‘Reducio’: The Magical Potential of New Technologies to Deliver and Evaluate Nutrition Interventions
My talk today

1. Scanner sales data
   a) Monitoring trends in population diets over time
   b) Evaluating natural experiments/new policies

2. Smartphone apps
   a) Undertaking a labelling RCT
   b) Co-designing an mHealth tool with communities

3. Wearable cameras
   a) Improving dietary assessment
   b) Measuring children’s exposure to food marketing

4. Virtual supermarket
   a) Experiments
   b) Education tool
New Zealand?
NZ also world leader in obesity

Note: The statistical data for Israel are supplied by and under the responsibility of the relevant Israel authorities. The
'Reducio'

Makes an enlarged object smaller
Obesity: shaped by global drivers & local environments

Swinburn et al, Lancet 2011

Population effect and political difficulty

(& research difficulty)
Food policy research challenges
Any sufficiently advanced technology is indistinguishable from magic

Arthur C. Clark
Welcome to DIET

Volunteers wanted!

A new and exciting Public Health study is being used to look at the effects of changing price on food and drink purchases. Check out more details, including how to join here.

Food composition & reformulation

Food taxes & subsidies

Food marketing to kids

www.diet.auckland.ac.nz
Scanner Sales Data
SHOP RCT 2006-2009

1,104 trial participants
8 supermarkets
15 months scanner sales data
55 supermarket shops per participant

Ni Mhurchu et al, Am J Clin Nutr 2010
**Nutritrack**

4 supermarket chains

20 fast food chains

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**Database of NZ packaged and fast foods**
- Nutritional composition
- Pack/serve size
- Labelling and claims
- Ingredients
- Photographs

<table>
<thead>
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</tr>
</thead>
<tbody>
<tr>
<td>Supermarket foods</td>
<td>6,020</td>
<td>8,440</td>
<td>13,406</td>
<td>14,191</td>
<td>14,436</td>
<td>15,370</td>
</tr>
<tr>
<td>Fast foods</td>
<td>608</td>
<td>2,310</td>
<td>2,940</td>
<td>2,945</td>
<td>3,055</td>
<td>3,589</td>
</tr>
<tr>
<td>Annual total</td>
<td>6,628</td>
<td>10,750</td>
<td>16,346</td>
<td>17,136</td>
<td>17,491</td>
<td>18,959</td>
</tr>
<tr>
<td>Total products in database</td>
<td>6,628</td>
<td>17,378</td>
<td>33,724</td>
<td>50,860</td>
<td>68,351</td>
<td>87,310</td>
</tr>
</tbody>
</table>
Monitoring the food supply

Figure 1: Mean difference in the sodium content of key processed food products available for sale in both 2003 and 2013 (n=182)

Changes in the Sodium Content of New Zealand Processed Foods: 2003–2013

David Monro 1, Cliona Ni Mhurchu 2, Yannan Jiang 2, Delvina Gorton 4 and Helen Eyles 2 3, 4

Article
Effects of voluntary programmes

Changes in the sodium content of bread in Australia and New Zealand between 2007 and 2010: implications for policy

Dunford et al, Med J Aust 2011
Integrating sales data: NutriSales

• Nielsen Homescan
• Household consumer panel (n~2,500), representative of NZ population
  – Scan all grocery items taken into the home
  – Geographically, demographically representative
  – Weighted data represent 75% of annual national grocery sales
  – 2 million rows of data
  – >29,000 unique food and non-alcoholic beverage products per year
Achieving the WHO sodium target: estimation of reductions required in the sodium content of packaged foods and other sources of dietary sodium¹⁻³

Helen Eyles,⁴,⁵* Emma Shields,⁴ Jacqui Webster,⁶ and Cliona Ni Mhurchu⁴

FIGURE 1  The 6-step process used to develop the sodium reduction model.

Eyles et al, Am J Clin Nutr 2016
Effects of labels on reformulation

The more stars, the healthier.

- **HEALTH STAR RATING**
  - 5

- **ENERGY**
  - 1520kJ

- **SAT FAT**
  - 0.3g

- **SUGARS**
  - 0.8g

- **SODIUM**
  - 5mg

**PER 100g**

- **Source of protein and fibre**

- **Reduced Sugar**

- **Low fat**

- **Choco Ice Flavoured**

- **Liquid Breakfast**

- **Up & Go**

- **Wattie’s Tomato Sauce**
Reformulation of labelled (HSR) vs non-labelled (non-HSR), 2014-16

Estimates weighted by household purchase volumes
Other examples

Effect of a price discount and consumer education strategy on food and beverage purchases in remote Indigenous Australia: a stepped-wedge randomised controlled trial

Julie Brimblecombe, Megan Ferguson, Mark D Chatfield, Selma C Liberato, Anthony Gunther, Kylie Ball, Marj Moodie, Edward Miles, Anne Magnus, Cliona Ni Mhurchu, Amanda Jane Leach, Ross Bailie, on behalf of the SHOP@RCH research collaborative

Influence of price discounts and skill-building strategies on purchase and consumption of healthy food and beverages: outcomes of the Supermarket Healthy Eating for Life randomized controlled trial1–3

Kylie Ball, Sarah A McNaughton, Hu ND Le, Lisa Gold, Cliona Ni Mhurchu, Gavin Abbott, Christina Pollard, and David Crawford

Beverage purchases from stores in Mexico under the excise tax on sugar sweetened beverages: observational study

M Arantxa Colchero,1 Barry M Popkin,2 Juan A Rivera,3 Shu Wen Ng2

By Lindsey Smith Taillie, Shu Wen Ng, and Barry M. Popkin

Gains Made By Walmart’s Healthier Food Initiative Mirror Preexisting Trends
Smartphone Apps
FoodSwitch app
SaltSwitch RCT

Significant reduction in household purchases of salt (mean difference 0.30 (-0.58 to -0.03) g/MJ), equivalent to reduction of ~0.7 g salt per person per day over 4-week intervention

Eyles et al, Eur J Prev Cardiol In press
Effects of nutrition labels on consumer food purchases
Research questions

1) What effects do interpretive nutrition labels have on the average healthiness (FSANZ nutrient profile score) of consumer packaged food purchases?

2) What effects do interpretive nutrition labels have on nutrients purchased (energy, sugar, sodium, saturated fat), food expenditure, and self-reported label usefulness and nutrition knowledge?
Study design

Registration and 1-week run-in

Randomisation

HSR

TLL

NIP

1-month follow-up of all packaged food purchases
Intervention delivery

Scan for Label

Yoplait Vanilla

Each serve (125 g) contains

- Energy: 470 kJ
- Fat: 3.6 g (5.0 %)
- Sat Fat: 2.4 g (13.0 %)
- Sugars: 12.8 g (14.0 %)
- Salt: 0.1 g (2.0 %)

of an adult’s daily intake

OTHER CHOICES

- Meadow Fresh Live Lit...
- Clearwater’s Cream To...
- Piaiko Gourmet Yoghurt
Consent & baseline data collection

Volkova et al, JMI\textit{R} m\textit{H}ealth u\textit{H}ealth 2016
Food purchasing data collection

Starlight study team
National Institute for Health Innovation
University of Auckland

Volkova et al, *JMIR mHealth uHealth* 2016
Flow chart

Registered ($n=2448$)

Excluded ($n=1035$)

Randomised ($n=1413$)

- **HSR** ($n=471$)
  - Analysed ($n=443$)

- **TLL** ($n=472$)
  - Analysed ($n=459$)

- **NIP** ($n=470$)
  - Analysed ($n=455$)

280,000 packaged food & beverage purchases recorded
Healthiness of food purchases

Co-design of mHealth tool for diabetes and obesity prevention
Community/academic partnership
Co-design theory

Work with users to establish goals

Learn about users’ needs and experiences

Turn ideas into possible interventions

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Boyd H et al, NZ Med J 2012
Co-design in practice
OL@-OR@ features

• General
  • Customizable content
  • Linkage with social media platforms
  • Share info with friends/family
  • Add and share recipes
  • Activity planner & calendar
  • Healthy tips (SMS or app notifications)
  • Achievement badges
  • Goal tracker

• Unique
  • Holistic model of wellbeing
  • Relationships and connectedness - group challenges, community/family goals
  • Indigenous knowledge
  • Use of ancestry and traditions to engage users
  • Culturally relevant healthy food information
Wearable cameras
Under-reporting remains a key limitation of self-reported dietary intake: an analysis of the 2008/09 New Zealand Adult Nutrition Survey

1997
Women: 21% Low energy reporters, 79% High energy reporters
Men: 12% Low energy reporters, 88% High energy reporters

2008/9
Women: 21% Low energy reporters, 75% High energy reporters
Men: 21% Low energy reporters, 79% High energy reporters
Image-assisted dietary assessment
Wearable cameras reduce dietary underreporting

- 40 healthy volunteers, Auckland, NZ
  - Wore SenseCam for 4 days over a 15-day period
  - Completed interviewer-administered 24hr recall on day 3, 9, 14
  - Viewed SenseCam images and provided additional information

- Viewing SenseCam images reduced energy under-reporting by 8% in men & 6% in women compared with 24h recall alone (p<0.001)

- Mainly due to reporting of 265 additional (forgotten/omitted) foods across a range of food groups

Social & environmental context

Contexts assessed

Location
- At home
- Occupation
- Restaurant/Bar/Café
- Other

Environment
- Indoor
- Outdoor
- In vehicle
- Mixed

Physical Position
- Sitting at table
- Sitting on sofa
- Sitting at desk
- Standing/Active
- Other

Social Interaction
- Social interaction
- Social – no interaction
- Not social

Media Screens
- Television
- Computer
- Handheld device
- Multiple devices
- No screen

Gemming et al, Appetite 2015
Measuring children’s exposure to food marketing

Kids’Cam
Research questions

1. What is the frequency and duration of children’s exposure to food and beverage marketing?

2. Are there differences by setting, ethnicity and socioeconomic position?
Methods

- 168 NZ children aged 11-13 years
- Data collection July 2014 – June 2015
- Wore automated cameras and GPS devices for 4 days (2 weekdays & 2 weekend days)
- Cameras captured images automatically every 7 seconds (~1.5 million images collected)
- All foods and beverages in images coded as core or non-core (WHO nutrient profiling system) by setting, marketing medium, product category

NZ children exposed to junk food marketing mean of 27.3 times a day; >twice their exposure to core food marketing (12.3/day)

Sugary drinks, fast food, confectionary and snack foods were most commonly encountered junk foods

Most junk food exposures occurred at home (33%), in public spaces (30%) and at school (19%)
Kids’Cam data also being used to measure kids’ exposure to:

• Alcohol
• Smoking & smoke-free promotions
• Gambling & Lotto signage
• Greenspace
• Active transport
• Housing quality etc.
Virtual Supermarket
Virtual Supermarkets

[Images of virtual supermarket graphics]
Research report

Effects of a price increase on purchases of sugar sweetened beverages. Results from a randomized controlled trial

Wilma Elzeline Waterlander a,b,*, Cliona Ni Mhurchu b, Ingrid H.M. Steenhuis a

a Department of Health Sciences and the EMGO Institute for Health and Care Research, Faculty of Earth and Life Sciences, VU University Amsterdam, De Boelelaan 1085, 1081 HV Amsterdam, The Netherlands
b National Institute for Health Innovation, School of Population Health, The University of Auckland, Tamaki Campus, Private Bag 52019, Auckland Mail Centre, Auckland 1142, New Zealand

Abstract

Sugar sweetened beverage (SSB) taxes are receiving increased political interest. However, there have been no experimental studies of the effects of price increases on SSBs or the effects on close substitutes such as diet drinks, alcohol or sugary snacks. Therefore, the aim of this study was to examine the effects of a price increase on SSBs on beverage and snack purchases using a randomized controlled design within a three-dimensional web-based supermarket. The trial contained two conditions: experimental condition with a 15% tax on SSBs (to reflect an increase in Dutch value added tax from 6% to 19%), and a control condition with regular prices. N = 102 participants were randomized and purchased groceries on a single occasion at a three-dimensional Virtual Supermarket. Data were analysed using independent t-tests and regression analysis. Results showed that participants in the price increase condition purchased significantly less SSBs than the control group (β = −0.90; 95% CI= −1.70 to −0.10 L per household per week). There were no significant effects on purchases in other beverage or snack food categories. This means that the higher VAT rate was effective in reducing SSB purchases and had no negative side-effects.

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Work to date

• 7 Virtual Supermarket experiments
  – Pricing, labelling, placement etc.

• High internal validity, independent of food manufacturers and retailers, adaptable, easy recruitment

• 4 regional variants
  – Netherlands, NZ, UK, Australia

• Testing impact of sound, smell, décor etc.
How real is Virtual Reality?

Original Paper

Using a 3D Virtual Supermarket to Measure Food Purchase Behavior: A Validation Study

Wilma Elzeline Waterlander¹, BSc, MSc, PhD; Yannan Jiang¹, BSc, MSc, PhD; Ingrid Hendrika Margaretha Steenhuis², MSc, PhD; Cliona Ni Mhurchu¹, BSc (Hons), PhD

¹National Institute for Health Innovation, School of Population Health, University of Auckland, Auckland, New Zealand
²Department of Health Sciences and the EMGO Institute for Health and Care Research, Faculty of Earth and Life Sciences, VU University Amsterdam, Amsterdam, Netherlands
How real is Virtual Reality?

% Expenditures

N=86

Virtual \hspace{1cm} Real
Improving food price elasticity estimates

Price ExAM study methods

5 tax/subsidies:
- SSB tax
- F&V subsidy
- Saturated fat tax
- Sugar tax
- Salt tax

1,132 participants
4,259 shops completed

Waterlander et al, BMC Public Health 2016
### Lunches: School Lunches

The table below contains pictures of lunches for a teacher and her Year 11 students at Carbo High School.

What do you think about each of the lunches? Make sure you think about the person’s activities during the afternoon.

Use the Virtual Supermarket and the traffic lights to look for foods that could be healthier options for these lunches.

<table>
<thead>
<tr>
<th>Scenario</th>
<th>Lunch</th>
<th>What do you think about the lunch?</th>
<th>How can they have healthier lunches?</th>
</tr>
</thead>
<tbody>
<tr>
<td>Mrs Potter is a teacher taking classes from 12 noon to 3.30 pm</td>
<td>Coffee and cake</td>
<td>Low in fat and low in sugar</td>
<td>Adding a fruit or vegetable snack would increase the nutritional value.</td>
</tr>
<tr>
<td>Jenny is a student with diabetes</td>
<td>Apple and sandwich</td>
<td>Low in fat and high in sugar</td>
<td>Using low-fat cheese and whole-grain bread would make it healthier.</td>
</tr>
<tr>
<td>Josh is a student with a 3 hour Biology exam in the afternoon</td>
<td>Banana and peanut butter sandwich</td>
<td>Low in fat and high in sugar</td>
<td>Choosing a sandwich with a different spread (e.g., hummus) would reduce sugar.</td>
</tr>
<tr>
<td>Blake is a student playing rugby after lunch</td>
<td>Cheese and vegetable sandwich</td>
<td>High in fat and low in sugar</td>
<td>Using low-fat cheese and adding more vegetables would improve the balance.</td>
</tr>
</tbody>
</table>

### Lunches: Planning for the Family

Design and prepare lunches for your family for an entire week.

Use the virtual supermarket to find food items and ingredients to design the lunches.

Do you think you should include the following food items in your lunch plan?

- Beetroot (canned), carrots, celery, cucumber, red peppers
- Cheese, chicken, eggs, ham, baked beans
- Pear, kiwifruit
- Pita bread, panini, wraps, crackers, pasta
- Peas, peanut butter, cream cheese, hummus

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**Tips:**

- When preparing lunches, think about the balance of nutrients.
- Consider including a variety of food groups.
- Think about the weather and physical activities to ensure the meals are appropriate.

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**Option:**

- You could make the lunches for your family!

**Action:**

- Take photos of your prepared lunches, post and share the pictures with friends through the LENS Science online forum:
  - [http://lenscience.ac.nz/community-groups/my-food-my-future](http://lenscience.ac.nz/community-groups/my-food-my-future)
Final words from a FoodSwitch user

Finally my smart phone, that has introduced me to a thousand things I didn't know I needed, has something useful and important to do!!!!!

Imagine if people in supermarkets up and down the country were seen to be regularly using this tool how much influence that would have on food manufacturers, government regulators and politicians.

Let all those consumers who care about what they eat but have difficulty using the existing food labelling effectively get out there and show those groups what we really want.
Now that’s magic!
Research teams and funders

DIET programme

- Tony Blakely, Boyd Swinburn, Helen Eyles, Wilma Waterlander, Yannan Jiang, Louise Signal, Bruce Neal, Mike Rayner, Katya Volkova, Rachel Carter, Luke Gemming
  - Funded by Health Research Council of New Zealand (13/724)

OL@-OR@

- Lisa Te Morenga, Riz Firestone, Andrew Jull, Robyn Whittaker, Marjolein Verbiest, Jacqui Grey, Debbie Goodwin, Callie Corrigan, Crystal Pekepo, Rangimarie Mules, Akarere Henry, Tevita Funaki, Sally Dalhousie, Mereauamate Vano, Gayl Humphrey
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Thank you

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