# The Future of Quitting: Emerging mHealth Strategies for Smoking Cessation

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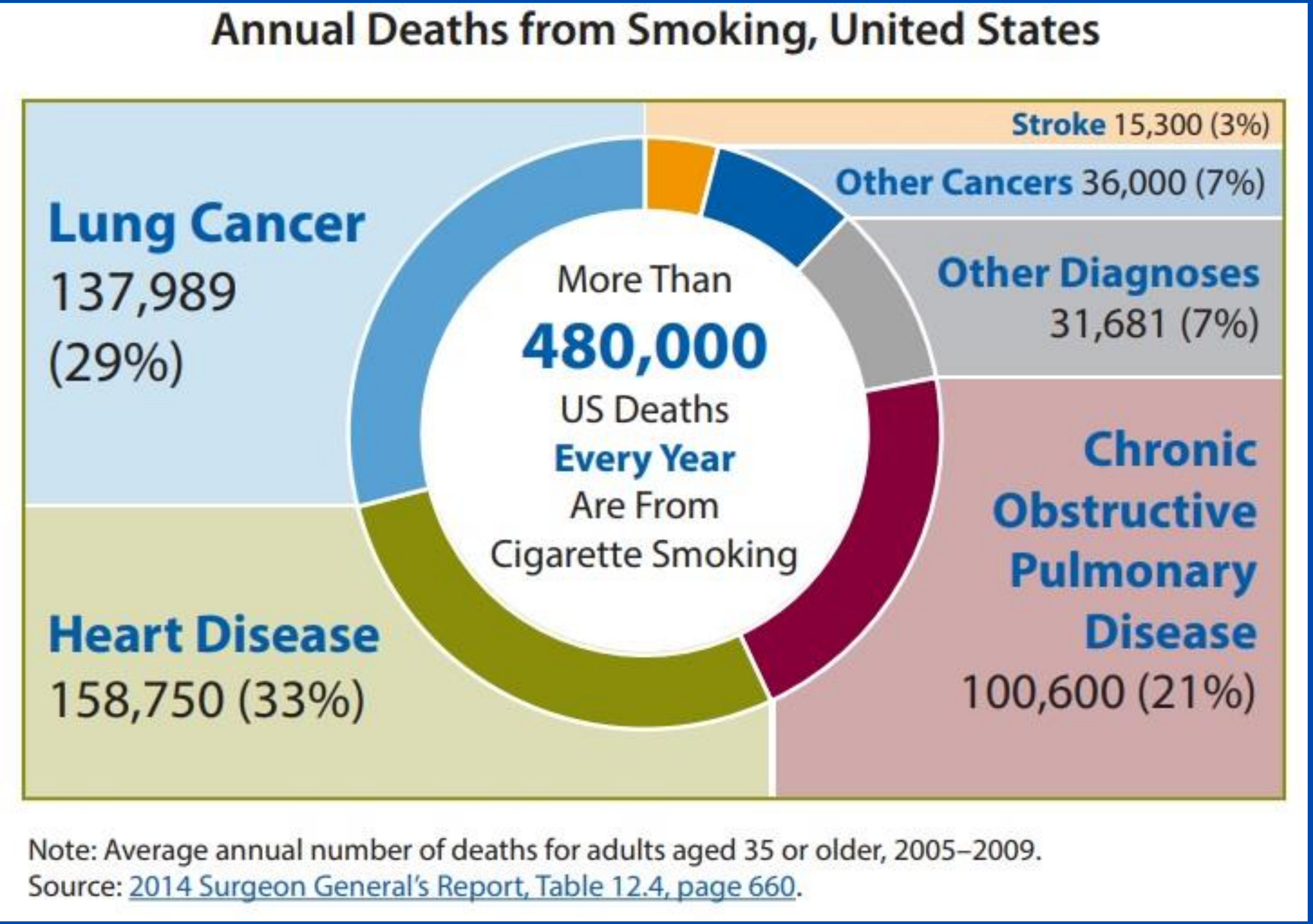
# The Tobacco Problem

**Cigarette smoking remains the leading cause of preventable death in the U.S.**

13.7% of U.S. adults are current smokers

4.6% of high school students reported smoking in the past 30 days



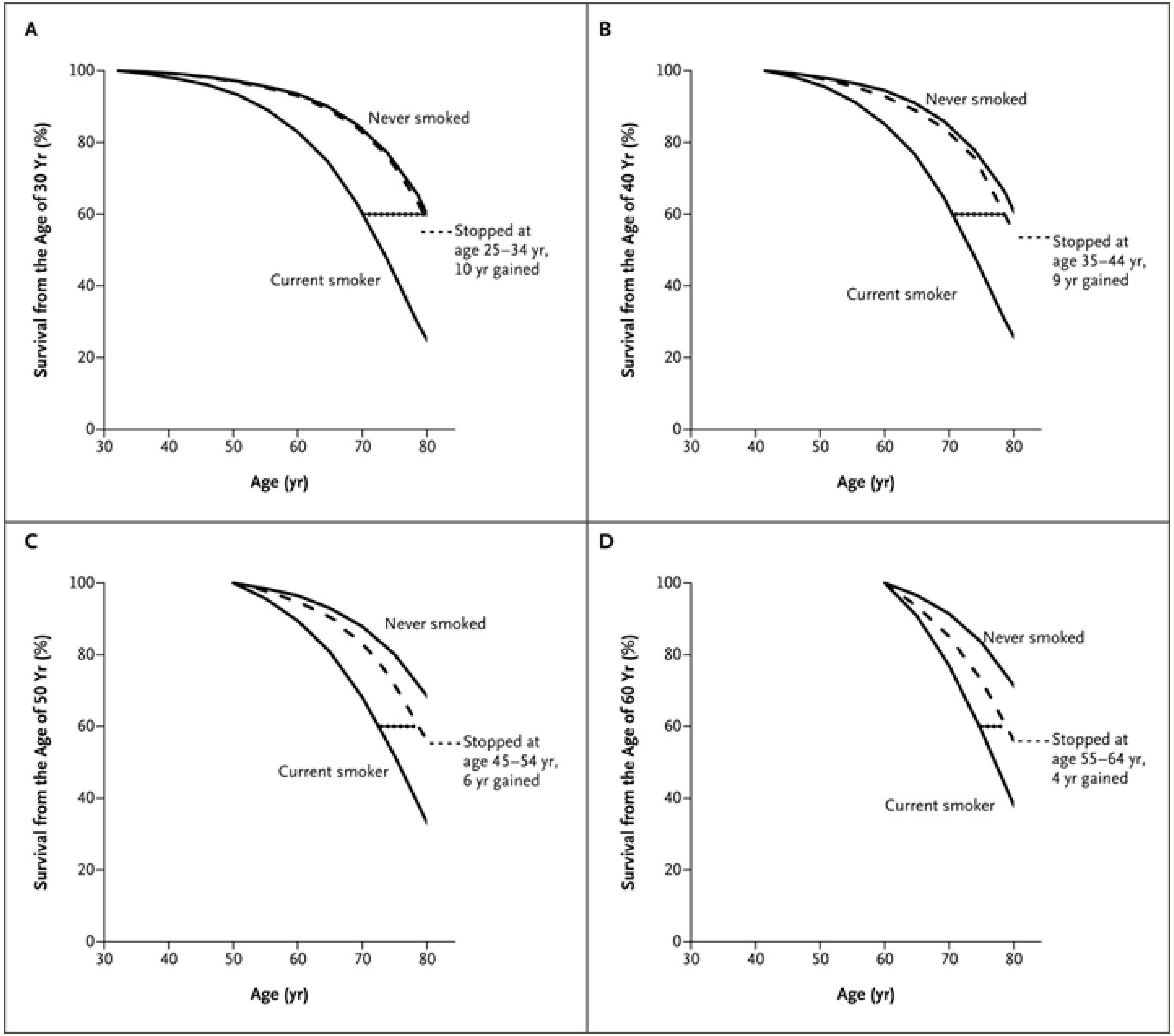
# Most smokers want to quit.

More than half of smokers report having made a quit attempt in the past year.

| 55.1% | 57.5% |
|---|---|
| ADULT SMOKERS | YOUTH SMOKERS |

# Effect of Smoking Cessation on Survival to 80 Years of Age, According to Age at the Time of Quitting

Jha, P., et al. (2013). 21st-century hazards of smoking and benefits of cessation in the United States. New England Journal of Medicine, 368(4), 341-350.



# Smoking Cessation Treatment: Current Best Practices

## COUNSELING

Individual, group, and telephone counseling

- Practical counseling (problem solving/skills training)
- Social support

## MEDICATION

Nicotine replacement therapy

Oral medications

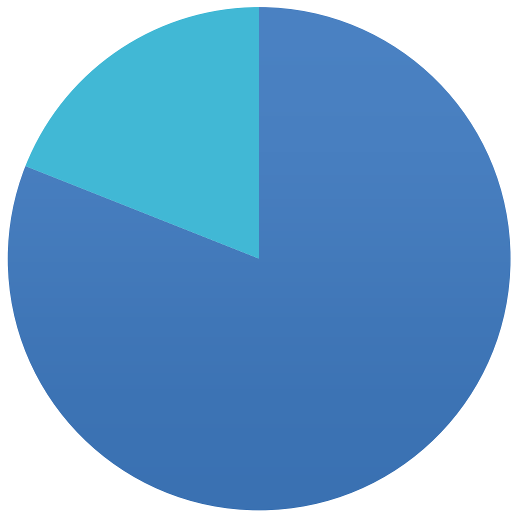
- Bupropion
- Varenicline

# Barriers to Treatment

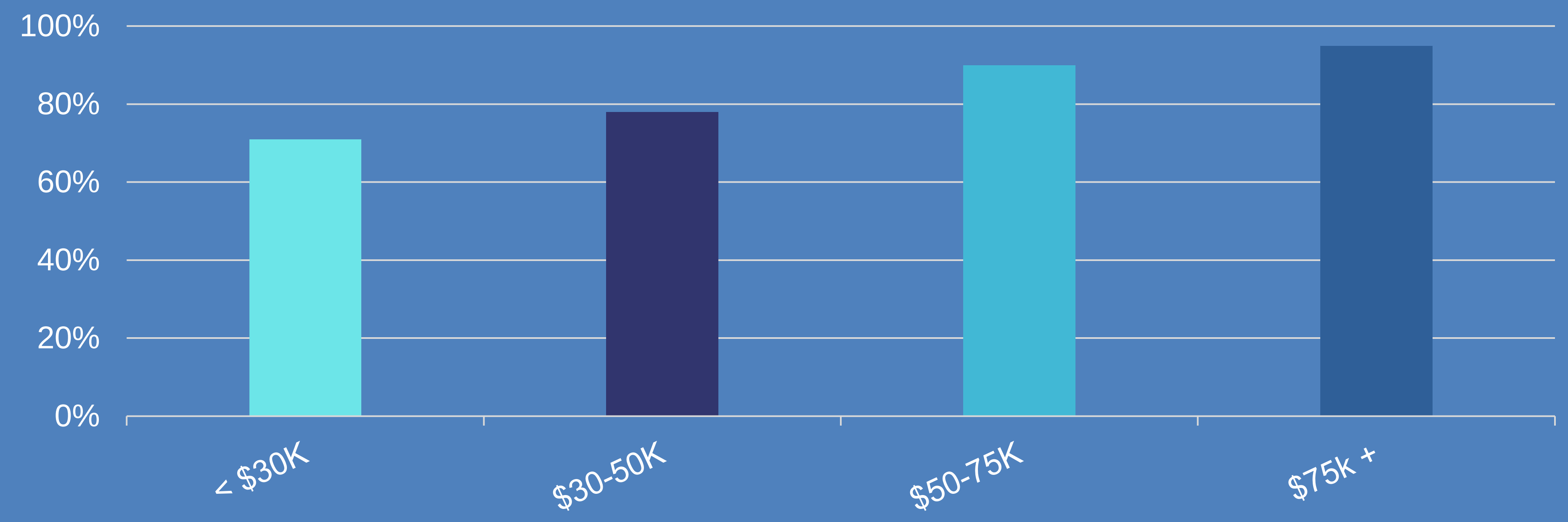
**MOST QUIT ATTEMPTS ARE UNAIDED AND UNSUCCESSFUL.**

- Lack of Time
- Transportation issues
- Cost
- Doubts about effectiveness

# The Potential of Smartphones



81% of all U.S. adults own smartphones




Smartphone ownership is high even among low SES individuals.

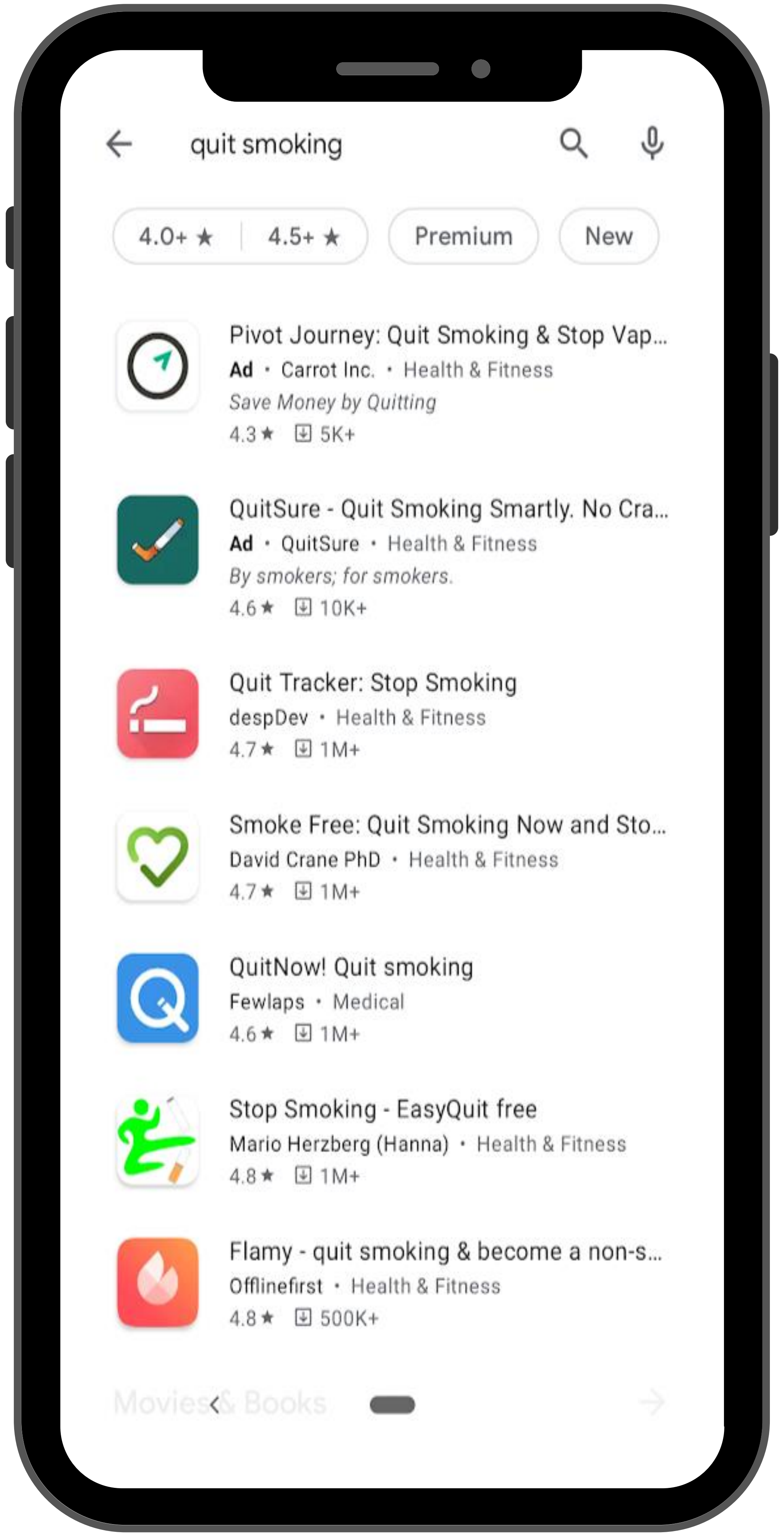
21% of Americans say they use smart watches or fitness trackers.

62% of smartphone owners have used their phone in the last year to look up information about a health condition.



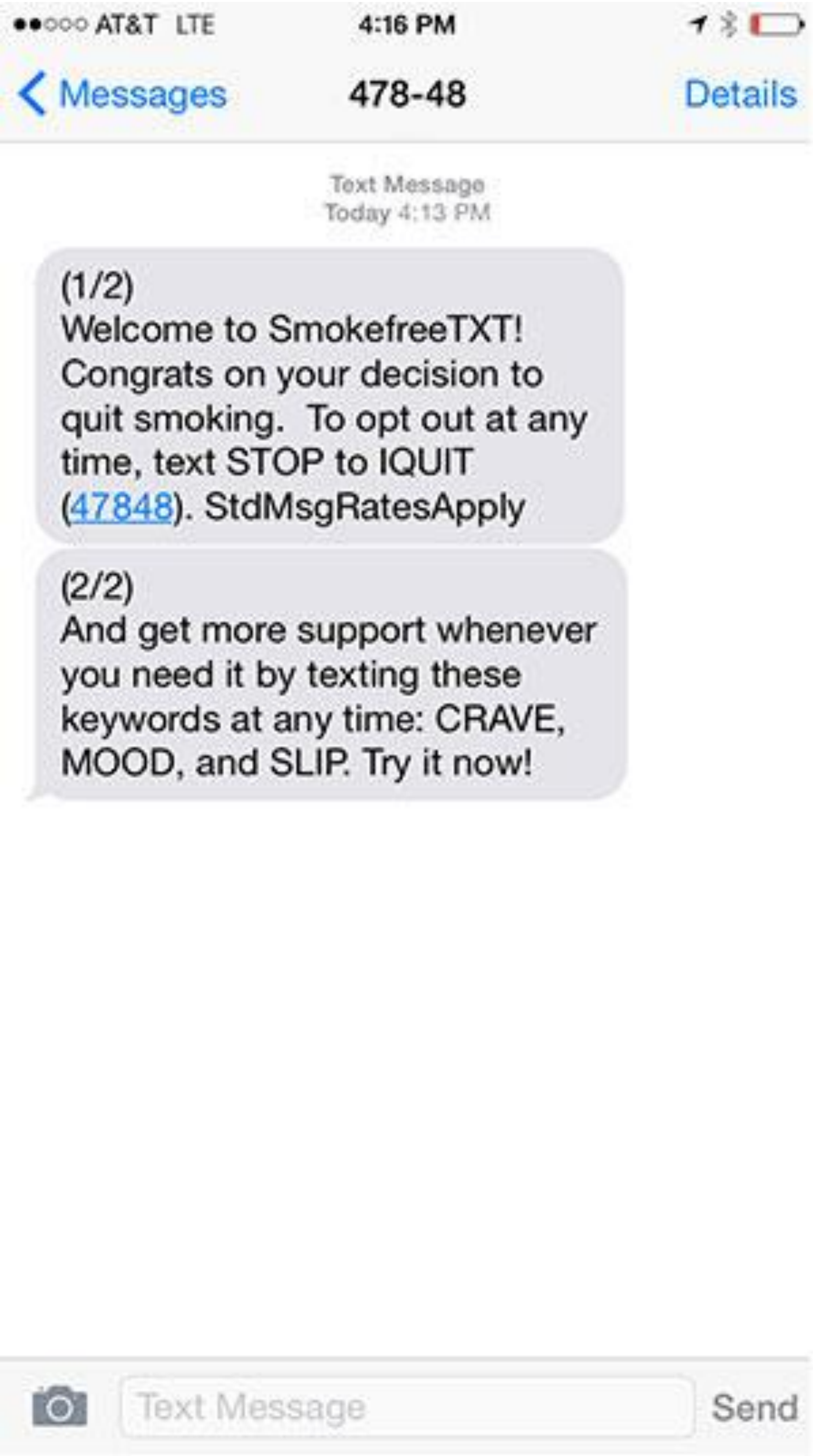
Pew Research Center

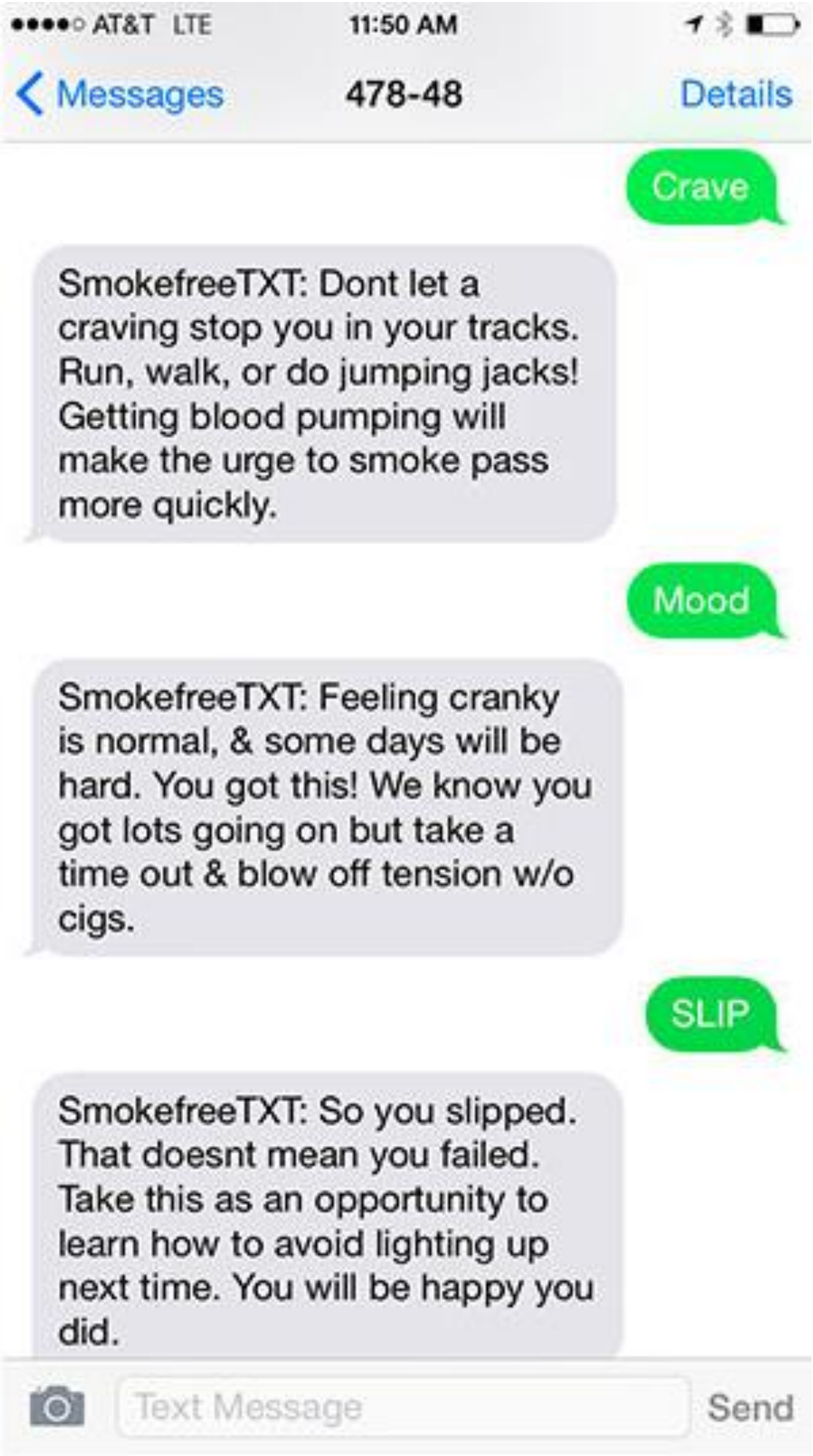
# Mobile phone-based smoking cessation support



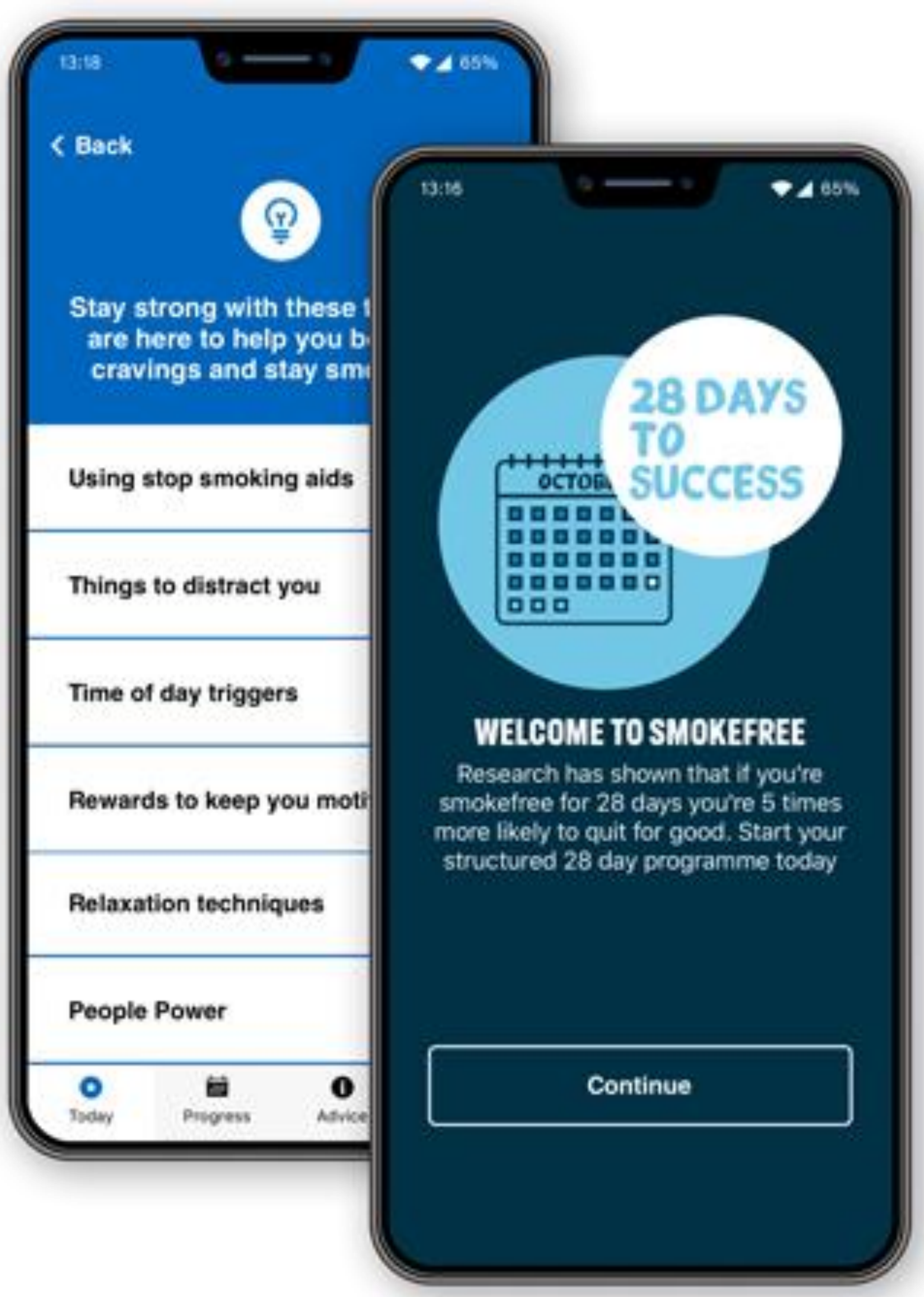
# Text Messaging Interventions

smokefreeTXT

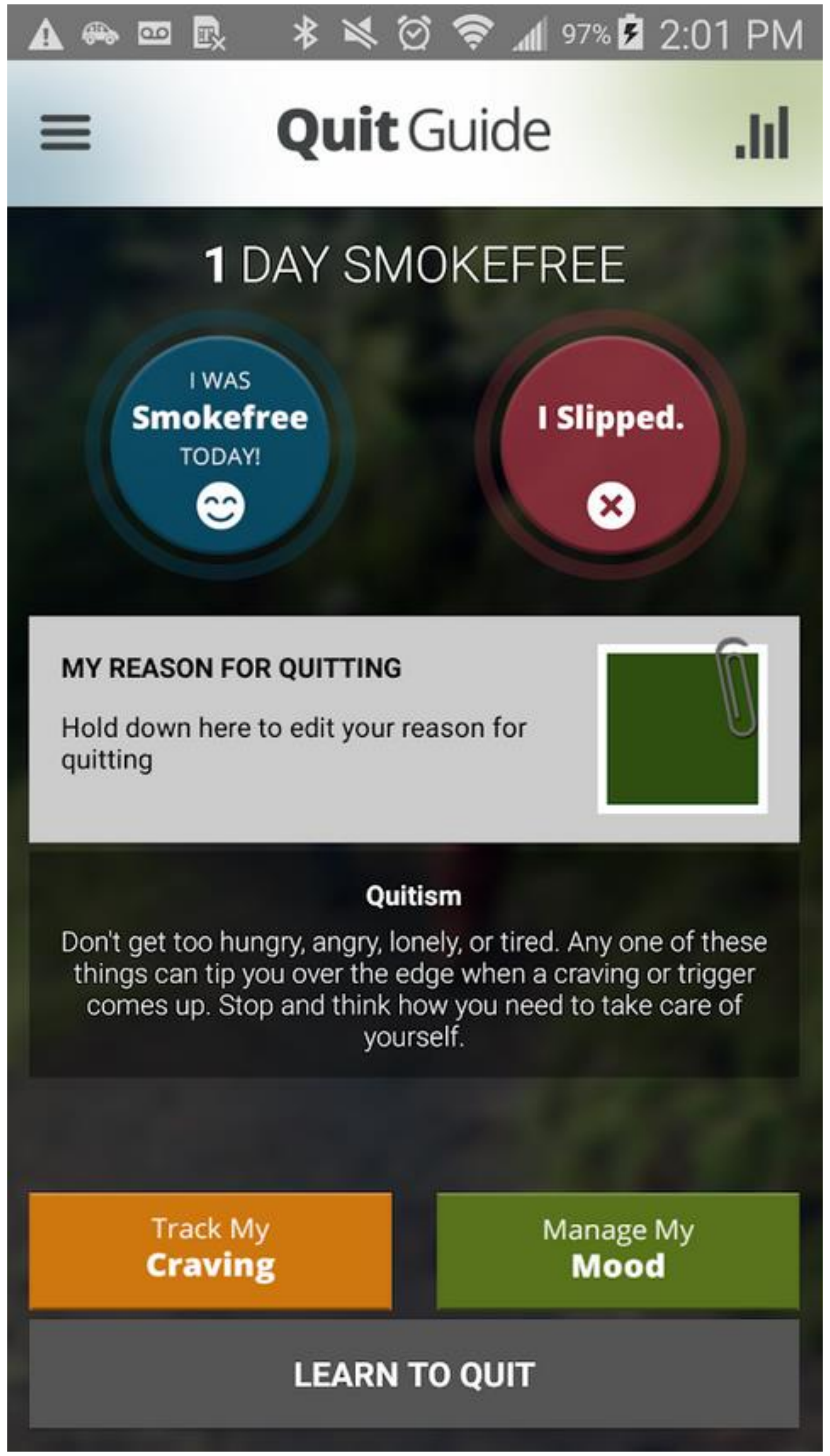


# Smoking Cessation Apps




**NHS Smokefree**
**Public Health England**




**QuitGuide**
**National Cancer Institute**

# What can we learn about smoking from smartphones?

# Ecological Momentary Assesment (EMA)

Methods using repeated collection of real-time data on subjects’ behavior and experience in their natural environments

| TRADITIONAL SURVEY |
| --- |
| "In the last 30 days, were you around any other smokers?" |

| EMA |
| --- |
| "Right now, are you around any other smokers?" |

# Why use EMA?

Retrospective recall is subject to serious bias.

Ideal for dynamic behaviors and experiences.

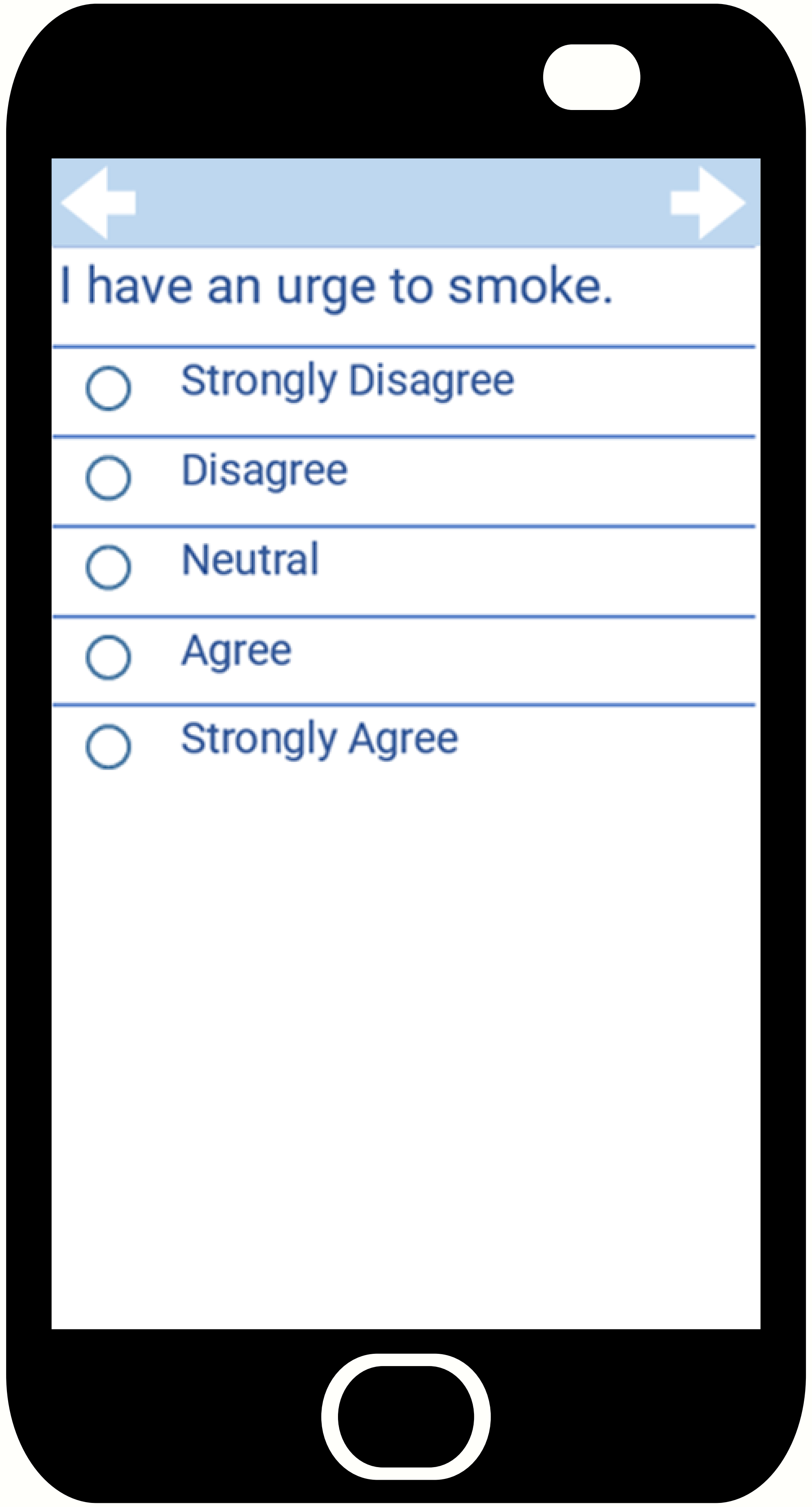
# EMA Sampling Methods

**Time-Based**

Daily diary
Random intervals

**Event-Based**

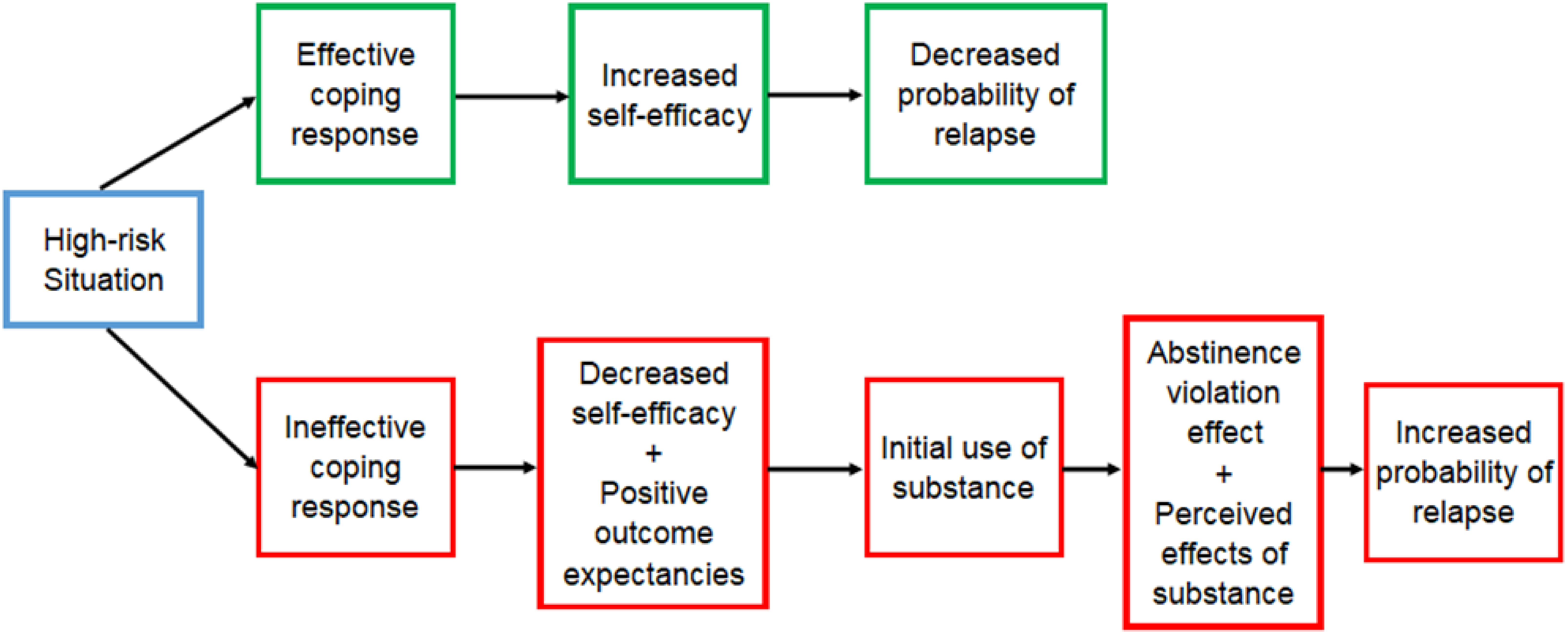
User-Initiated
Sensor-triggered



# Momentary Antecedents of Smoking Behavior

- Urge to smoke
- Stress
- Alcohol use
- Cigarette availability
- Proximity to others smoking
- Proximity to tobacco retail outlets
- Low motivation to quit

# Relapse Prevention Model





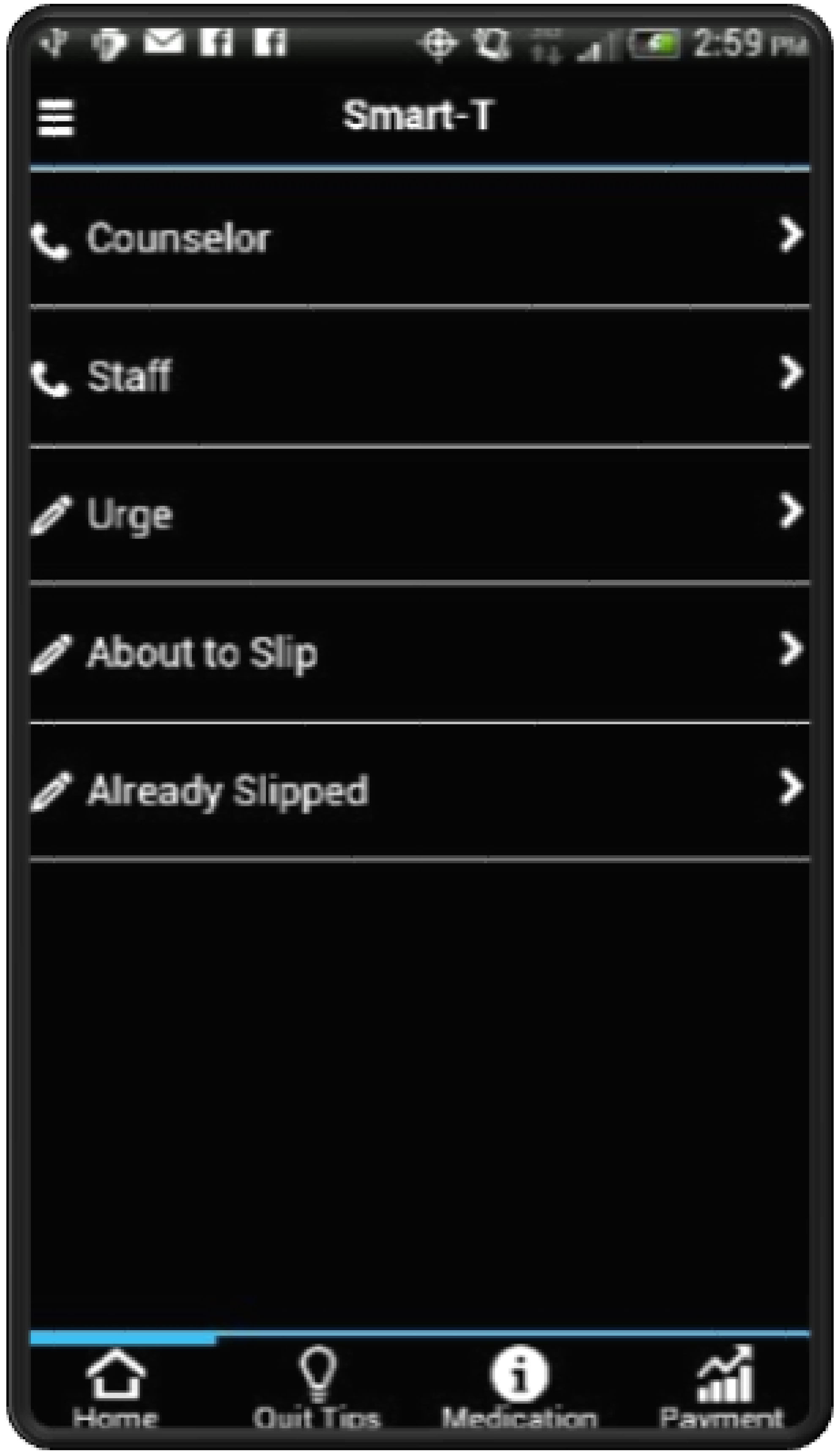

(Marlatt & Gordon, 1985)

# Just-in-Time Adaptive Interventions (JITAI)

**Tailored support delivered in the moments when it is most needed**

Attempts to provide the right type of support, at the right time, while eliminating support provision that is interruptive or otherwise not beneficial

Uses dynamic information to modify type, amount, and timing of support



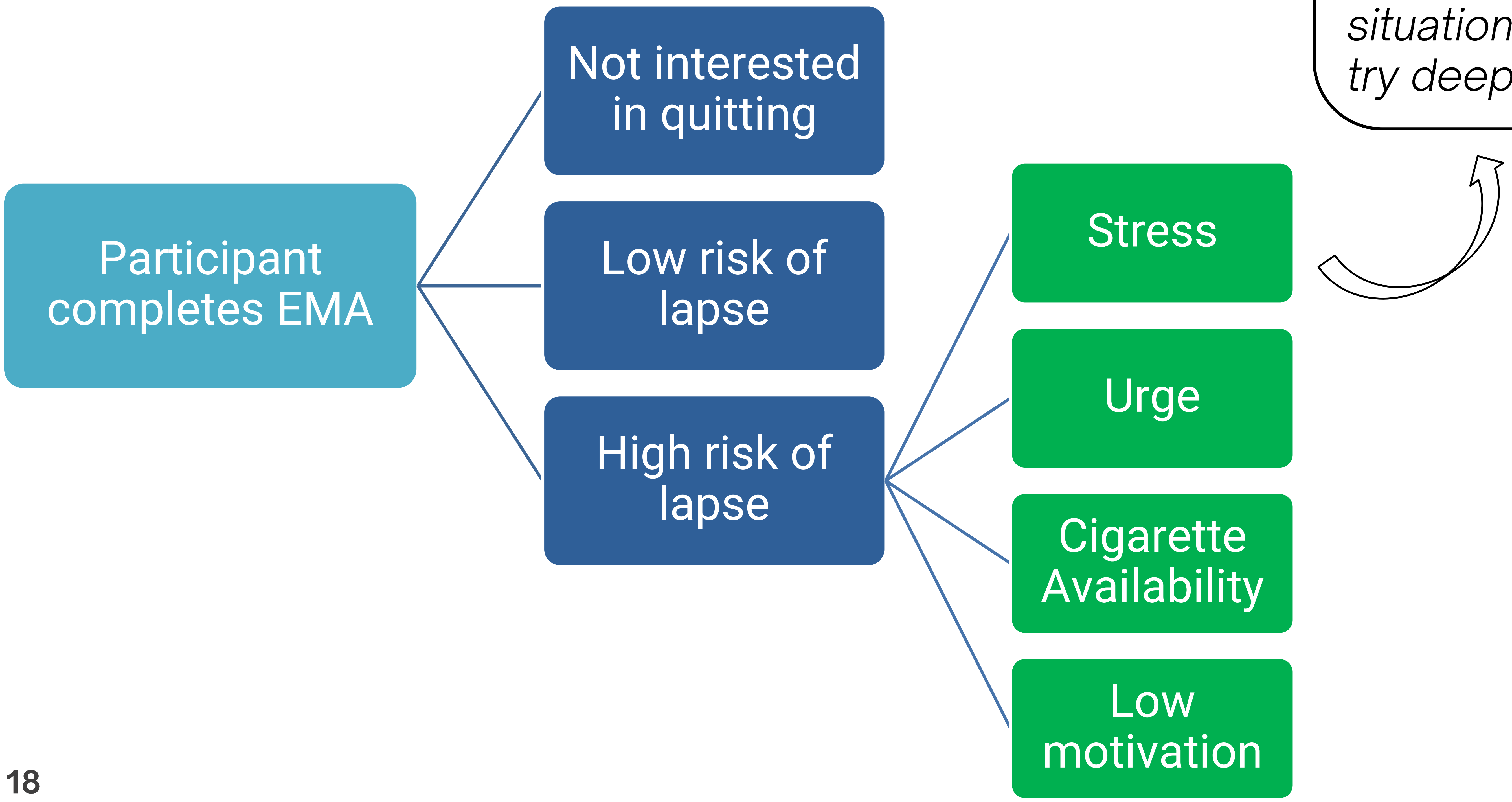

# Smart-T: Adjunctive Smartphone Based Smoking Cessation Treatment

PI: Michael Businelle, Ph.D.

- Participants (N=59) from a safety-net hospital smoking cessation program
- Completed EMAs 5 times a day for 3 consecutive weeks (1 week pre-quit, 2 weeks post-quit)
- Used EMA responses to assess current risk of smoking lapse and automatically push tailored messages

# Types of Messages

*Don't let negative emotions keep you from a healthier life! When you feel stressed or angry, distract yourself, go for a walk, get out of the situation for a few minutes, try deep breathing exercises.*



# Do tailored messages reduce smoking lapse triggers?

Addictive Behaviors 78 (2018) 30–35

Contents lists available at ScienceDirect

Addictive Behaviors

journal homepage: www.elsevier.com/locate/addictbeh

## An ecological momentary intervention for smoking cessation: The associations of just-in-time, tailored messages with lapse risk factors

Emily T. Hébert[a,*], Elise M. Stevens[a], Summer G. Frank[a], Darla E. Kendzor[a,b], David W. Wetter[d], Michael J. Zvolensky[c], Julia D. Buckner[e], Michael S. Businelle[a,b]

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[b] Department of Family and Preventive Medicine, University of Oklahoma Health Sciences Center, Oklahoma City, OK, United States
[c] The University of Houston, College of Liberal Arts and Social Sciences, Department of Psychology, Houston, TX, United States
[d] Department of Population Health Sciences and the Huntsman Cancer Institute, University of Utah, Salt Lake City, UT, United States
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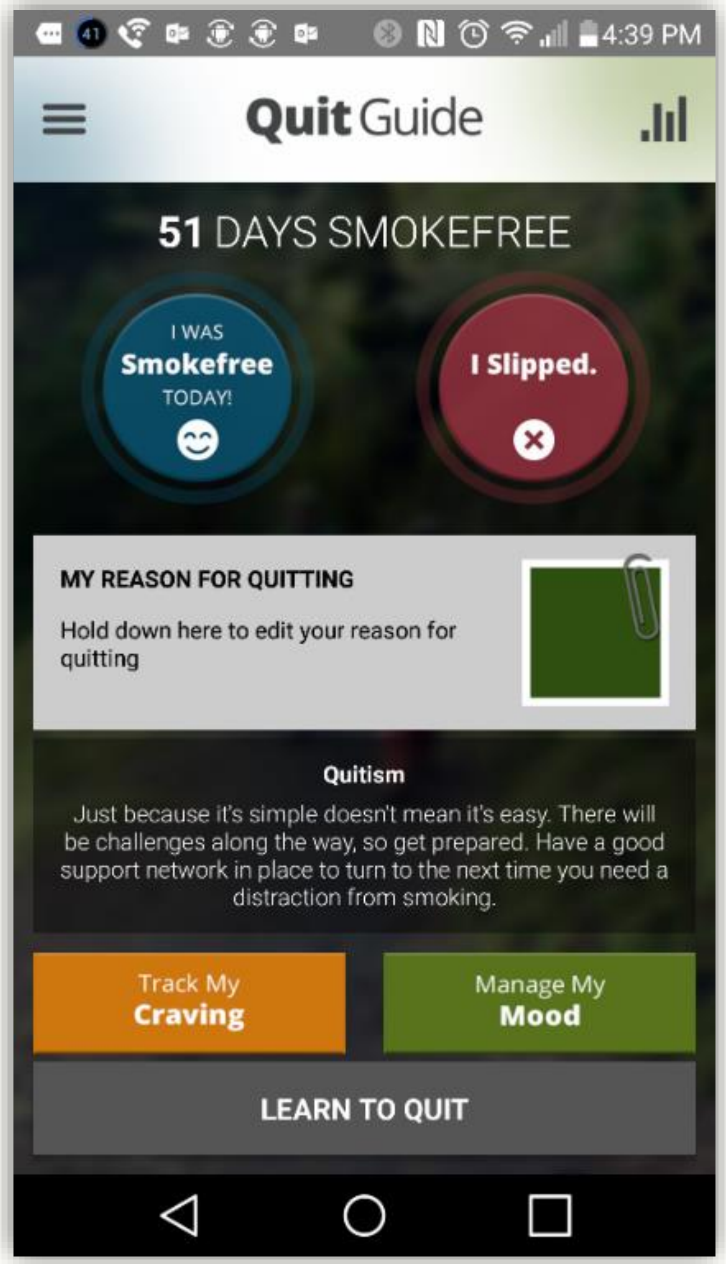
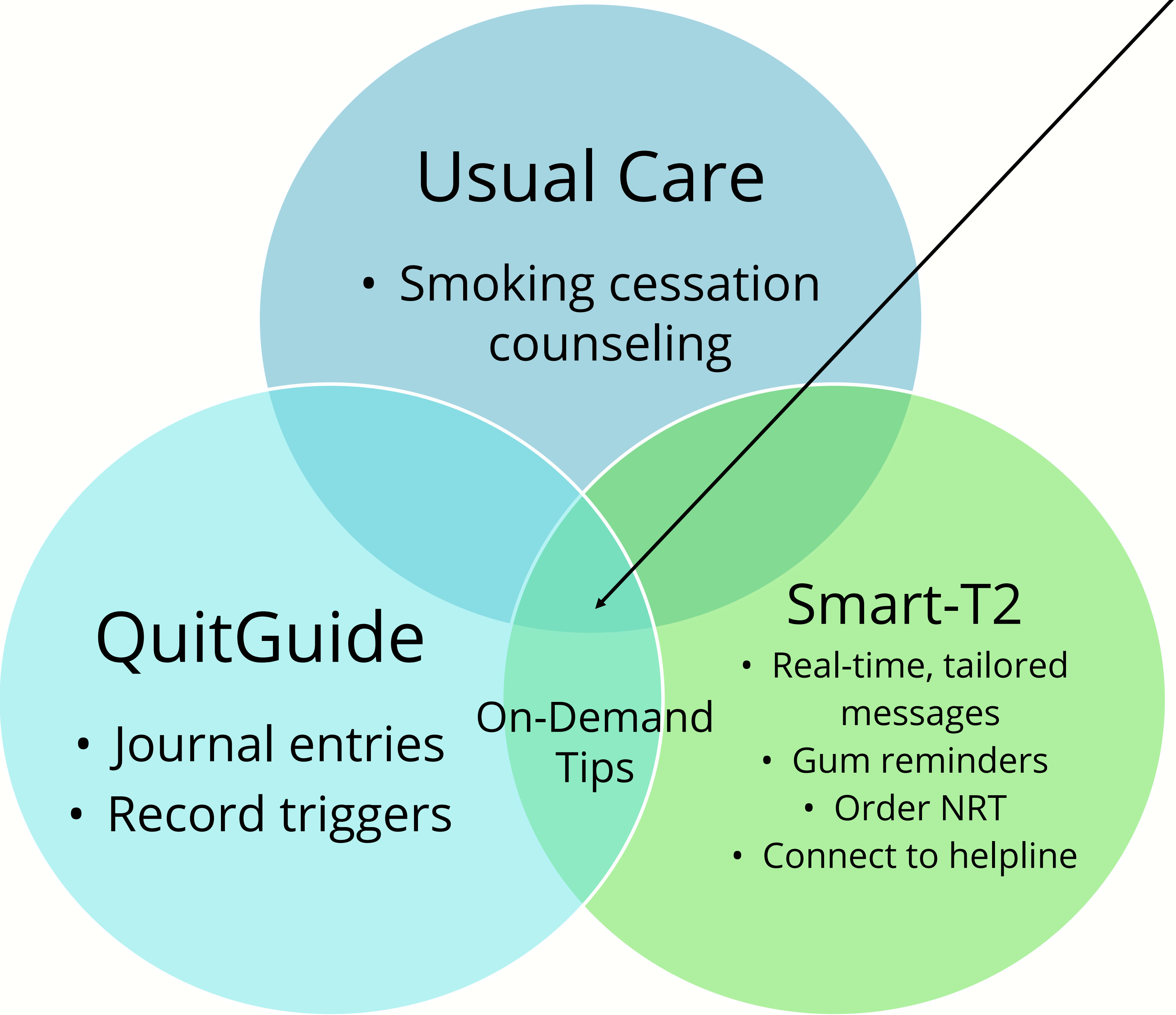
Messages tailored to the situation were more effective in reducing lapse triggers than non-tailored messages.

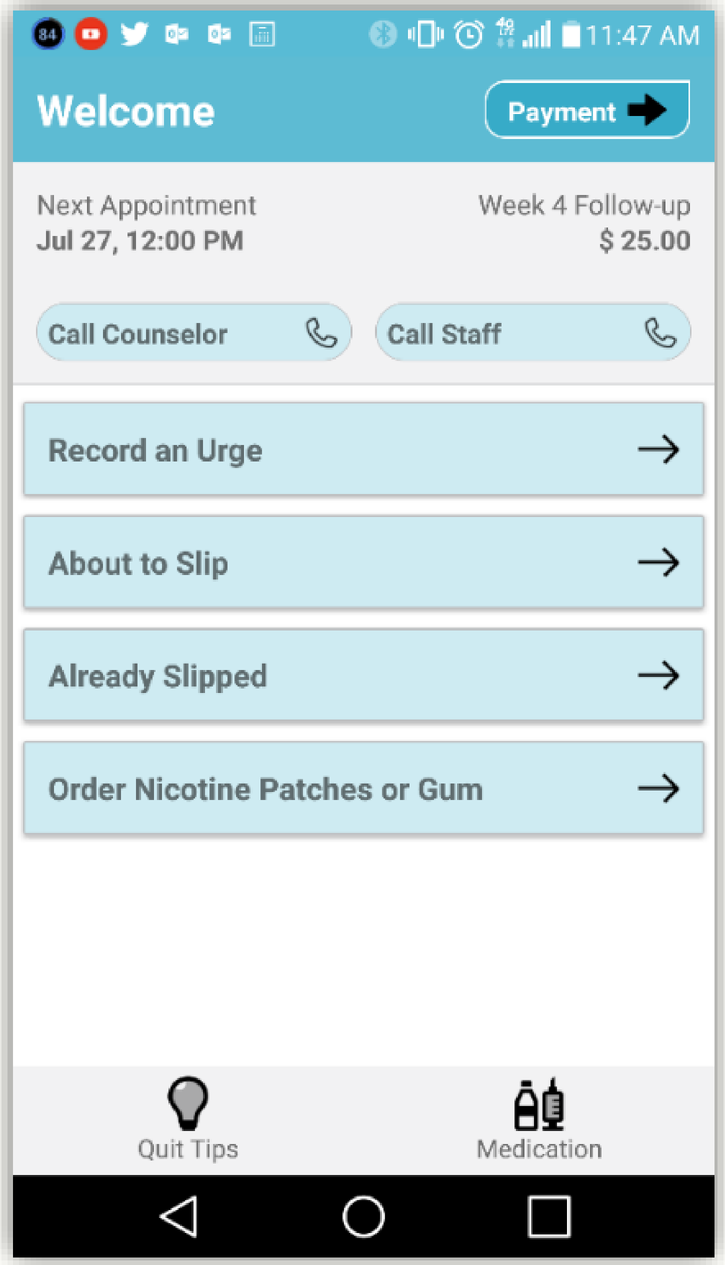
# Smart-T2

PI: Michael Businelle, Ph.D.

EMA
Nicotine Replacement Therapy



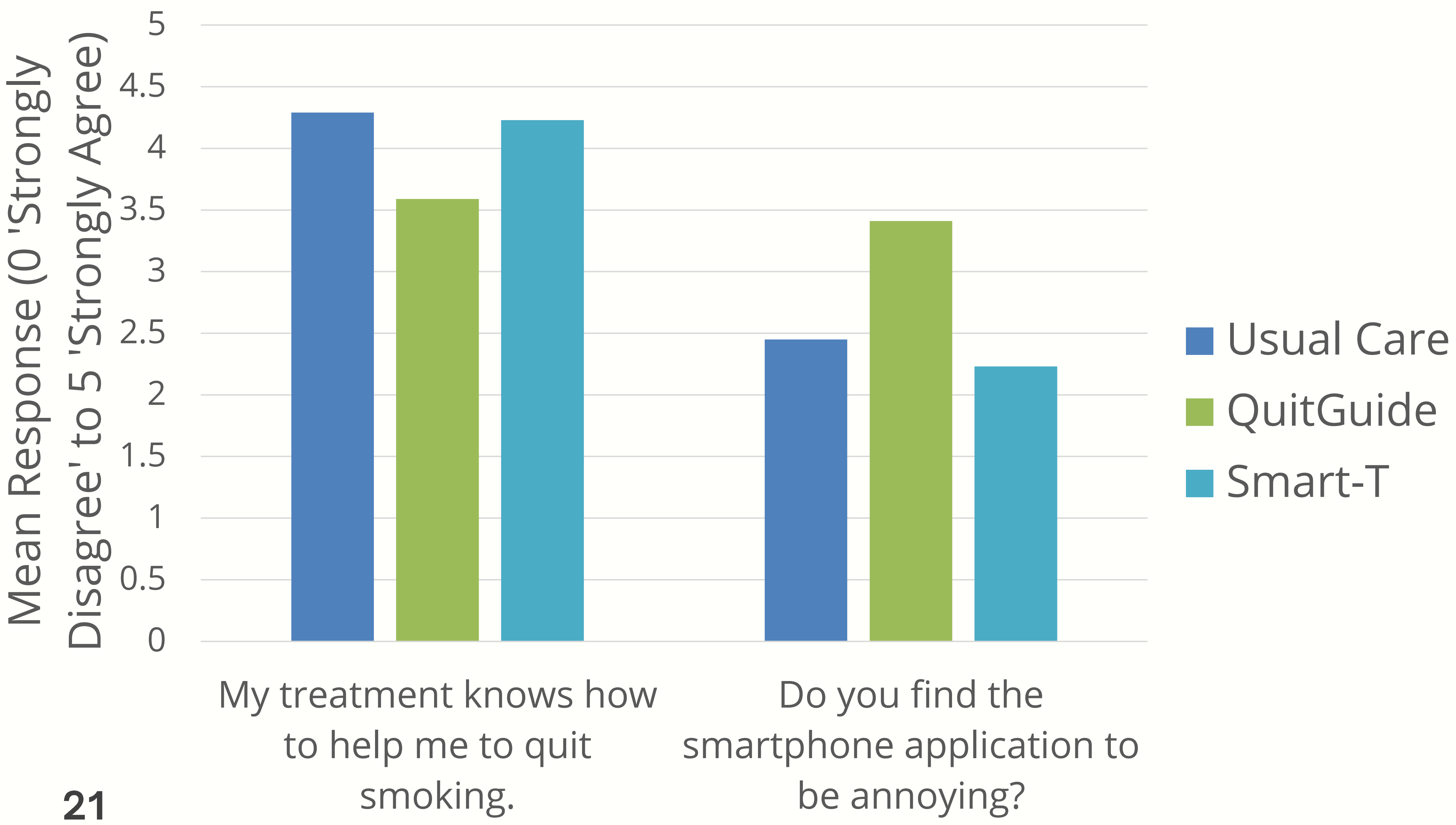



JOURNAL OF MEDICAL INTERNET RESEARCH Hébert et al

Original Paper

# A Mobile Just-in-Time Adaptive Intervention for Smoking Cessation: Pilot Randomized Controlled Trial

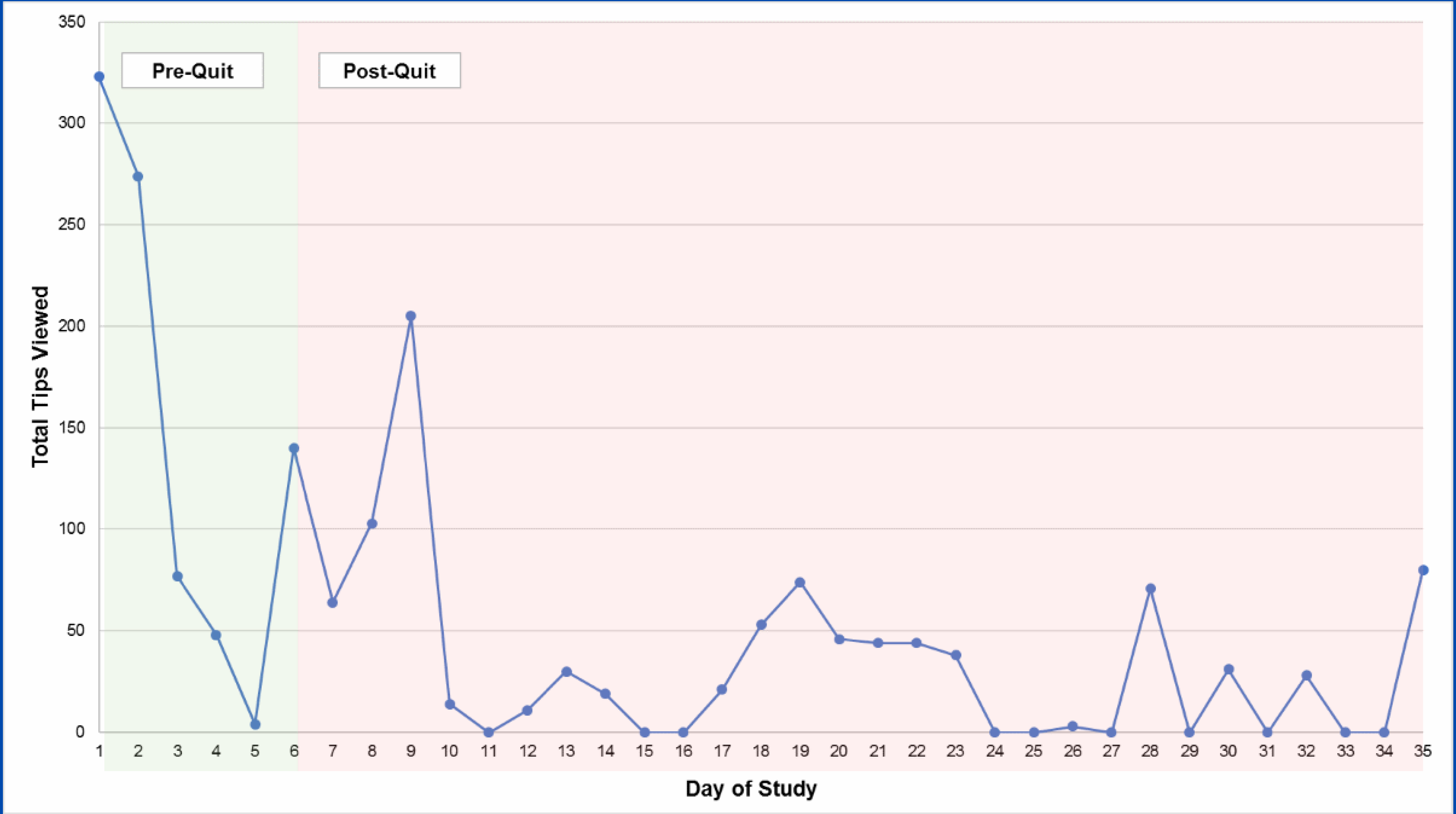
Emily T Hébert[1], DrPH; Chaelin K Ra[1], PhD; Adam C Alexander[1], PhD; Angela Helt[1], MA; Rachel Moisiuc[1], BS; Darla E Kendzor[1], PhD; Damon J Vidrine[2], DrPH; Rachel K Funk-Lawler[3], PhD; Michael S Businelle[1], PhD



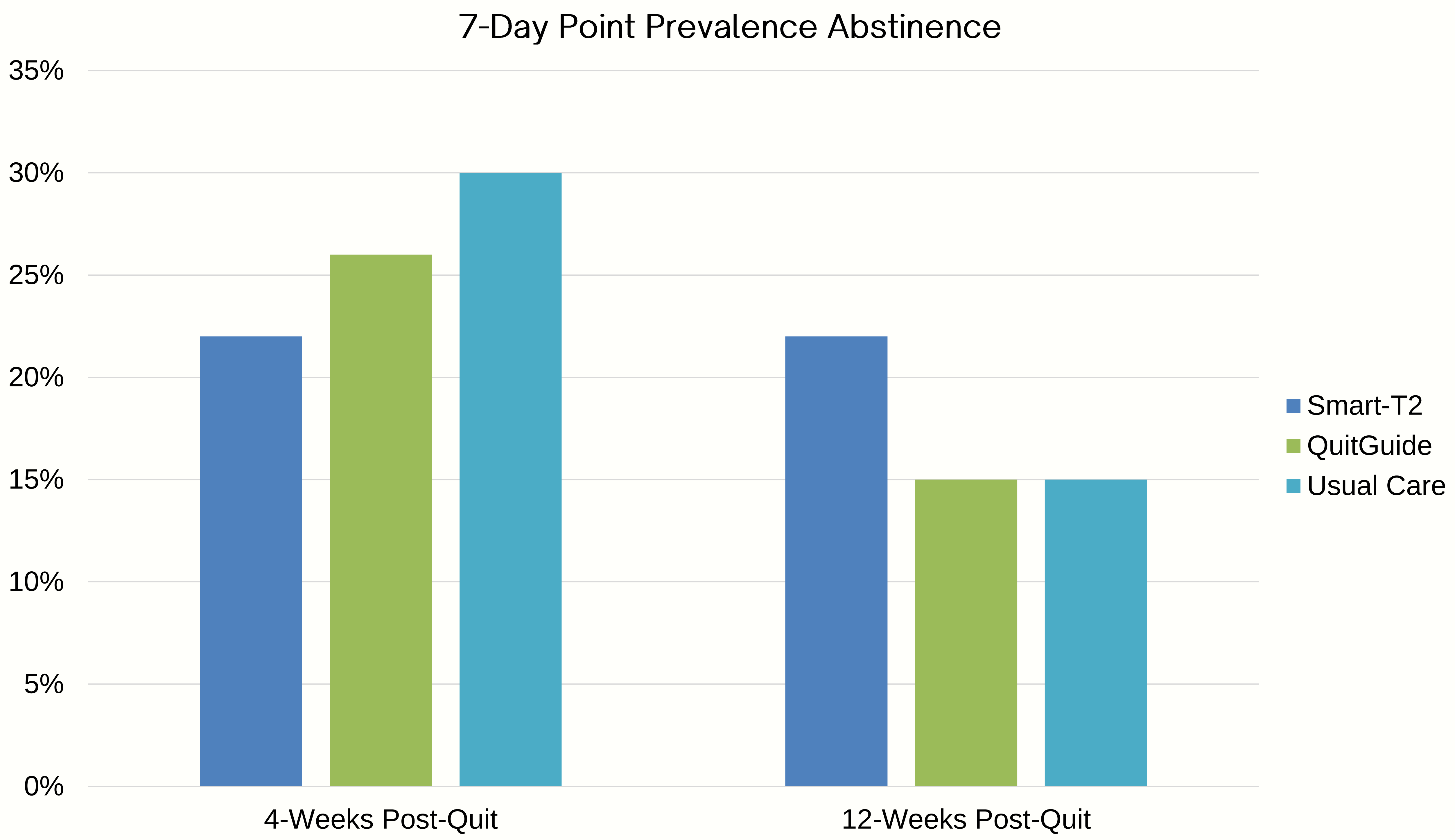

Both app-based interventions (Smart-T2 and QuitGuide) performed at least as well as traditional, in-person counseling in terms of:

- response rates
- loss to follow-up
- participant perceptions of the treatment
- engagement

# Engagement with On-Demand Quit Tips



# Smoking Cessation Outcomes




**Smartphone-based smoking cessation treatments may be capable of providing similar outcomes to traditional, in-person counseling.**

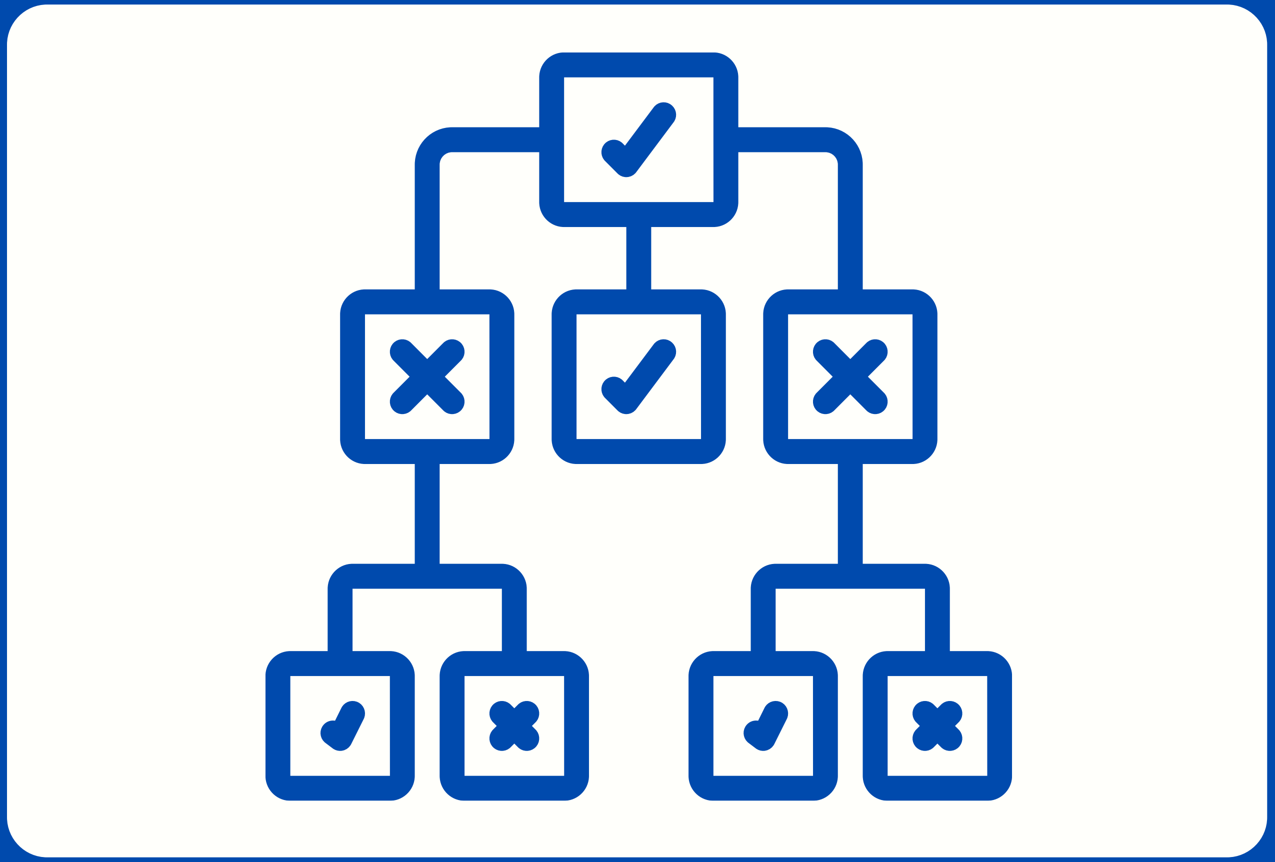
# What we've learned...

EMA is a useful tool to collect ecologically valid data about smoking behavior and experiences in real time.

Just-in-time adaptive interventions may be a promising strategy for health behavior change.

# But...

EMA can be burdensome and disruptive.



Decision rules for delivering JITAI are typically static and based on group-level trends.

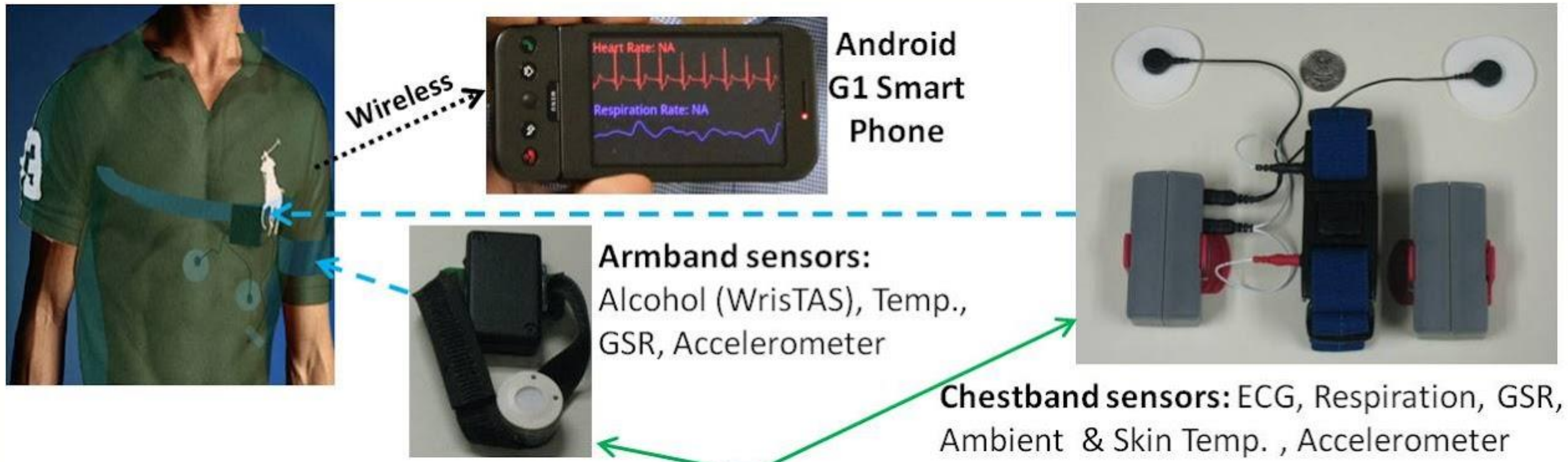
# Future Directions

EMA can be burdensome and disruptive.

→

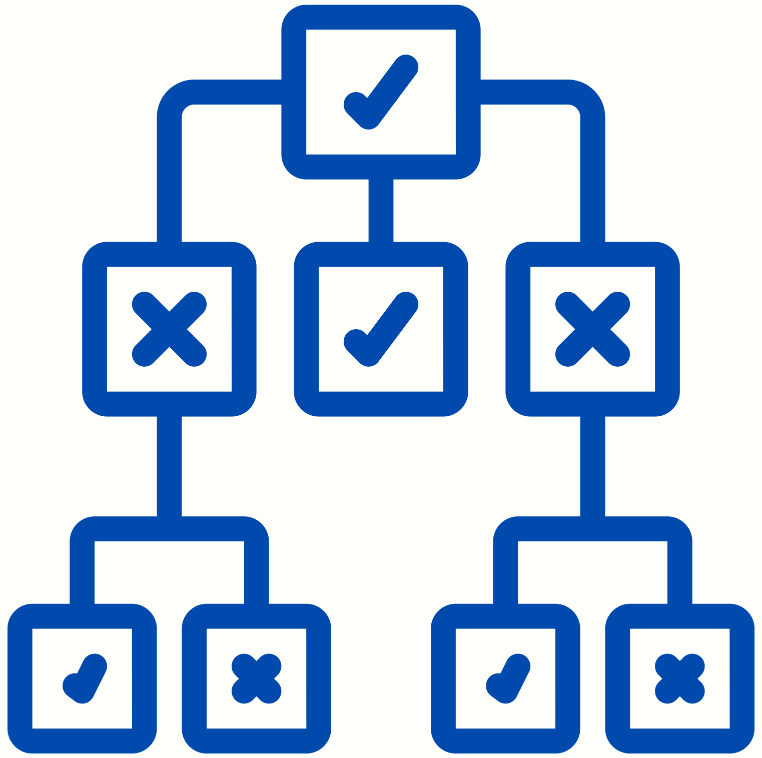
Use passively collected data.

# Passive Detection of Smoking and Smoking Antecedents




Ertin, E. et al. (2011). AutoSense: unobtrusively wearable sensor suite for inferring the onset, causality, and consequences of stress in the field. In Proceedings of the 9th ACM Conference on Embedded Networked Sensor Systems (pp. 274-287).

Imtiaz, M. H., Ramos-Garcia, R. I., Wattal, S., Tiffany, S., & Sazonov, E. (2019). Wearable sensors for monitoring of cigarette smoking in free-living: A systematic review. Sensors, 19(21), 4678.



Decision rules for delivering **JITAI are typically** static and based on group-level trends.

Why is that a problem?

*Nicotine & Tobacco Research*, 2018, 1231–1236
doi:10.1093/ntr/ntx225
Original investigation
Received November 21, 2016; Editorial Decision September 23, 2017; Accepted September 28, 2017

Original investigation

# The Time-Varying Relations Between Risk Factors and Smoking Before and After a Quit Attempt

**Matthew D. Koslovsky PhD[1], Emily T. Hébert DrPH[2], Michael D. Swartz PhD[1], Wenyaw Chan PhD[1], Luis Leon-Novelo PhD[1], Anna V. Wilkinson PhD[3], Darla E. Kendzor PhD[2,4], Michael S. Businelle PhD[2,4]**

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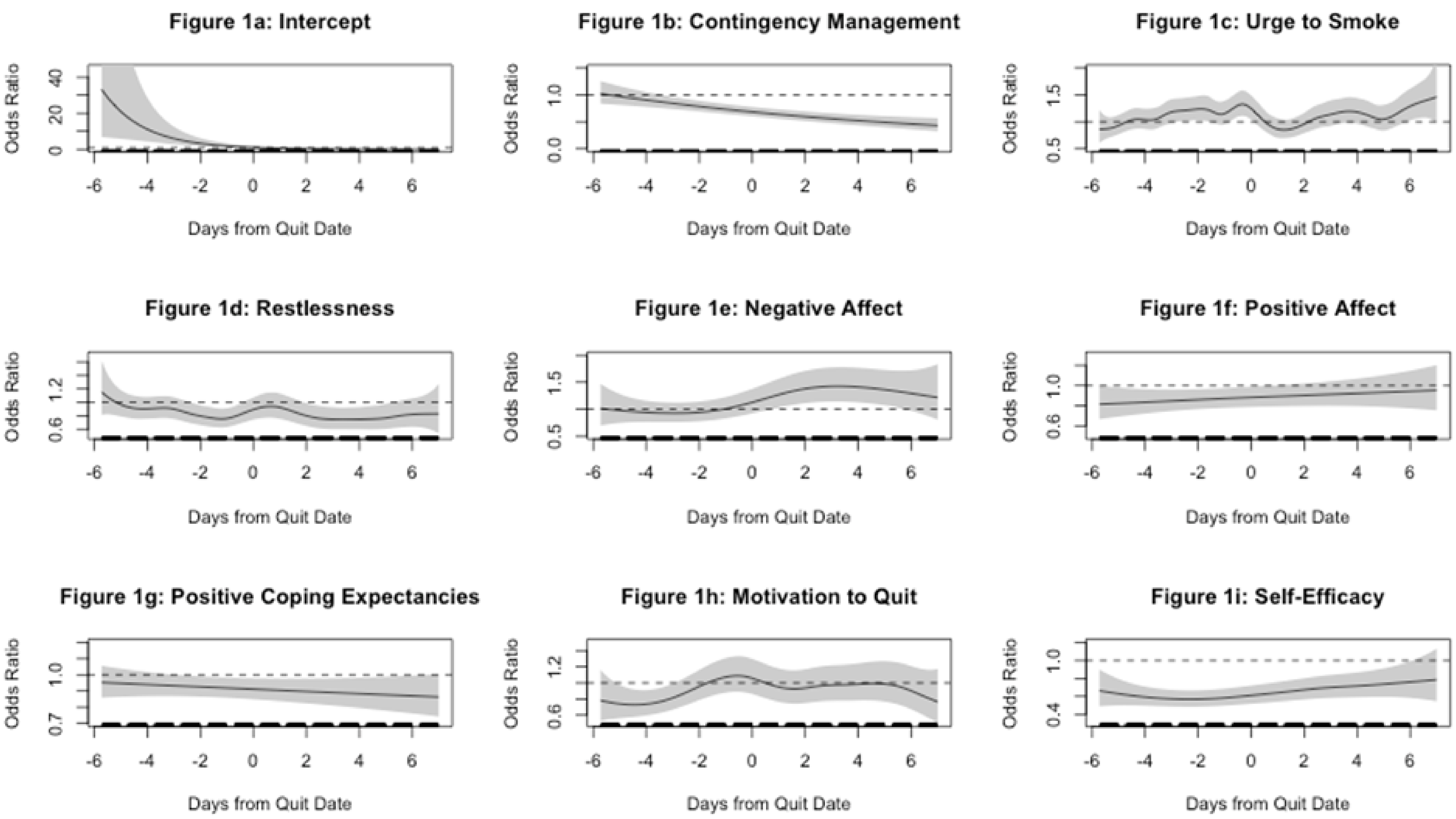
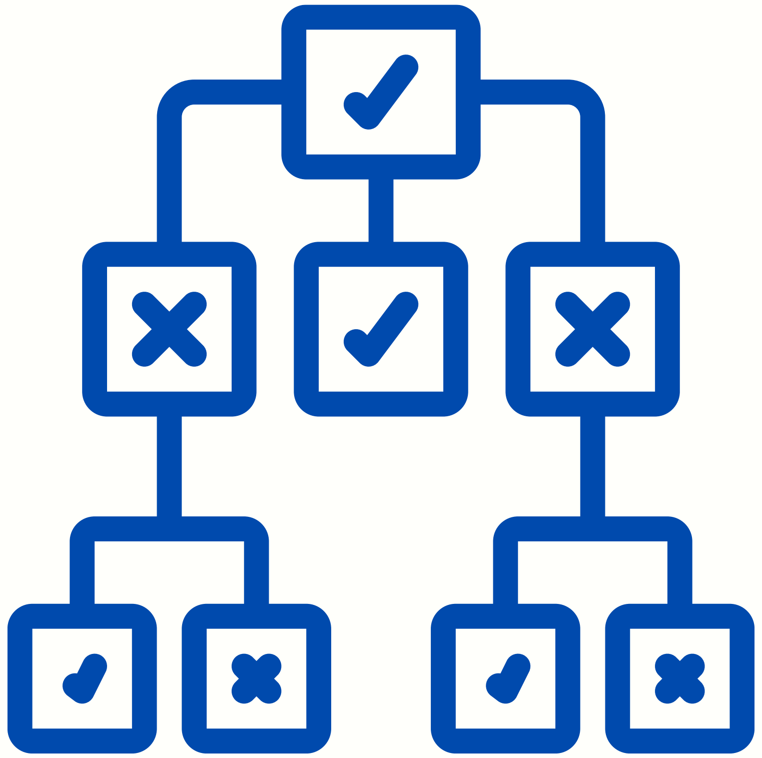
# Smoking lapse is dynamic.





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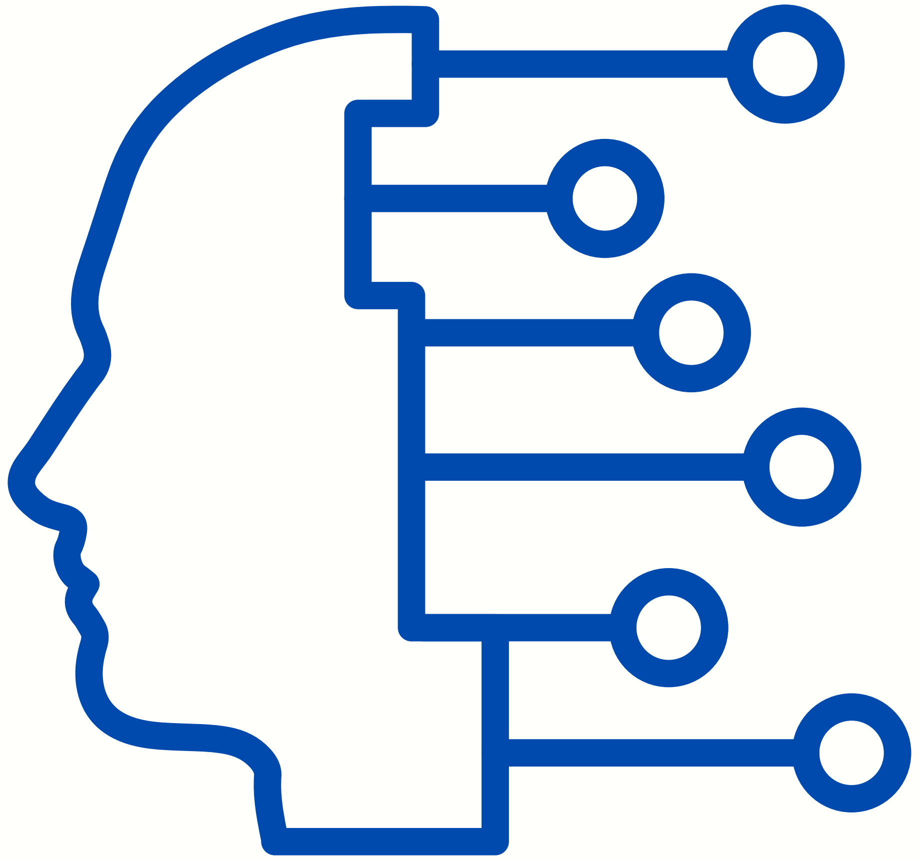
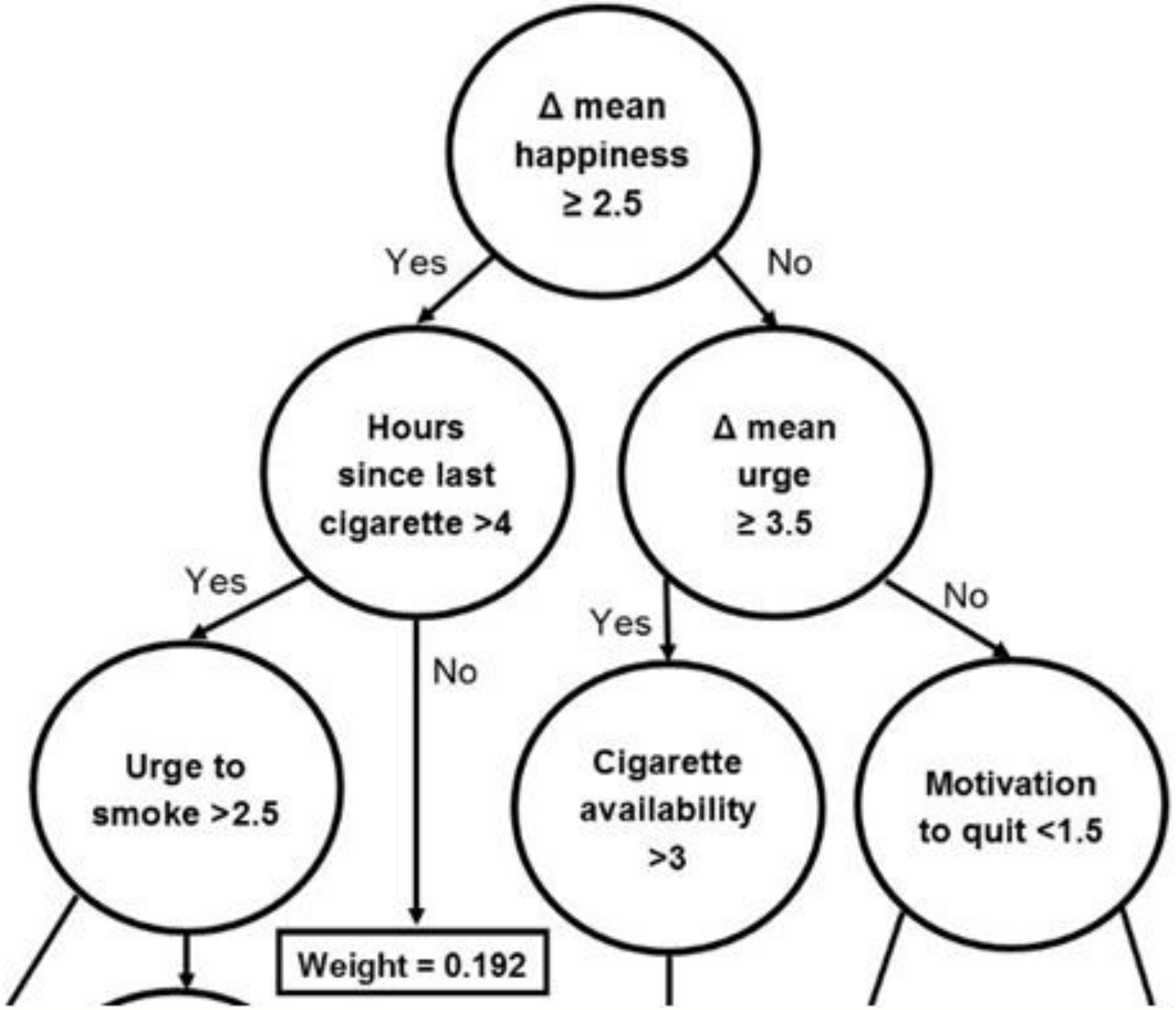


Use different analytic methods such as machine learning.

# Machine Learning




Can quickly handle massive amounts of data

Is exploratory

Can adapt to new data

# Personalized Interventions for Smoking Cessation


# Acknowledgements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# Questions?

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