness of telehealth for patients with long term conditions (Whole Systems Demonstrator telehealth questionnaire study): nested economic evaluation in a pragmatic, cluster randomised controlled trial

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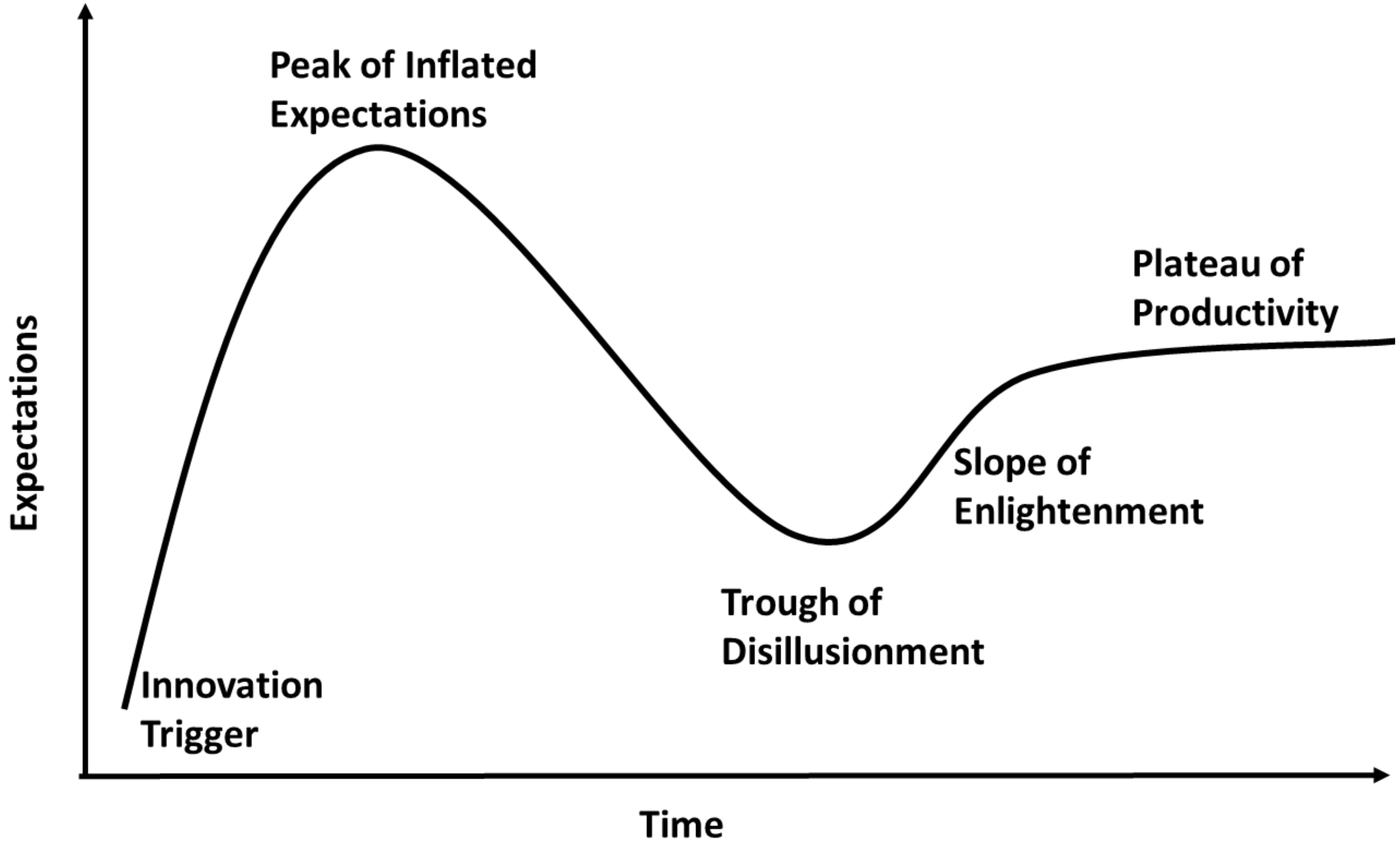
Promising Approaches: Just in time adaptive interventions (JITAI)

- Monitor the state and the context of the individual then provide the appropriate amount and type of intervention at the right time.
  - For example, when sedentary behavior is detected by a worn accelerometer, an app-based JITAI might suggest that the individual engage in physical activity.
  - The system might suggest a specific activity based on the time and weather conditions
    - Wang & Miller (2019)
    - Hardeman, Houghton, Lane, Jones, & Naughton (2019)
      - Both recommended high-powered studies to determine success of JTAI

Technology Hype Cycle (after Gartner)



Clinical Trial Success Rate for Drug Development

- Using a sample of 406,038 entries of clinical trial data for over 21,143 compounds from January 1, 2000 to October 31, 2015
- Oncology has a 3.4% success rate in our sample vs. 5.1% in prior studies.
    - However, after declining to 1.7% in 2012, this rate has improved to 2.5% and 8.3% in 2014 and 2015, respectively.
    - In addition, trials that use biomarkers in patient-selection have higher overall success probabilities than trials without biomarkers.

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Estimation of clinical trial success rates and related parameters

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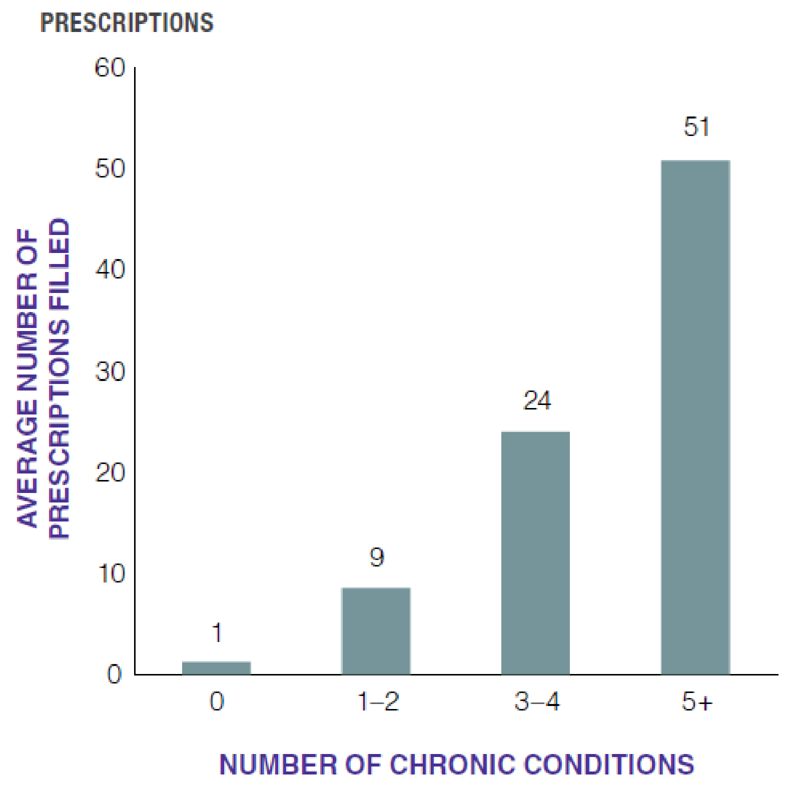
SUMMARY

Previous estimates of drug development success rates rely on relatively small samples from databases curated by the pharmaceutical industry and are subject to potential selection biases. Using a sample of 406 038 entries of clinical trial data for over 21 143 compounds from January 1, 2000 to October 31, 2015, we estimate aggregate clinical trial success rates and durations. We also compute disaggregated estimates across several trial features including disease type, clinical phase, industry or academic sponsor, biomarker presence, lead indication status, and time. In several cases, our results differ significantly in detail from widely cited statistics. For example, oncology has a 3.4% success rate in our sample vs. 5.1% in prior studies. However, after declining to 1.7% in 2012, this rate has improved to 2.5% and 8.3% in 2014 and 2015, respectively. In addition, trials that use biomarkers in patient-selection have higher overall success probabilities than trials without biomarkers.

Keywords: Clinical phase transition probabilities; Clinical trial statistics; Probabilities of success.

What are targets for intervention?

- Medication adherence for those with chronic conditions
  - 81% of those age 65+ have multiple
- Loneliness & Social Isolation
- Cognitive decline & dementia
- Falls
- Suicide



Recommendations: MMI Study Design

- Future studies need to avoid major weaknesses such as use of small (and unrepresentative) older adult samples, lack of adequate control groups (for demonstrating efficacy), and lack of long-term assessment (where adherence support will be needed).
  - Remedying those problems will likely require significant long-term funding for a large, multi-site (to address representativeness issues) study akin to that for the ACTIVE study (Ball et al., 2002).
- Effective MMI systems will likely require partnerships between the research community and industry to enhance usability, scalability, and deployment of MMI systems
  - Mobile platforms relying on iOS and Android can break when Apple and Google update an OS
- Given that multi-morbidity (including cognitive impairment) becomes the norm in very old age, MMI studies need to relax exclusion rules to enhance generalizability of results.
- MMI systems should be designed to honor privacy rights
  - the OECD privacy policies (2013) are a good start.

Recommendations: MMI Technology Acceptance

- Support is needed for studies of adoption and use of MMI technology over extended time frames.
- Technology may also need to be designed differently for young-old (age 65-74), middle-old (age 75-84), and old-old (age 85+) users, for those with significant disabilities, and for disadvantaged groups.
  - For instance, adults in the older age bands might benefit more from passive sensor technology deployed in homes, whereas younger age bands may benefit more from wearables (MMI systems)
- It would be ideal to tap into existing representative longitudinal studies such as NHATS, HRS, NHANES, for sub-sample MMI studies.
- It would be ideal for agencies such as NIA to team up with other NIH institutes and other federal agencies (e.g., NSF) to generate long-term funding (e.g., 10 years) of interdisciplinary teams.
  - Innovative MMI technology development requires expertise in fields such as engineering, computer science, health, and behavioral science.