THE UNIVERSITY OF TEXAS
MD Anderson ~~Cancer~~ Center

Making Cancer History®

Next-gen mHealth: Integrating body sensors with smart technology to motivate health behavior change

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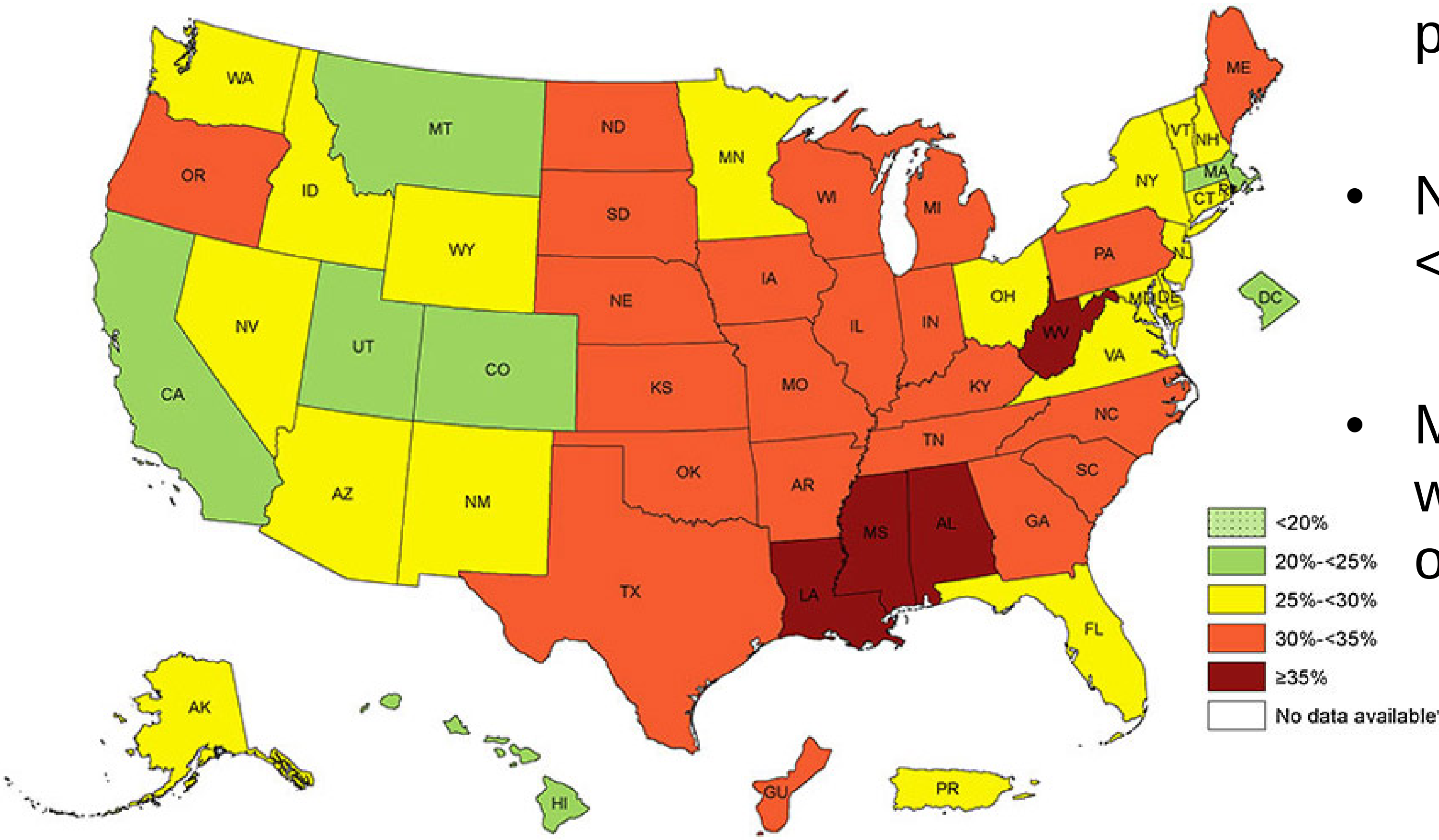
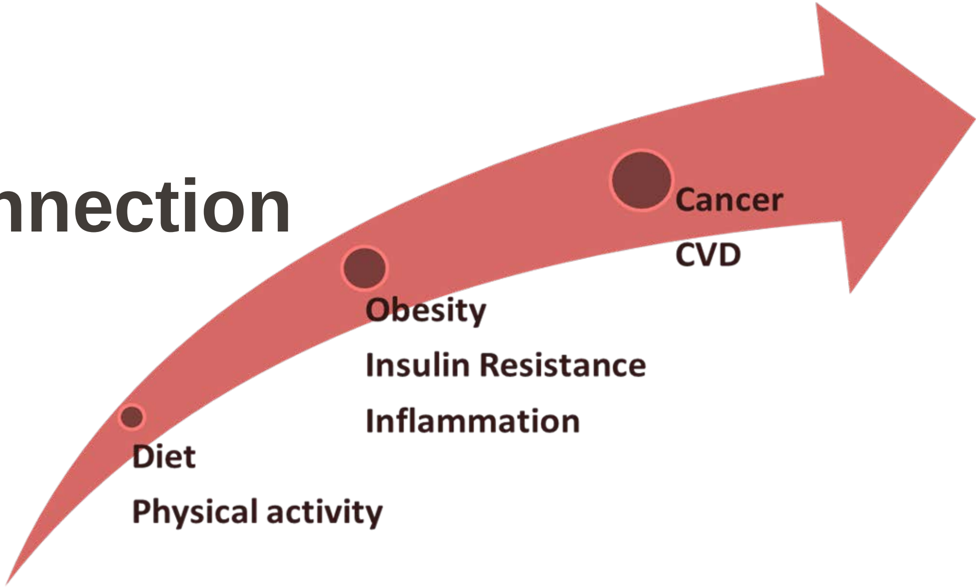
Center for Energy Balance Seminar July 20, 2017

2015 Obesity Prevalence Across US States and Territories



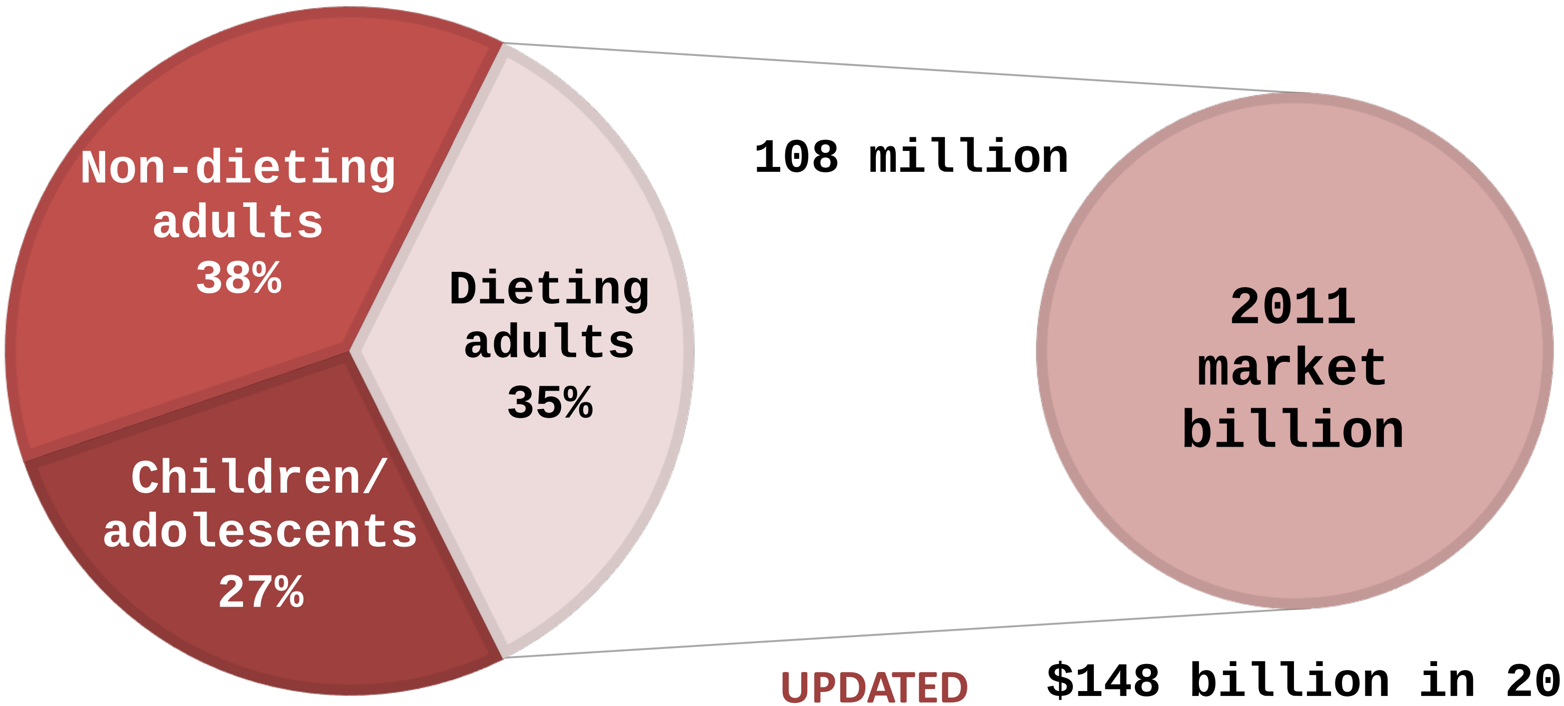
- 2013-2014 obesity prevalence: 38%
- No states with <20% obesity
- More than half with 30%+ obesity

The Obesity-Cancer Connection



- Obesity is now the #1 ranked cause of all cancers in non-smokers.
- 30% of cancer risk is attributed to poor diet, physical inactivity, and obesity.
- Directly and indirectly impacts cancer risk via insulin resistance, inflammation, etc.
- Weight losses of 5-10% can reduce the risk of some chronic diseases. Greater weight losses might be necessary to reduce cancer risk.
- Weight loss maintenance will likely be necessary to reduce long-term risk.
- Without more effective weight loss and health behavior change interventions the prevalence of obesity and obesity-related disease will remain high.

The US Weight Loss and Weight Management Market



UPDATED

$148 billion in 2014

$206 billion by 2019

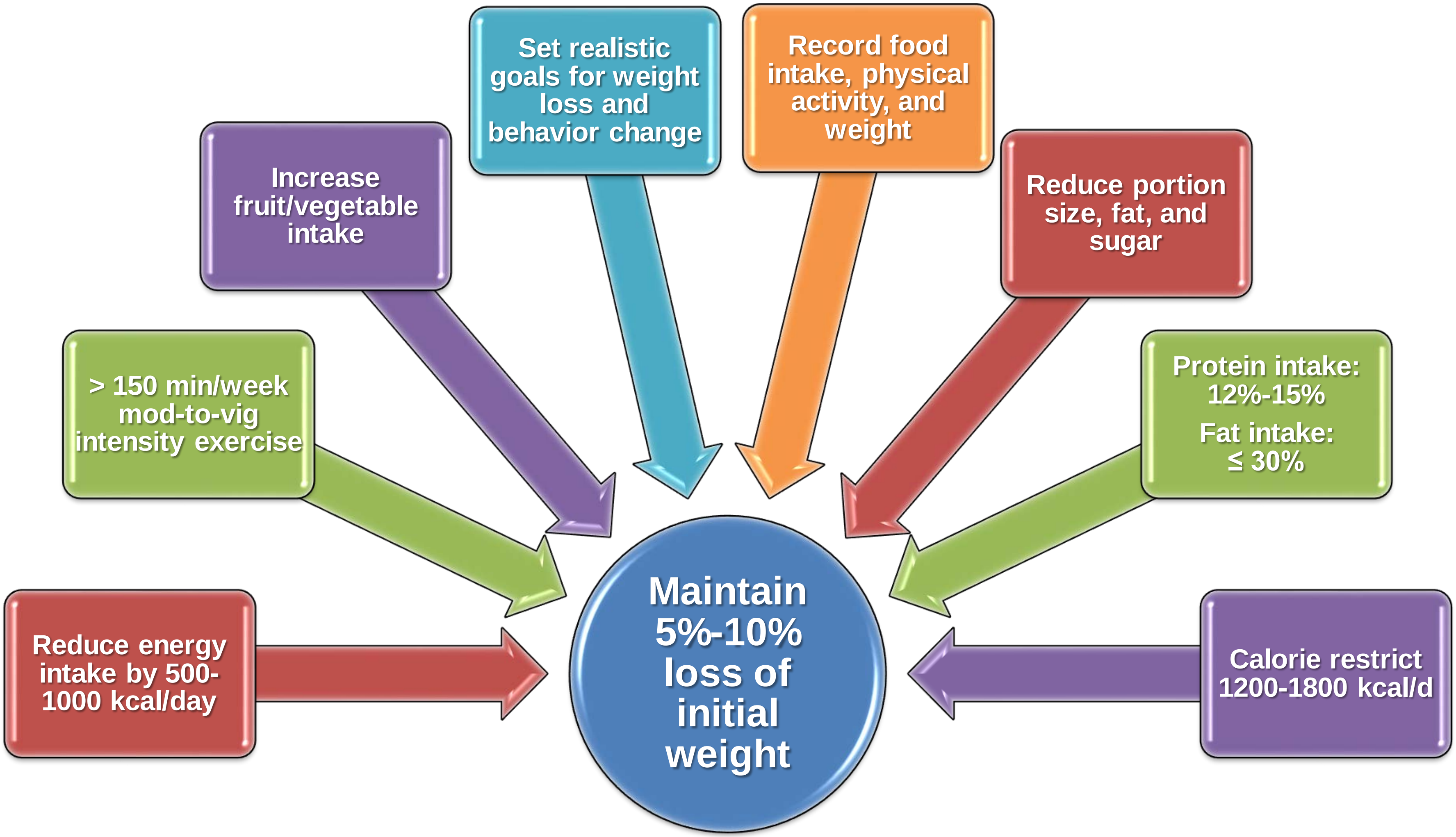
Diet products (meals, beverages, and supplements); Equipment (fitness and surgical equipment); and Services(e.g., Weight Watchers)

Body-weight trajectories do not vary by intention to lose weight

	Intentional weight loss (36%)	**No intentional weight loss (64%)**
Weight gain	31%	33%
Weight stable	30%	30%
Weight loss	39%	37%

Sorensen TI et al. (2005) PLoS Med
Wing RR and Phelan S (2005) Am J Clin Nutr
Bosomworth NJ (2012) Can Fam Physician

The current evidence-based weight control paradigm



Selected from over 200 LEARN program strategies (Brownell, 1989)

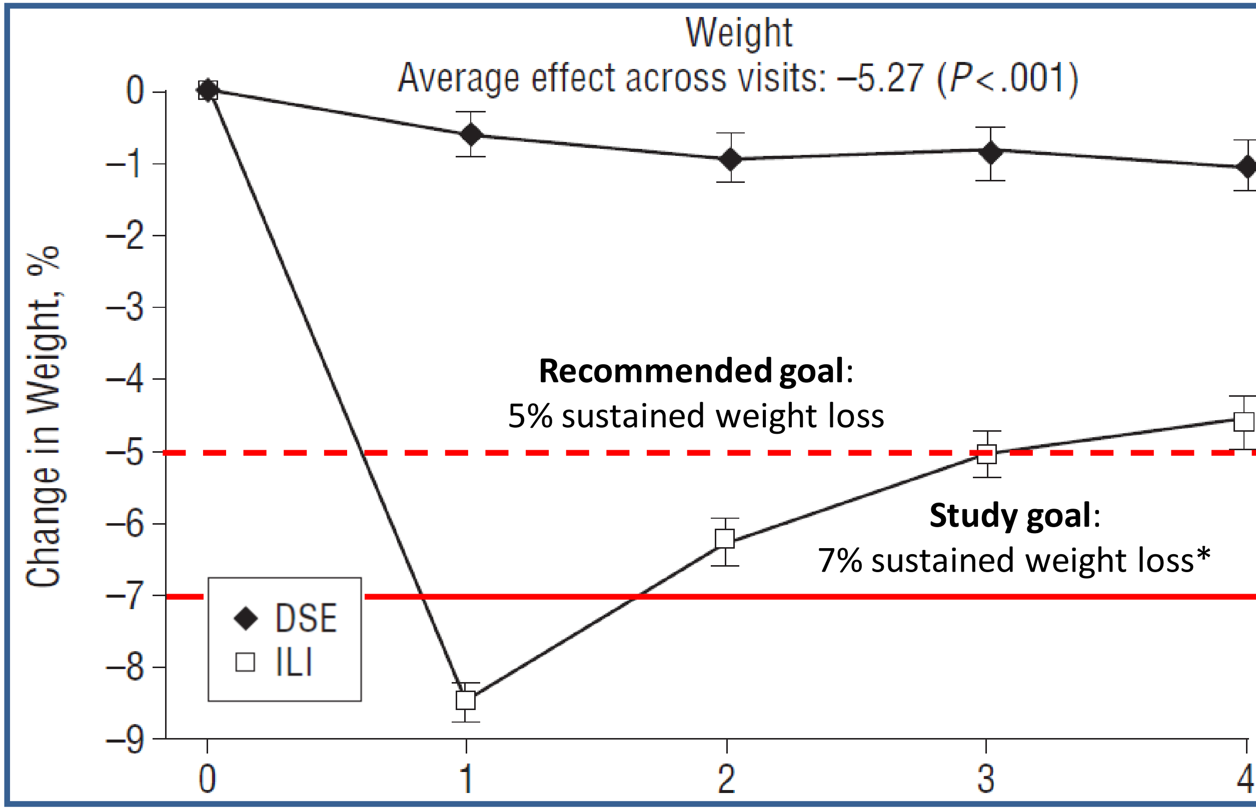
Look AHEAD Trial

The LOOK Ahead Trial was a multicenter randomized clinical trial comparing the effects of an intensive lifestyle intervention (ILI) to traditional diabetes support and education (DSE; the control group) on the incidence of major CVD events in over 5,000 overweight or obese men and women with type 2 diabetes.

Four-Year Results of the Look AHEAD Trial

The Look AHEAD Research Group

Arch Intern Med. 2010;170(17):1566-1575



- >7% weight loss in year 1
- Steady weight regain years 2-4 with counseling 2x/month and optional monthly group sessions.

Diabetes Prevention Program

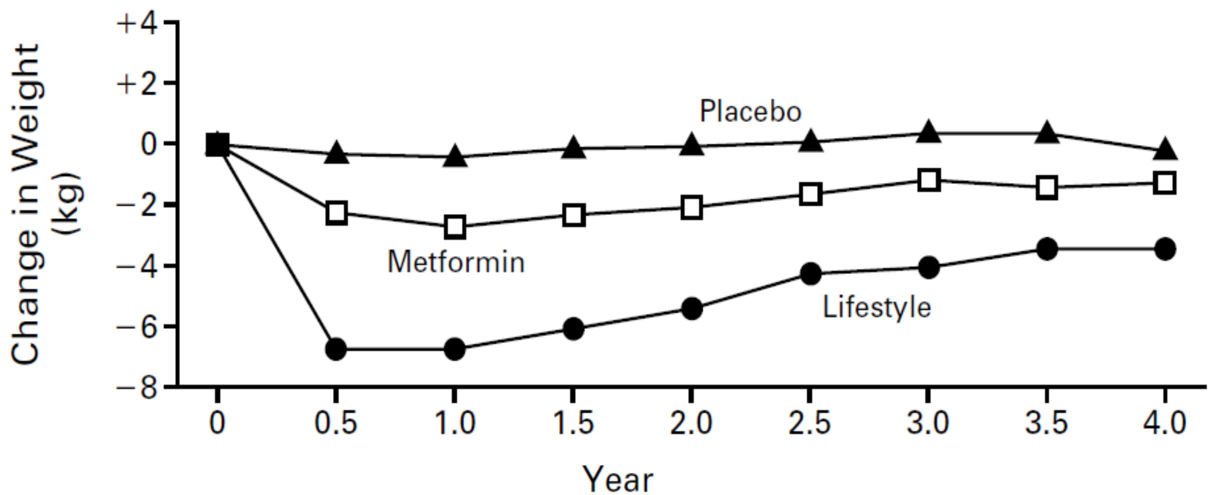
The DPP was a large, randomized clinical trial involving more than 3,000 non-diabetic US overweight and obese men and women at risk for diabetes. The trial compared the effects of an intensive lifestyle intervention to metformin and a placebo group on the incidence of diabetes.

The New England Journal of Medicine

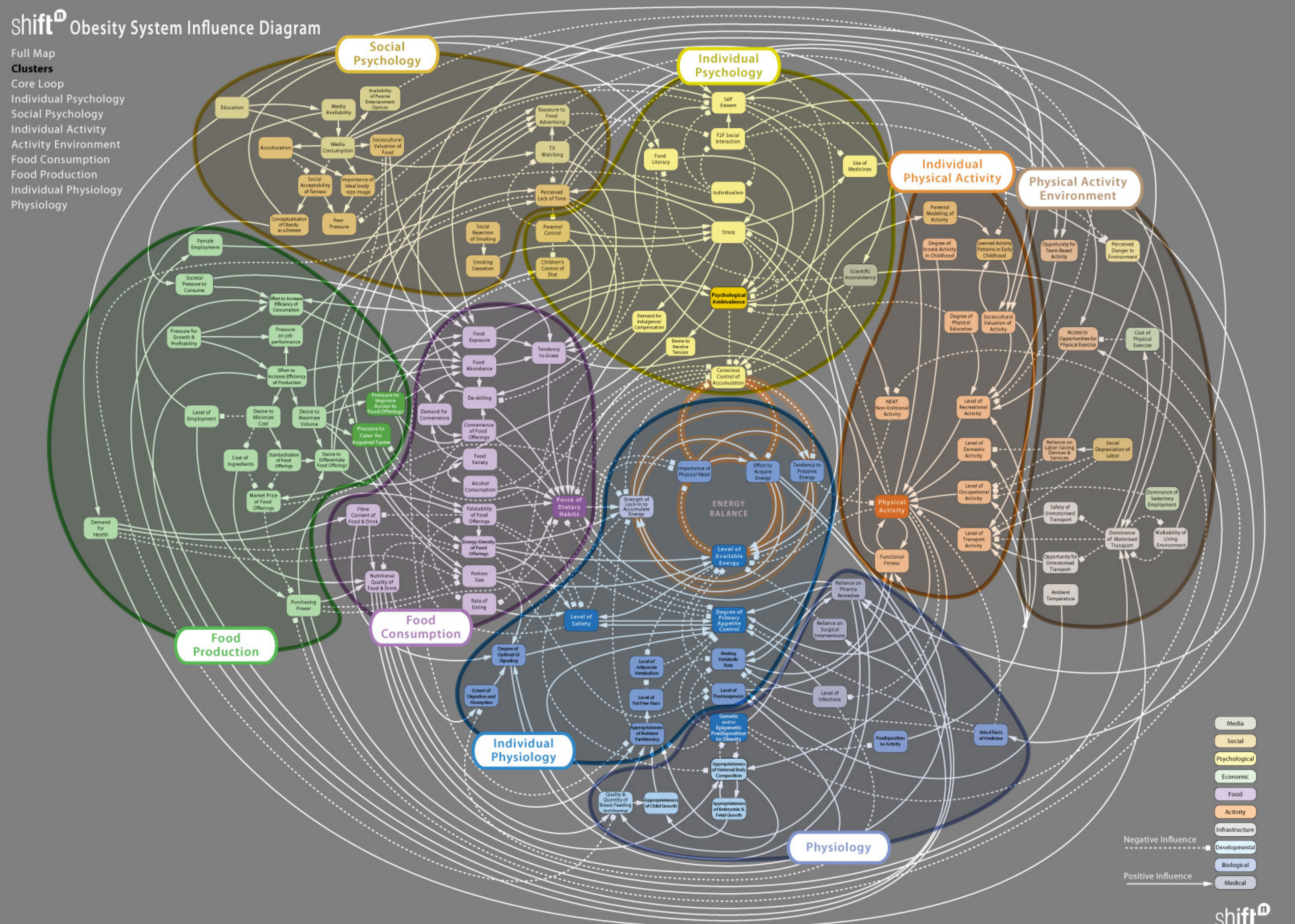
REDUCTION IN THE INCIDENCE OF TYPE 2 DIABETES WITH LIFESTYLE INTERVENTION OR METFORMIN

DIABETES PREVENTION PROGRAM RESEARCH GROUP*

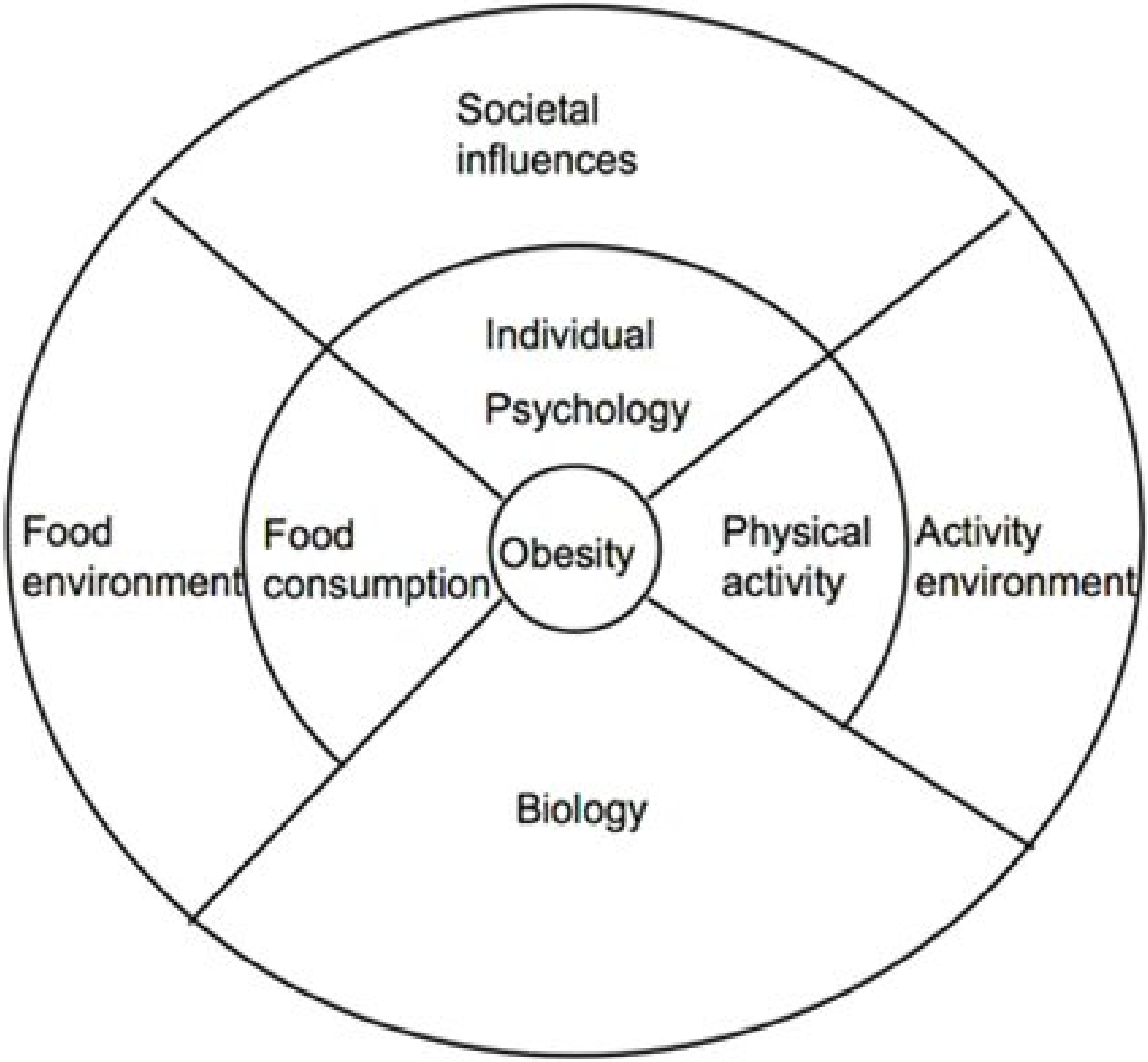
VOLUME 346 FEBRUARY 7, 2002 NUMBER 6



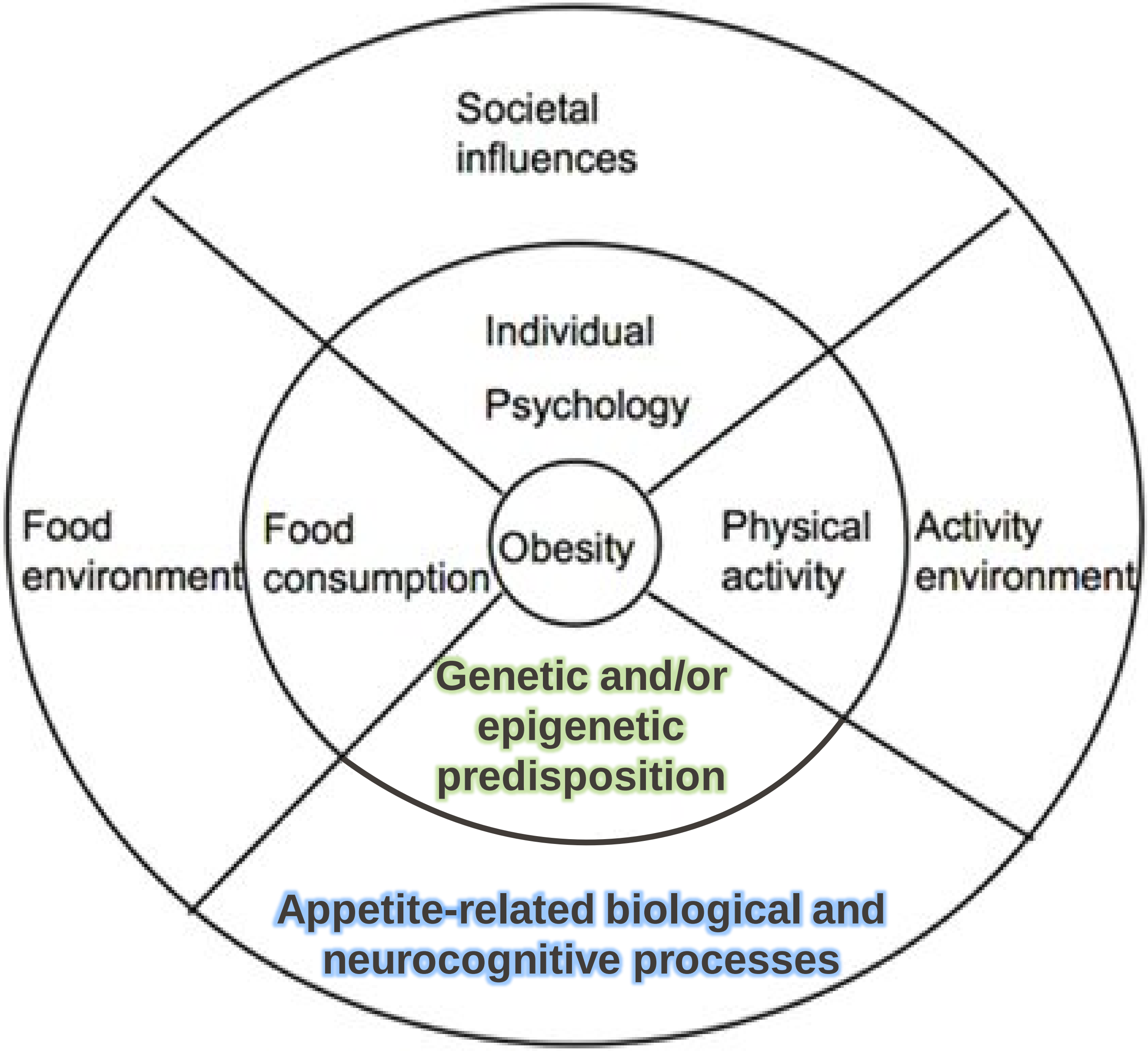
- 6% weight loss achieved in lifestyle group after 24 intervention weeks
- Intervention effects were maintained at 1 year with monthly sessions
- Steady weight regain thereafter



ttp://www.bis.gov.uk/assets/foresight/docs/obesity/12.pdf

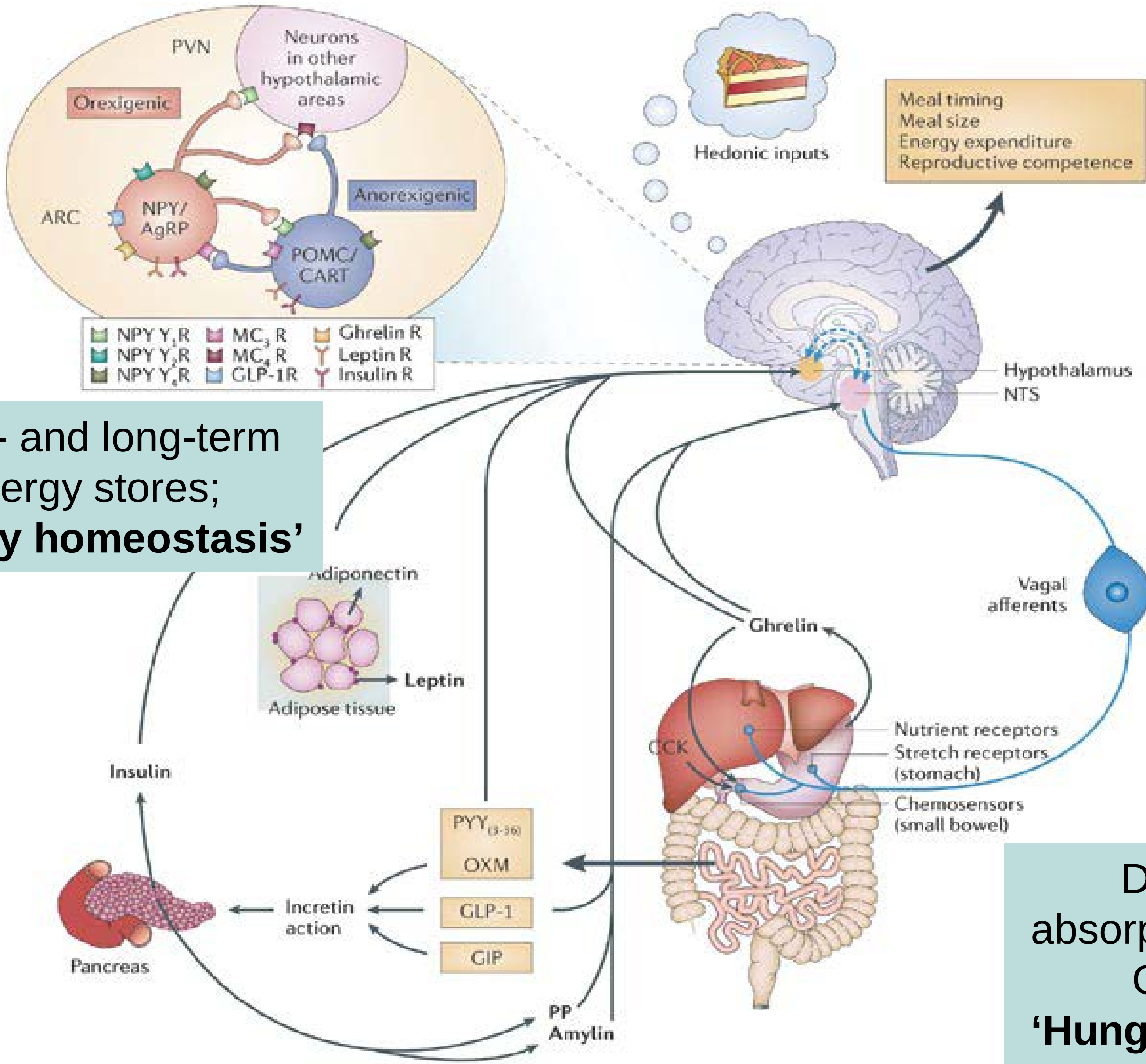


Source: 2007. Foresight Tackling Obesities : Future Choices — Obesity System Atlas



Source: 2007. Foresight Tackling Obesities : Future Choices — Obesity System Atlas

Homeostatic model of energy balance



Short- and long-term energy stores;
'energy homeostasis'

Learned behaviors and the perception of appetite-related cues

Digestion and absorption, and optimal GI signaling;
'Hunger and Fullness'

“Disruption” of energy homeostasis

Eating can be highly rewarding

- Celebratory or happy social settings
- Behavior modeling – food as reward
- Emotional cues – food as comfort

Learned behavior become automatic/habitual when repeated

- Environmental/food-related cues can trigger eating

Desire to eat “mistaken” for physiological hunger

Access to high fat/ high sugar foods

Environmental cues

Social cues

Emotional eating

In today’s plentiful food environment:

Reward homeostasis > Energy homeostasis

Learned eating behaviors

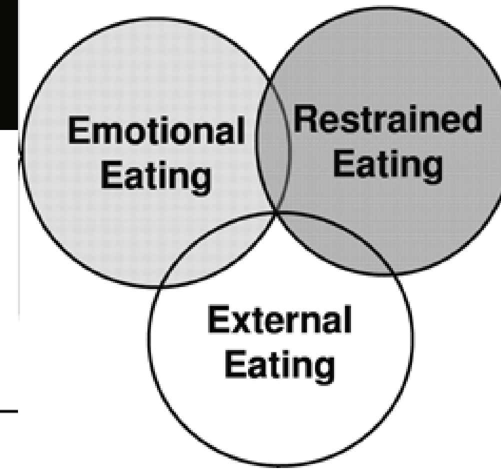


Table 218.1 Key features of eating behavior theories

Psychosomatic theory

- Proposed in the late 1950s based on observations that obese individuals used food as a coping mechanism
- Emotional eating episodes are driven by pleasure and reward seeking in response to negative affect
- Low uptake of dopamine and a preference for highly palatable, energy-dense foods are the proposed mechanisms linking emotional eating to obesity

Theory of externality

- Proposed in the 1960s, it suggests that eating behaviors of obese individuals are driven primarily by external cues (e.g., taste of food or time of day) rather than internal cues to eat (e.g., hunger and satiety)
- External eating episodes are primarily triggered by the sensory properties of food
- Individuals who are susceptible to external cues have more food cravings and greater neuronal activity in the reward and motivation centers of the brain

Theory of restraint

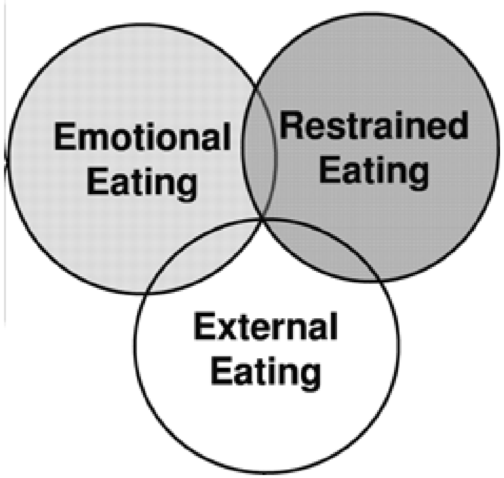
- Proposed in 1975, it suggests that episodes of overeating and weight (re)gain are the consequences of chronic caloric deprivation
- Such episodes are triggered by situations that undermine the cognitive resolve to diet
- Two components of restraint have been identified: rigid and flexible control
- Rigid control is most consistent with the theory of restraint, whereas flexible control promotes weight control

Schembre, S.M. (2011) In: Preedy VR, Watson RR, Martin CR, eds. Handbook of behavior, food and nutrition. New York: Springer, pp. 487-506.

Developing and validating a theory-based scale to assess weight-related eating behaviors

Weight-Related Eating Questionnaire

- External Eating (5-items)
- Emotional Eating (5-items)
- Routine Restraint (3-items)
- Compensatory Restraint (3-items)



Appendix A. Weight-related eating questionnaire

Directions: Please choose a response that *best* expresses how well each statement *describes* you.

1. I purposefully hold back at meals in order not to gain weight.
2. I tend to eat more when I am anxious, worried, or tense.
3. I count calories as a conscious means of controlling my weight.
4. When I feel lonely I console myself by eating.
5. I tend to eat more food than usual when I have more available places that serve or sell food.
6. I tend to eat when I am disappointed or feel let down.
7. I often refuse foods or drinks offered because I am concerned about my weight.
8. If I see others eating, I have a strong desire to eat too.
9. Some foods taste so good I eat more even when I am no longer hungry.
10. When I have eaten too much during the day, I will often eat less than usual the following day.
11. I often eat so quickly I don't notice I'm full until I've eaten too much.
12. If I eat more than usual during a meal, I try to make up for it at another meal.
13. When I'm offered delicious food, it's hard to resist eating it even if I've just eaten.
14. I eat more when I'm having relationship problems.
15. When I'm under a lot of stress, I eat more than I usually do.
16. When I know I'll be eating a big meal during the day, I try to make up for it by eating less before or after that meal.

Schembre, S. et al. (2009) Eating Behaviors 10(2);119-124
Schembre S. and Geller K. S. (2011) Obesity 449(12);2336-44
Schembre, S.M. (2011) In: Preedy VR, Watson RR, Martin CR, eds. Handbook of behavior, food and nutrition. New York: Springer, pp. 487-506.

Eating Behaviors 10 (2009) 119–124

Contents lists available at ScienceDirect

Eating Behaviors

Development and validation of a weight-related eating questionnaire

Susan Schembre *, Geoffrey Greene, Kathleen Melanson

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nature publishing group

ARTICLES
BEHAVIOR AND PSYCHOLOGY

Psychometric Properties and Construct Validity of the Weight-Related Eating Questionnaire in a Diverse Population

Susan M. Schembre[1] and Karly S. Geller[1]

Race/Ethnic Differences in Desired Body Mass Index and Dieting Practices Among Young Women Attending College in Hawai‘i

Susan M. Schembre PhD, RD; Claudio R. Nigg PhD; and Cheryl L. Albright PhD, MPH

Contents lists available at ScienceDirect

Physiology & Behavior

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

Emotional eating and routine restraint scores are associated with activity in brain regions involved in urge and self-control

Samantha M.W. Wood [a,*], Susan M. Schembre [b], Qinghua He [a,c], Jeffrey M. Engelmann [b], Susan L. Ames [d], & Antoine Bechara [a]

Contents lists available at ScienceDirect

Appetite

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

The Weight-Related Eating Questionnaire offers a concise alternative to the Three-Factor Eating Questionnaire for measuring eating behaviors related to weight loss☆,☆☆,☆☆☆

Brittany L. James [a], Eric Loken [b], Liane S. Roe [a], Barbara J. Rolls [a,*]

Contents lists available at SciVerse ScienceDirect

Physiology & Behavior

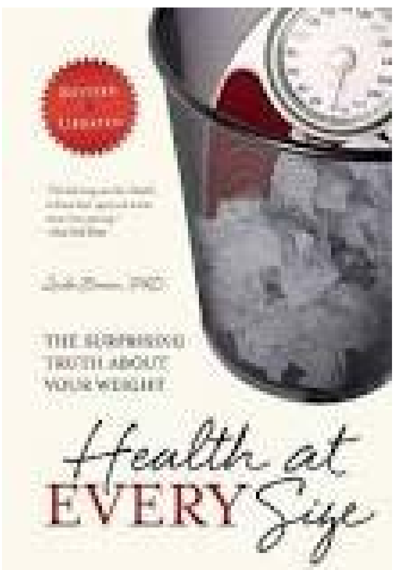
journal homepage: www.elsevier.com/locate/phb

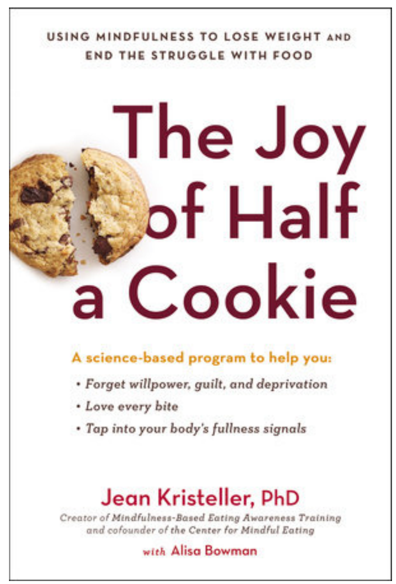
Associations between weight-related eating behaviors and adiposity in postmenopausal Japanese American and white women

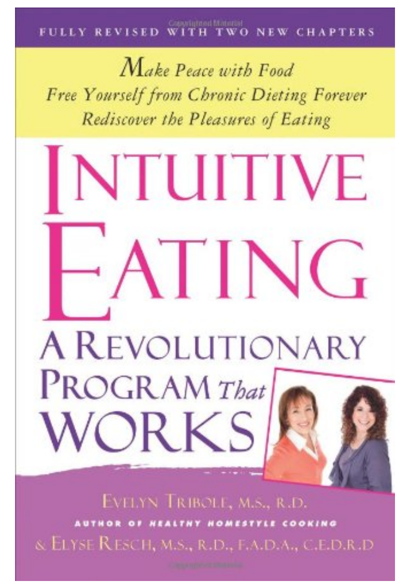
Susan M. Schembre [a,*], Cheryl L. Albright [b,c], Unhee Lim [d], Lynne R. Wilkens [d], Suzanne P. Murphy [d], Rachel Novotny [d,e], Thomas Ernst [f], Linda Chang [f], Laurence N. Kolonel [d], Loïc Le Marchand [d]

Non-diet approach to improving health outcomes

HEALTHY AT EVERY SIZE	MINDFULNESS-BASED EATING AWARENESS	INTUITIVE EATING







- <u>Key assumption</u>: People can correctly distinguish between the desire to eat and physiological hunger, if they pay attention to it.

Individuals with high vs low susceptibility to external and emotional cues (EE) "perceive" greater levels of hunger

Subjective Appetite Ratings	High EE (n=30) M ± SD	Low EE (n=24) M ± SD	
Fasting Hunger (mm)	**54.5±24.2**	**38.3±26.9**	**p=0.016**
Fasting Satiety (mm)	60.0±27.2	59.1±25.8	
Appetite-Related Fasting Plasma Biomarkers			
Fasting Total Ghrelin (pg/ml)	661.1±166.3	653.0±214.9	
Fasting Glucose (mg/dl)	95.2±37.8	88.2±10.2	
Fasting Insulin (µIU/mL)	11.6±10.2	9.1±6.4	

Participants fasted for 12 hours

Analyses controlled for gender (28% males) and BMI (74% normal weight).

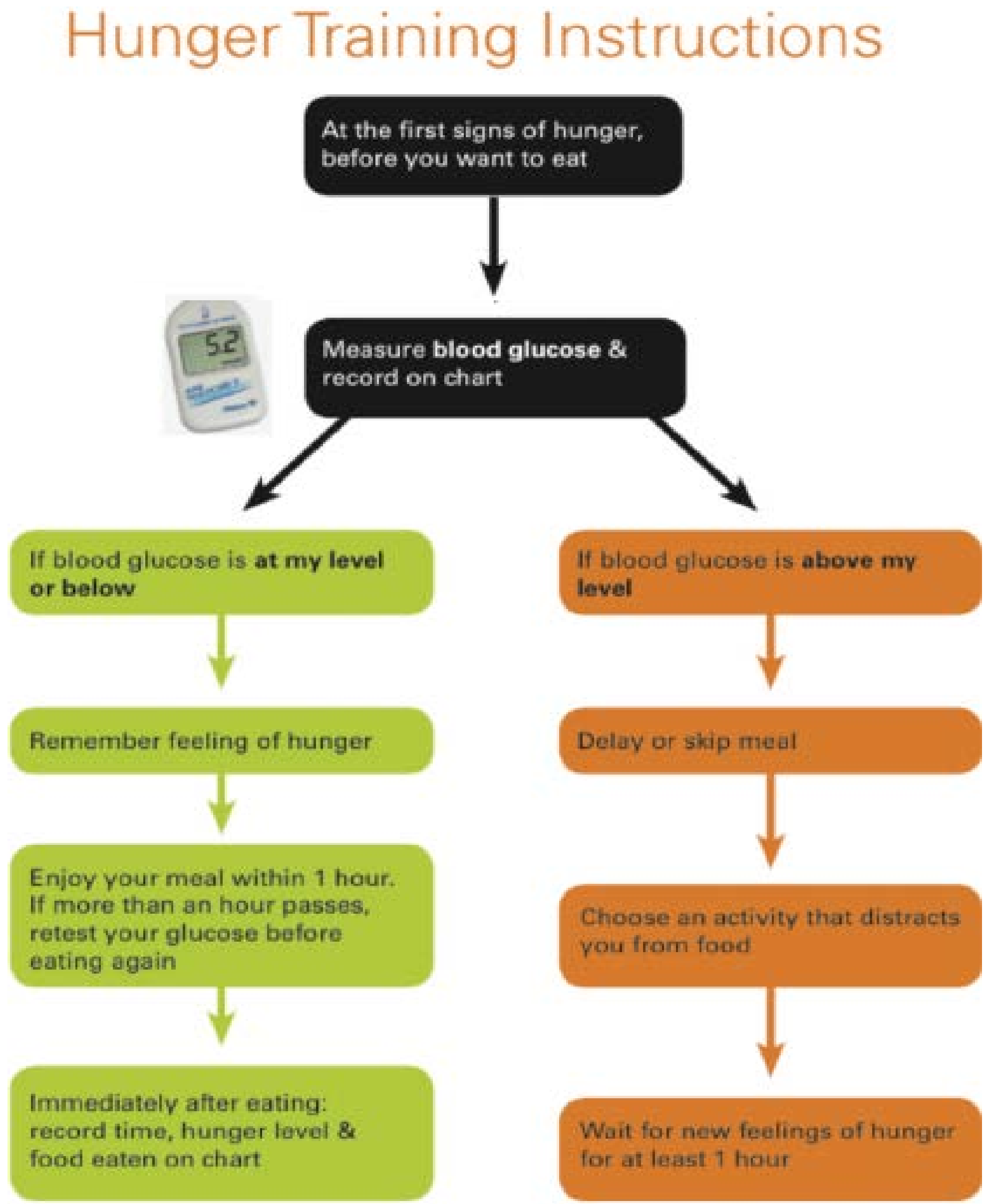
Maladaptive eating traits are associated with a over-sensitivity to hunger cues (not satiety).

Schembre, S. et al. / FASEB J. 23:B424.1 (2009) Meeting abstract

Using glucose monitoring to self-regulate eating behavior

Principles/Assumptions of Hunger training

- Eating in response to hunger facilitates energy homeostasis as an intermediary step in weight regulation.
- Eating behaviors that are not regulated by physiological signals of hunger have been empirically linked to weight gain.
- Blood glucose levels are an indicator of available short-term energy
- Individuals who are obese are less sensitive to elevated BG levels;
- Decreased sensitivity to BG levels - less likely to distinguish between ‘true’ hunger and the hedonic desire to eat.
- Sensitivity to physiological hunger cues can be (re)taught.



Hunger Training effectively reduces weight than traditional intensive lifestyle interventions

7 weeks of hunger training + 3 months follow-up

Ciampolini et al. 2010 Pre-meal BG< 85 mg/dl	Control (n=21)	All trained (n=38)	Trained Low BG (n=12)	Trained High BG (n=26)
5 month changes	Standard education	Standard education & 7 weeks hunger training		
Pre-meal BG (mg/dl)	+3.6	-8.0	+0.1	-11.7
Weight loss (kg)	-2.3	-5.8	-4.0	-6.7
Weight loss (%)	-3.0	-7.4	-5.2	-8.5
Energy intake (kcals)	-418	-687	-668	-697

Overweight and obese men and women

2 weeks of hunger training

Jospe et al. 2015	Cohort A (n=19)	Cohort B (n=10)
2 week changes	Pre-meal BG < 85 mg/dl	Pre-meal BG ≤ fasting
Weight loss (kg)	-1.1	-2.1
Weight loss (%)	-1.2	-2.3

Normal weight, overweight, and obese men and women

Ciampolini et al. (2010) Nutr. Metab.
Jospe et al. (2015) Nutr. Metab.

Project TwEATs using EMA to identify and classify maladaptive eating events

Remember these TREATs!!!

Text

Respond to hourly text messages asking you to rate your levels of hunger and stress for 7 days.

Record

Keep a record of every time you eat, how hungry you are, and your stress level at that time.

Email

Email us a picture (optional)

And **T**est

Blood glucose test

Goal: Provide empirical support for the principles of Hunger Training

Aim 1: Feasibility of collecting EMA data

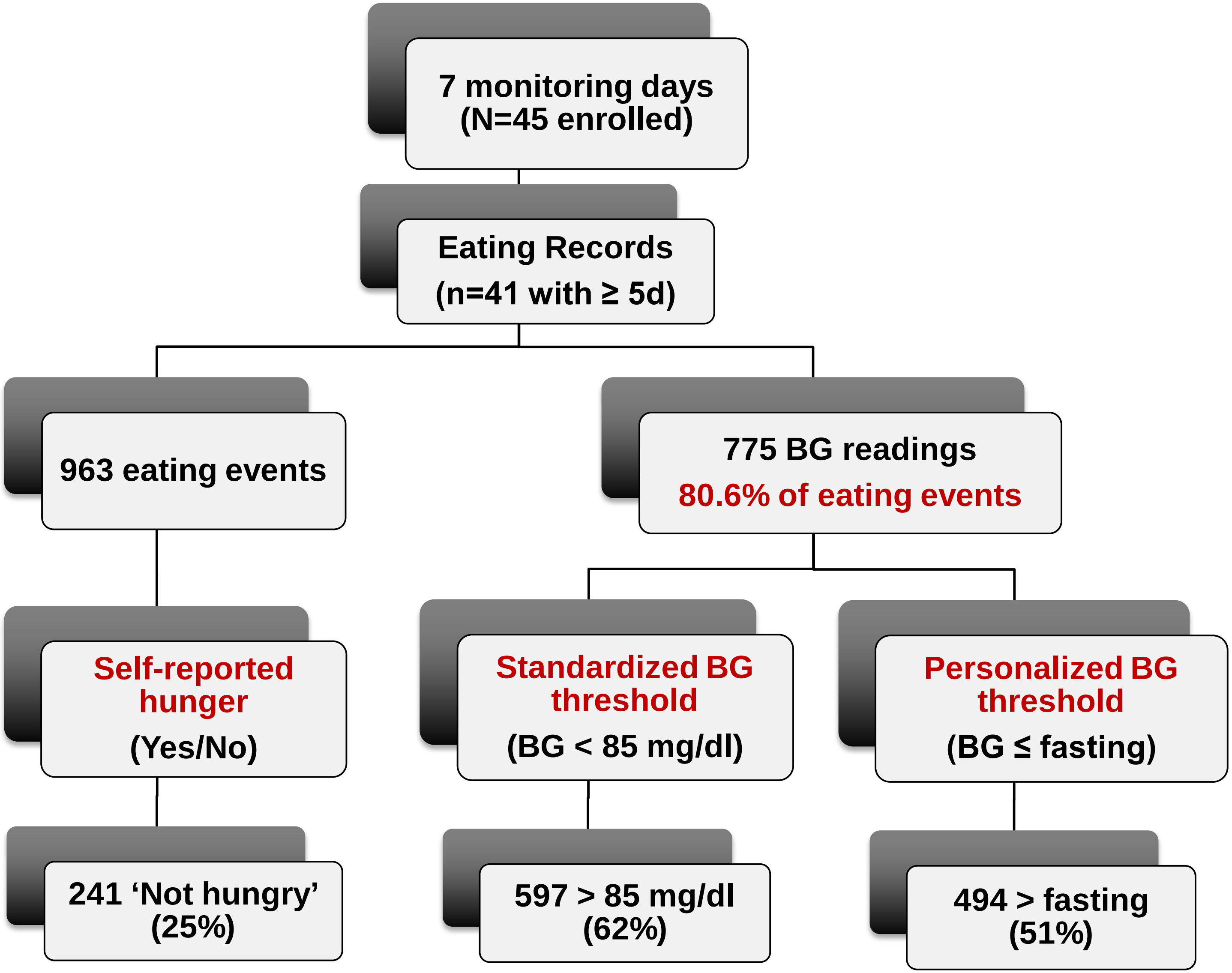
Aim 2: Explore discordance between perceived hunger and pre-defined BG thresholds

Aim 2a: Lean vs. overweight/obese

Aim 2b: Meals vs. snacks

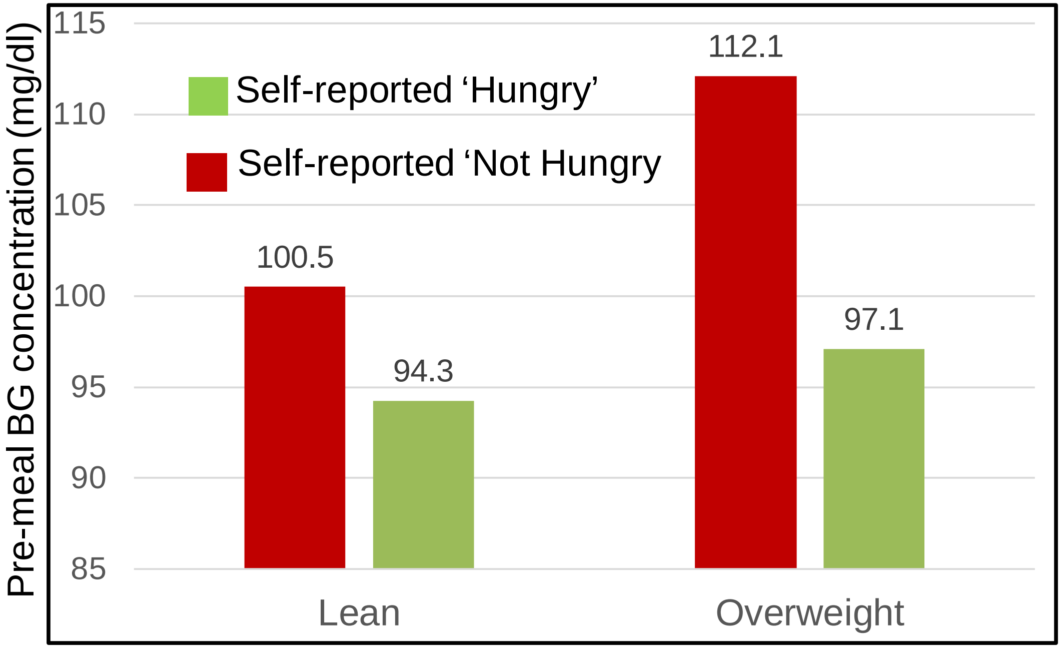
N=45 young men and women age 18-24 years; 38% overweight or obese

Project TwEATs event sampling results



Schembre and Yuen, 2012, Appetite
Schembre et al., In press

Project TwEATs results



Discordance rates (%)		All	Lean	Obese
Self-reported 'Hungry'	Standardized BG threshold (BG>85 mg/dl)	57.7%**	53.1%	66.9%
	Personalized BG threshold (BG>fasting)	47.7%*	43.8%	54.5%

** p<0.01; * p<0.05)

Summary of findings

- Lean were more sensitive than obese to pre-meal BG levels; reported being "Not hungry" at lower pre-meal BG levels ($p<0.01$)
- Eating when 'not hungry' was more likely to occur when snacking (not shown, $p<0.01$)
- Lean were less likely than obese to misclassify a 'not hungry' event ($p<0.05$)
- Snacks were less likely to be misclassified as a 'not hungry' eating event (not shown, $p=0.01$)
- Feasible, but 80% compliance with glucose monitoring protocol not optimal

Schembre and Yuen, 2012, Appetite
Schembre et al., Under review

Using Blood Glucose Dynamics to Provide Personalized Actionable Feedback in Interventions

Blood glucose (BG) represents short-term energy status (Campfield & Smith, 2003)

- Pre-meal BG indicates a biological need to eat

Pre-to-post-meal changes in BG results from the absorption of carbohydrates – a major dietary macronutrient

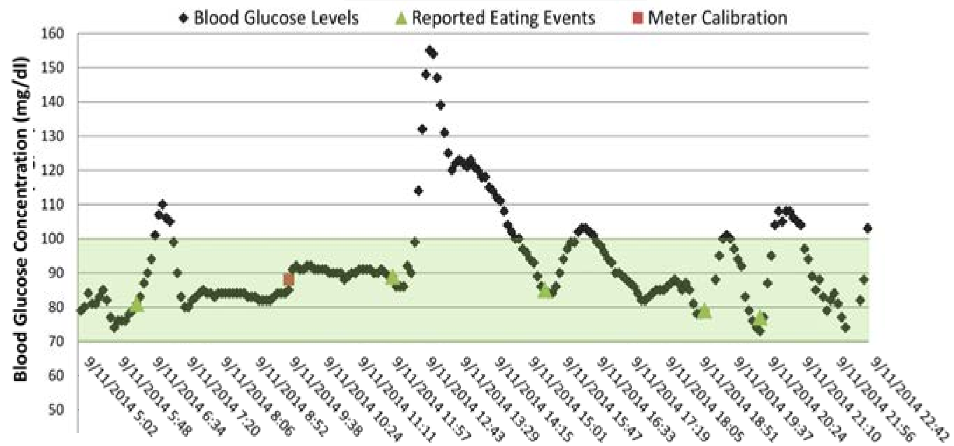
- BG dynamics as a biomarker of food intake and dietary glycemic quality

Elevated post-meal BG (≥ 140 mg/dl) is a risk factor for cardiovascular disease, type 2 diabetes, and diet-related cancers (Gerich et al., 2003; Liu et al., 2000; Barclay et al., 2008)

- Affects cell proliferation and tumorigenesis via modulation of the IGF axis, even in the absence of diabetes (Giovannucci, 2001 and 2007)

Today

The Future



Aims of Project SENSE

Primary aim: Examine the feasibility of collecting continuous glucose monitoring (CGM) data among free-living non-diabetic individuals

- Will healthy people wear a CGM and what do they think of it?
- Can we get useful data from the CGM?

Secondary aim: Explore the utility of using CGM data with the intent to provide actionable decision support for eating behaviors.

Pre-meal BG: To eat, or not to eat?

- Characterize eating events as occurring without physiological need

Post-meal BG: What was the (glycemic) quality of what I ate?

- Identify hyperglycemic responses.
- Characterize the glycemic response to foods.

Pre-to-post-meal BG: Did an eating event occur?

- Automating the detection of food intake.
- To what extent can we do the above without the self-report of eating.

Project SENSE – data collection

A 7-day* free-living observational study

- **Blood glucose monitoring**: Dexcom G4 continuous blood glucose monitor (CGM)
  - CGM measures BG in the interstitial fluid via small insertable sensor.
  - BG readings every 5 minutes during wear

- **Dietary intake**: (1) time-stamped in CGM, (2) food diaries self-reported in MyFitnessPal app, (3) time-stamped food photos by mobile phones.

- **Physical activity**: (1) time-stamped in CGM, (2) self-reported in MyFitnessPal app, (3) objectively measured by accelerometer

* 5 days of data used: first 2 days are “run-in” period and data are not intended for analyses

Sample Collected Data in One Day

Sunday, November 20, 2016

10:55 AM
Oatmeal, milk, coffee (**GL=39**)

1:51 PM
Turkey sandwich, lima beans, Cheetos (**GL=35**)

6:55 PM
Rice, chicken, squash, zucchini, beer (**GL=35**)

8:22 PM Ice cream (**GL=8**)

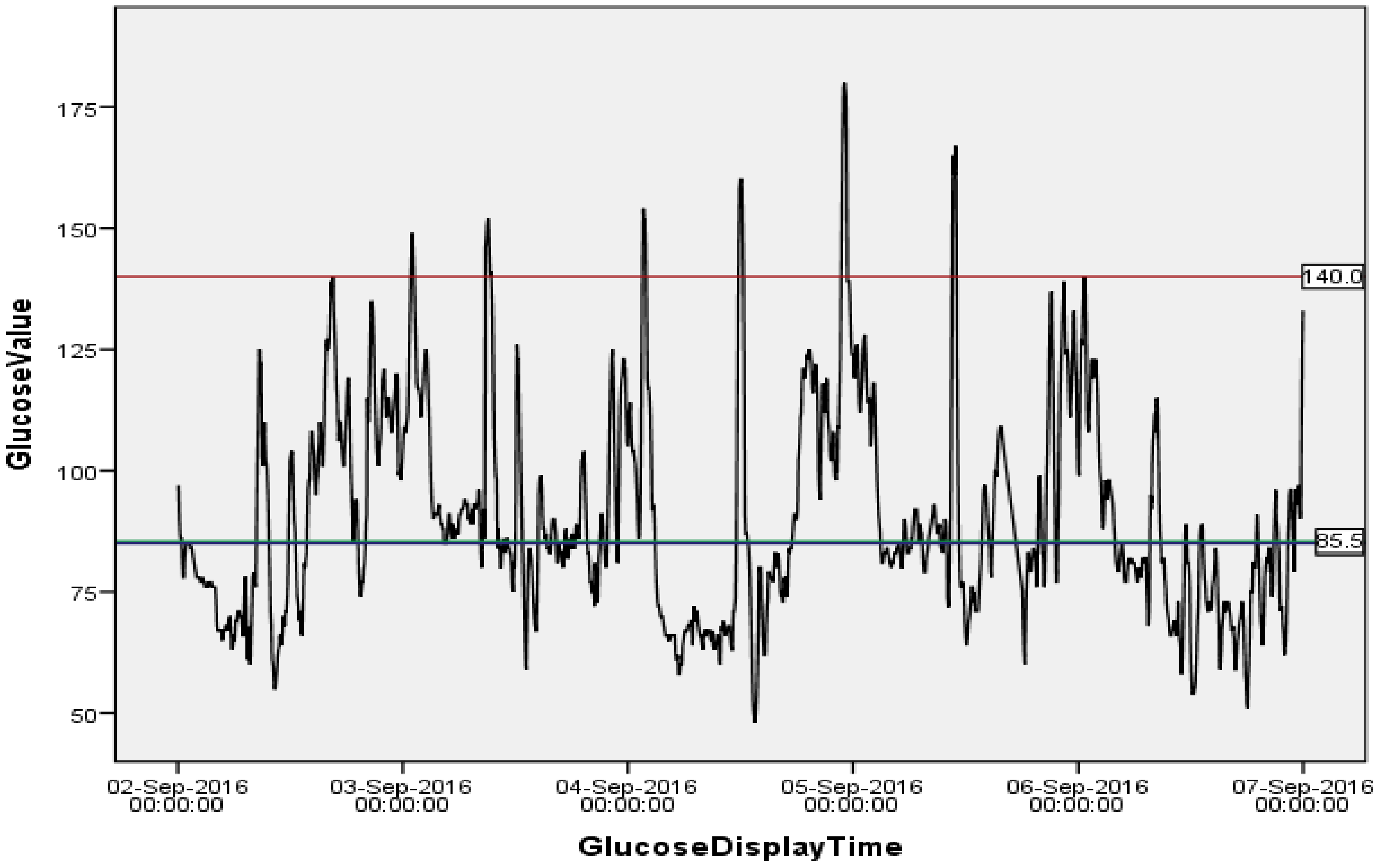
8:56 PM Popcorn (**GL=20**)

9:45 PM Beer (**GL=40**)

- 24 non-diabetic participants, 24 to 64 years old (M = 34.75, SD = 11.30), 75% female, 33.3% normal weight, 45.8% overweight, and 20.8% obese

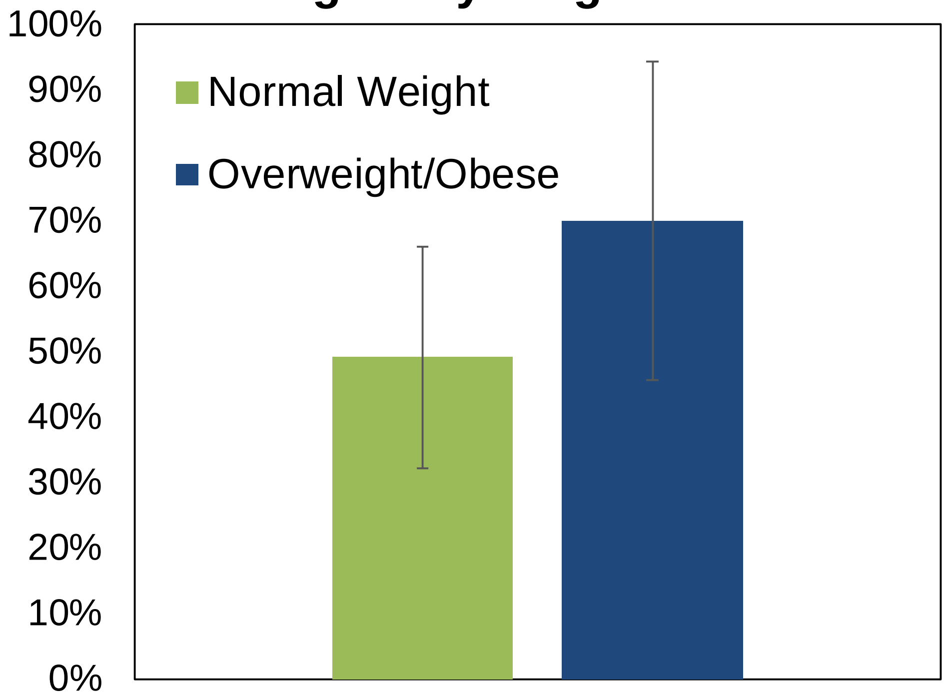
GL=Glycemic load, estimated from Nutrition Data System for Research (NDSR) based on food record from MyFitnessPal.

Sample Collected Data in One Week



Results from Project SENSE

Eating events occurring at BG > 85 mg/dL by weight status



t = -.17, *df* = 22, *p* = .041

Summary of findings: Participants on average reported 29 (SD = 11.8) eating events across the 5 analytical days

- 62.0% of those eating events occurred when BG > 85 mg/dL
- 43.5% occurred when BG > personalized fasting level
- Overweight or obese vs. lean had significantly more eating events occurring at a BG that was above the standardized threshold.
- On average, participants had 3 (SD = 4.4) hyperglycemic events

Frequency of hyperglycemic events by BMI status

	All	BMI<25	BMI≥25
Hyperglycemic events (freq.)	2.9±3.0	2.5±2.4	3.2±3.5

Schembre et al., In preparation

Automating the detection and characterization of food intake

Figure 4. Rates of blood glucose change in the 30 minutes before and after an eating event are significantly different (p < 0.001).

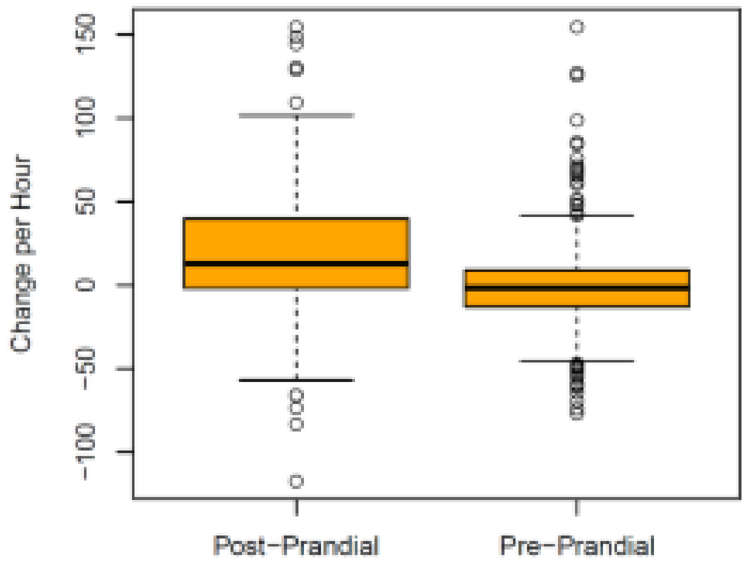
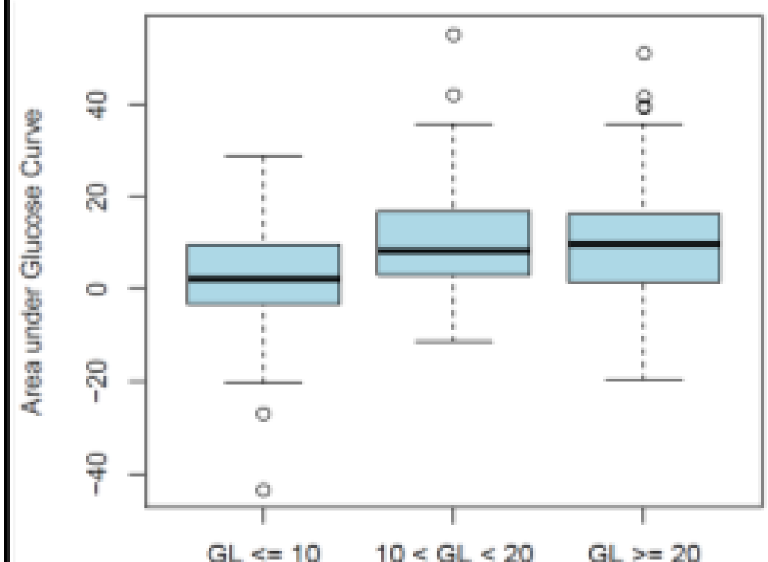


Figure 5. Blood glucose area under the curve varies significantly by eating events of low, medium, and high glycemic load (p < 0.001).



Rate of change in BG 30 minutes after a self-reported eating event are greater than in the 30 minutes prior to eating (p<0.001).

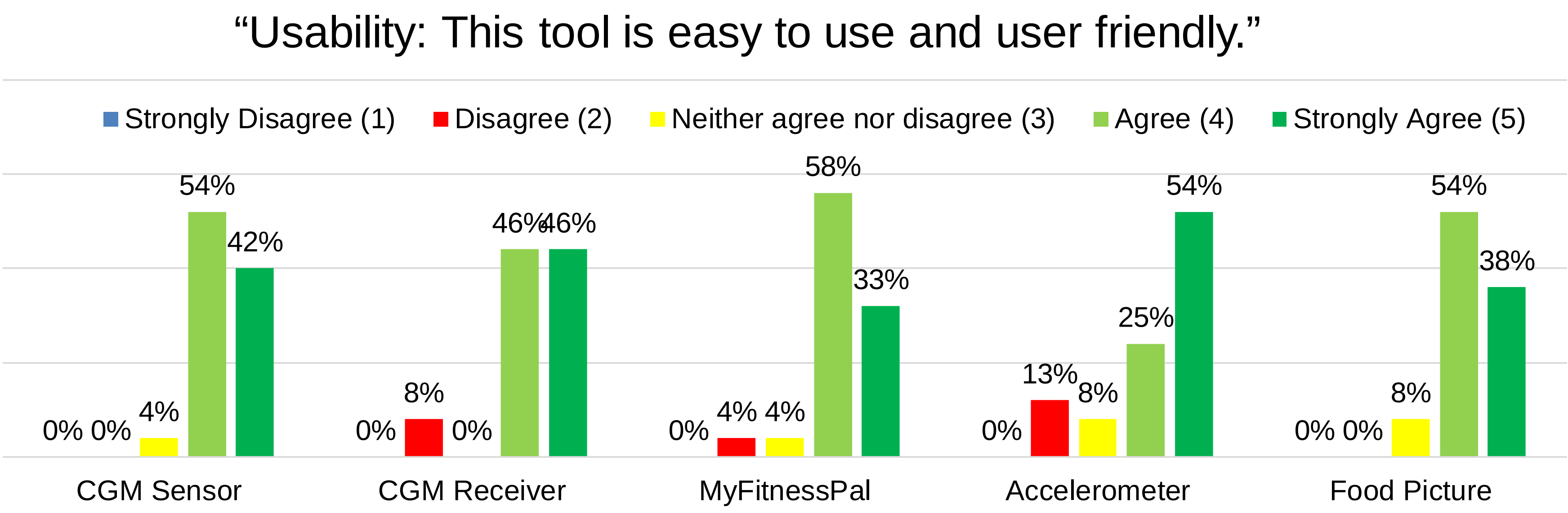
60 minute BG AUC vary by the computed glycemic load of a reported eating event (p<0.001).

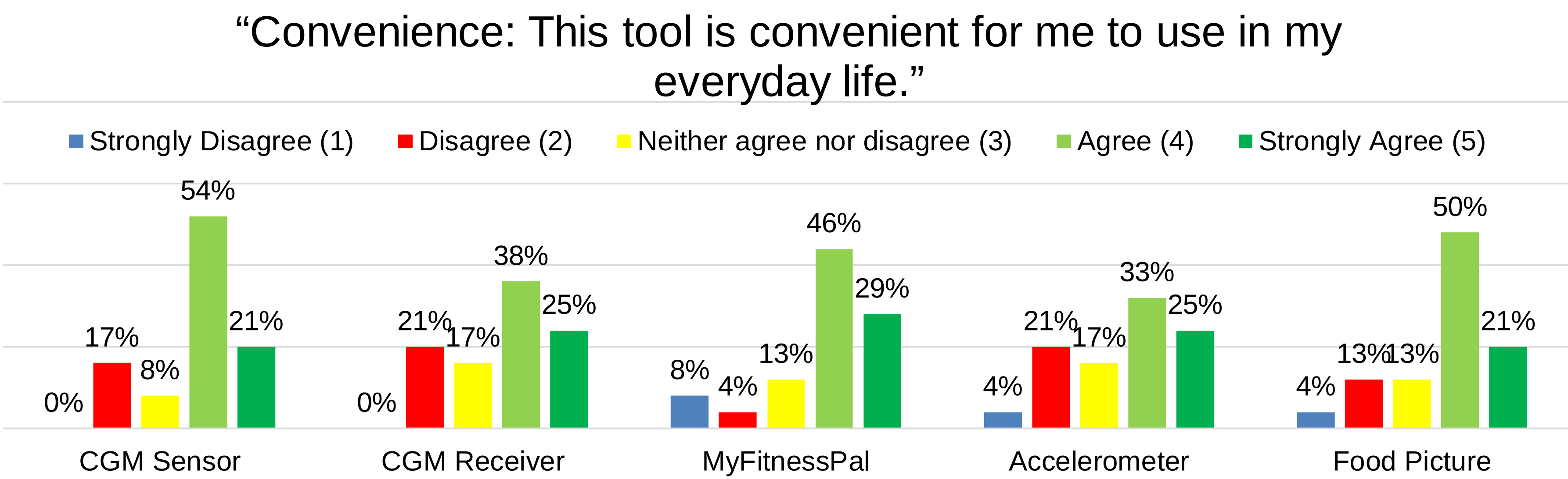
Schembre et al., In preparation

Participants' Experience with CGM

- 92% of participants agreed that the CGM device "was easy to use"
- 88% of participants agreed that the CGM sensor "was comfortable to wear"
- 64% of participants indicated that they would be willing to use a CGM device to help them achieve their health and wellness goals
- 91% indicated they would do so if the CGM sensor was non-invasive

Selected process evaluation data





Future Directions

SENSE 2.0: Automating food intake detection

- Just-in-time adaptive interventions
  - Personalized diet (and physical activity) feedback
  - Proactive decision support for people with diabetes
  - Weight control

Take CHARGE: **C**hoosing **H**ealth **a**nd Cancer **R**isk Reduction through **G**ood **E**ating and Exercise (NIH/NCI R21)

- Adding Hunger Training to the Diabetes Prevention Program (DPP)
- 50 obese women at risk for breast cancer
- 16 week pilot intervention
- Goal: Test synergistic effect of hunger training and DPP on weight loss
  - Feasibility of integrating hunger training (via CGM) into a ILI
  - Effects size estimates on weight loss (and cancer-related plasma biomarker outcomes)
- Future large-scale RCT will examine weight maintenance outcomes

Advancing health behavior interventions

MD2K
https://www.youtube.com/watch?v=uSQn2puExxM#action=share

- **Thrust 1:** Mobile Sensor Data-to-Information
- **Thrust 2:** Mobile Sensor Information-to-Knowledge
  - Decision making
  - JITAI
- **Thrust 3:** MD2K – Computation
- **Thrust 4:** MD2K-Applications

Sensor-Based Feedback in Health Behavioral Change Interventions

- Advancement in wearable sensor technologies has automated the self-monitoring and feedback process.
- Use body sensors to unobtrusively and automatically detect health behaviors.
- Process the data through algorithms designed to quantify current performance.
- Enhance the bi-directional communication between participants/patients and researchers.
- Deliver messages that prompt healthy decision making at critical moments to achieve health-related goals.
- Sensors that measure health-related biomarkers could be used to define critical moments – glucose, heart rate variability.

A new paradigm shift in behavior change science

- Sensor-based, real-time interventions reflect a new paradigm shift in behavior change science.

- How do we get the most of just-in-time interventions?

- How do we optimize the delivery of real-time feedback?
  - Timing
  - Content

- Optimization of real-time feedback content and timing and frequency
  - Micro-randomization – timing and frequency
  - Multiphase optimization strategy (MOST) – content

Systematic review of real-time feedback used in energy-balance related interventions

Objective

- Synthesize data on the content characteristics of real-time feedback used in energy balance-related behavior change interventions
- Propose a framework for the design of real-time feedback in future interventions.

Theoretical foundation

- Control Theory - behavior is goal-driven; behavior change occurs in response to feedback on current performance relative to a behavioral goal.
- Feedback Intervention Theory - feedback motivates behavior change by focusing one's attention on the behavioral task itself

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Included studies

- N=32 intervention studies published through 2016
  - Physical activity (47%)
  - Diet and physical activity (41%)
  - Diet only (9%)
  - Self-weighing (3%)

4 key characteristics of real-time feedback

- Consistent with Control Theory 4 key characteristics emerged:
  - **Timeliness** of feedback
    - Continuous feedback 31%
    - Multiple times of day 10%
    - Daily 69%
  - Level of **personalization**
    - Team-based feedback 3%
    - Person-level feedback 97%
  - **Goal-orientation**
    - Self-selected, incremental, or adaptive goals 38%
    - Static/standardized recommendations 38%
  - **Action-orientation**
    - Included explicit communication of what to do and how and when to do it 16%

Real-time feedback efficacy

	Significant effects (n=4)	**Non-significant effects (n=5)**
Timely*	100%	100%
Personalized	100%	100%
Continuously-available	75%	20%
Goal-oriented	75%	60%
Actionable	75%	40%

*Study inclusion criteria

Real-time feedback that is <u>continuously-available</u>, <u>personalized</u>, and <u>actionable</u> relative to a known <u>behavioral objective or goal</u> is prominent in intervention studies with significant behavior change outcomes.

Testable model for real-time feedback content design

Real-Time Behavioral Objectives

Goals

- Reflects a desired outcome.
- Self-selected, adaptive, or standardized.
- Incrementally achieved over the day.

Targets

- Intermediate marker of a desired outcome.
- Pre-set range or threshold.
- Maintained within a specific time-interval or moment-to-moment.

Key Feedback Components

Timely

- Reflects recent behavior.
- Aims to improve the likelihood of meeting goal/target.
- Communicated passively (vs. user-initiated) to proactively motivate behavioral adjustments.

Personalized

- Based on the individual's own performance.
- Aims to redirect one's attention to their current performance relative to a behavioral goal/target.
- Communicated visually as graphs/charts or quantified verbally or as text.

Actionable

- Specifies an action plan (WHAT, WHEN, and HOW).
- Aims to reduce the discrepancy between current performance and the behavioral goal/target.
- Communicated as a behavioral prompt.

Assessment

- Cognitive load: Passive monitoring vs. self-monitoring
- Quality: Objective vs. self-reported
- Frequency: Continuous vs. specified intervals

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Considerations for future mHealth interventions

- Objective vs. subjective data
- Privacy concerns
  - Big brother
  - People trust doctors to keep information confidential
- HIPAA compliance
  - Compromised transmission of PHI
- Security issues
  - Third-party hackers
  - Terrorist threat

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