Evaluation of Public Health Interventions: Recent Developments in Cluster Randomized Trials and Related Designs

Department of Epidemiology & Biostatistics, GWU, March 26 2018

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Overview

1. Motivating example
2. Clustering
3. Small # clusters & baseline covariate imbalance
4. Stepped wedge designs
Cluster randomized trials
Motivating example
Background and motivation

Health and Literacy Intervention (HALI) cluster randomized trial (CRT)

• 101 schools: 51 intervention and 50 control
  ~ 5000 children → ~ 50/school

• Intervention: screen & treat 1/term for 2 years

• Primary endpoint: malaria (yes vs. no) at 24 months
Background and motivation
Health and Literacy Intervention (HALI) cluster randomized trial (CRT)

Hypothesis: screening and treating children for malaria will lead to reduced prevalence of malaria
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Factors related to malaria: age, geographic location, bed-net use etc.
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Health and Literacy Intervention (HALI) cluster randomized trial (CRT)

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Health and Literacy Intervention (HALI) cluster randomized trial (CRT)

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Health and Literacy Intervention (HALI) cluster randomized trial (CRT)

Level 2: Randomization at clinic (i.e., cluster) level

- Malaria screening and treatment
- Factors related to malaria (e.g., age, bednet use)

Level 1: Individual-level outcomes nested in schools
Background and motivation
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Level 1: Individual-level outcomes nested in schools

Child-level outcomes within same school expected to be correlated with each other (i.e., to cluster)
Background and motivation

Health and Literacy Intervention (HALI) cluster randomized trial (CRT)

Level 2: Randomization at clinic (i.e., cluster) level

Malaria screening and treatment

Factors related to malaria (e.g., age, bednet use)

Malaria

Level 1: Individual-level outcomes nested in schools

Child-level outcomes within same school expected to be correlated with each other (i.e., to cluster)

Reduces power to detect treatment effect if same sample size used as under individual randomization
Implications of using CRT design

• CRT (statistical) price to pay
  • Lower power for same total sample size under individual randomization
  • Harder to detect an intervention effect

• So why use CRT design?
  • Intervention at cluster level (e.g., pump in village)
  • To avoid treatment contamination under individual randomization (e.g., HALI trial)
  • Logistically easier to implement trial
HALI trial
Two published outcomes papers

Impact of Intermittent Screening and Treatment for Malaria among School Children in Kenya: A Cluster Randomised Trial

Katherine E. Halliday\textsuperscript{1*}, George Okello\textsuperscript{2}, Elizabeth L. Turner\textsuperscript{3}, Kiambo Njagi\textsuperscript{4}, Carlos Mcharo\textsuperscript{5}, Juddy Kengo\textsuperscript{5}, Elizabeth Allen\textsuperscript{6}, Margaret M. Dubeck\textsuperscript{7}, Matthew C. H. Jukes\textsuperscript{8}, Simon J. Brooker\textsuperscript{1,9}

Improving Literacy Instruction in Kenya Through Teacher Professional Development and Text Messages Support: A Cluster Randomized Trial

Matthew C. H. Jukes\textsuperscript{a,b}, Elizabeth L. Turner\textsuperscript{c}, Margaret M. Dubeck\textsuperscript{a,b,d}, Katherine E. Halliday\textsuperscript{e}, Hellen N. Inyega\textsuperscript{f}, Sharon Wolf\textsuperscript{g}, Stephanie Simmons Zuilkowski\textsuperscript{h}, and Simon J. Brooker\textsuperscript{e}
HALI trial
Two published outcomes papers

Impact of Intermittent Screening and Treatment for Malaria among School Children in Kenya: A Cluster Randomised Trial

Katherine E. Halliday*, George Okello², Elizabeth L. Turner³, Kiambo Njagi⁴, Carlos Mcharo⁵, Juddy Kengo⁶, Elizabeth Allen⁶, Margaret M. Dubeck⁷, Matthew C. H. Jukes⁸, Simon J. Brooker¹,⁹

Note: no evidence of an effect of intervention on malaria prevalence
HALI trial
Two published outcomes papers

Evidence of an effect on literacy outcomes due to a teacher intervention evaluated in same trial
Cluster randomized trials

Design challenge: clustering
Baseline clustering: malaria prevalence by school

Halliday, Karanja, Turner et al. (2012), Tropical Medicine & International Health, 17(5): 532-549
Complete clustering (ICC = 1)

>1 child /school gives no more information than 1 child/school since every child in a given school has the same outcome
No clustering (ICC = 0)

- Malaria
- No malaria

20% prevalence of malaria in each school
No structure by school - more like a random sample of children
Some clustering ($0 < \text{ICC} < 1$)

- Malaria
- No malaria

A more typical situation: e.g., cluster-prevalence 0% - 80%
Clustering in CRTs

• Outcomes in same clusters more similar to each other than to those in other clusters

• Previous example
  • 50 children in 10 schools
  • Effective sample size between 10 – 50

• Implications for statistical inference

• Major challenge in design & analysis
Measure of clustering: ICC

Intra-cluster correlation coefficient (ICC, $\rho$)

- Most commonly used measure of clustering
- Ranges: 0-1; 0 = no clustering; 1 = total clustering
- Typically < 0.2, commonly around 0.01 - 0.05

ICC for continuous outcomes:

$$\rho = \frac{\sigma^2_B}{\sigma^2_B + \sigma^2_W} = \frac{\sigma^2_B}{\sigma^2_{Total}}$$

- Involves both Between-cluster & Within-cluster variance
Clustering in CRTs: implications for analysis

- 5 schools each randomized to control and intervention
- 100 eligible participants per clinic measured

Example from Hayes & Moulton (2009)
Clustering in CRTs: implications for analysis

- 5 schools each randomized to control and intervention
- 100 eligible participants per clinic measured

Overall malaria prevalence in each trial: 10% vs 6%

**Question**: is intervention effective?
Clustering in CRTs: implications for analysis

Which trial shows more evidence of benefit?

Example from Hayes & Moulton (2009)
Clustering in CRTs: implications for analysis

Study features

*Example from Hayes & Moulton (2009)*
Clustering in CRTs: implications for analysis

Study features
- Trial A:
  - Lower between-school variability
  - Little overlap of I & C clinic-level proportions
- Trial B: overlap of I & C school-level proportions

Example from Hayes & Moulton (2009)
Clustering in CRTs: implications for analysis

- If ignore clustering: p-value = 0.02 for both trials
- Comparison of 10% (50/500) vs 6% (30/500) by chi-sq. test

Example from Hayes & Moulton (2009)
Clustering in CRTs: implications for analysis

- Trial B p-value accounting for clustered design = ?
- If ignore clustering: p-value = 0.02

Example from Hayes & Moulton (2009)
Clustering in CRTs: implications for analysis

• Trial B p-value accounting for clustered design = 0.17
• If ignore clustering: p-value = 0.02

Example from Hayes & Moulton (2009)
Clustering in CRTs: implications for analysis

- Trial A p-value accounting for clustered design = ?
- If ignore clustering: p-value = 0.02

Example from Hayes & Moulton (2009)
Clustering in CRTs: implications for analysis

- Trial A p-value accounting for clustered design = 0.01
- If ignore clustering: p-value = 0.02

Example from Hayes & Moulton (2009)
Clustering in CRTs: implications for analysis

- Trial A p-value accounting for clustered design* = 0.01
- Trial B p-value accounting for clustered design* = 0.17

*By using a cluster-level analysis where the 10 cluster-level proportions (5 per arm) are treated as continuous variables and analyzed with Wilcoxon rank sum test

Example from Hayes & Moulton (2009)
Summary: clustering & analysis

- Two example trials
  - Analyzed with cluster-level analysis
  - Overall sample size (# schools/trial) = 10
- Both trials had same signal (10% vs 6%)
  - Totally different conclusions from each trial
  - Between-cluster variability Trial A < Trial B
  - P-value Trial A < P-value Trial B
- Important: If ignore clustered design, could claim ‘significant’ when not (eg, Trial B)
Summary: clustering & analysis

- Cluster-level analysis rarely used
- Typically use regression methods
  - Random effects / mixed effects models
  - Generalized estimating equations (GEE)
- Analyze individual-level data
  - e.g., N=1000 participants/trial not N=10 schools
Recent examples from my research

CRT methods

Review of Recent Methodological Developments in Group-Randomized Trials: Part 1—Design

In 2004, Murray et al. reviewed Elizabeth L. Turner, PhD, Fan Li, MSc, John A. Gallis, ScM, Melanie Prague, PhD, and David M. Murray, PhD

Review of Recent Methodological Developments in Group-Randomized Trials: Part 2—Analysis

In 2004, Murray et al. reviewed methodological developments Elizabeth L. Turner, PhD, Melanie Prague, PhD, John A. Gallis, ScM, Fan Li, MSc, and David M. Murray, PhD
Recent examples from my research

**CRT design**

**BMJ Open** Innovative public–private partnership to target subsidised antimalarials: a study protocol for a cluster randomised controlled trial to evaluate a community intervention in Western Kenya

Jeremiah Laktabai,1 Adriane Lesser,2 Alyssa Platt,2,3 Elisa Maffioli,2,4 Manoj Mohanan,2,4,5 Diana Menya,6 Wendy Prudhomme O’Meara,2,6,7 Elizabeth L. Turner2,3

**STUDY PROTOCOL**

Reducing stigma among healthcare providers to improve mental health services (RESHAPE): protocol for a pilot cluster randomized controlled trial of a stigma reduction intervention for training primary healthcare workers in Nepal

Brandon A. Kohrt1,2,3, Mark J. D. Jordans2,4, Elizabeth L. Turner1,5, Kathleen J. Sikkema1,6, Nagendu Sauharada Rai1,2,3, Daisy R. Singla7,8, Jagannath Lamicchhane9, Crick Lund4,10 and Vikram Patel1,11,12
Cluster randomized trials
Design challenge: clustering

Solution: design & analyze accounting for it
Cluster randomized trials

Design challenge: baseline imbalance
Motivating example CRT
Health and Literacy Intervention (HALI)

Goal: randomization $\rightarrow$ baseline balance of covariates
Check: baseline tables for 101 clusters (schools)
Table 1. Baseline characteristics of 5,233 study children in the 50 control and 51 IST intervention schools.

<table>
<thead>
<tr>
<th>Characteristics; n (%)</th>
<th>Measure/Subcharacteristic</th>
<th>Control 50 schools</th>
<th>Intervention 51 schools</th>
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<tbody>
<tr>
<td>School characteristics</td>
<td>Exam score Mean (SD)</td>
<td>223.4 (27.7)</td>
<td>225.8 (29.0)</td>
</tr>
<tr>
<td></td>
<td>School size Median (IQR) [min, max]</td>
<td>505 (308, 961) [85, 4,891]</td>
<td>568 (389, 692) [2,136]</td>
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<td>Enrolled class 1 Mean (SD) [min, max]</td>
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<td>School programmes Feeding</td>
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<td>Last night†</td>
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Halliday (2014), PLOS Medicine, 11(1) e1001594
http://www.plosmedicine.org/article/info%3Adoi%2F10.1371%2Fjournal.pmed.1001594
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Good balance of age
Some imbalance of bednet use

http://www.plosmedicine.org/article/info%3Adoi%2F10.1371%2Fjournal.pmed.1001594
Small # of clusters & baseline imbalance

- CRTs often enroll small # (<40) clusters
- Randomization may not balance baseline covariates
- Baseline imbalance threatens internal validity
- Could address with adjusted analysis
- Better to use design strategy: ‘Restricted randomization’
  - Pair-matching
  - Stratification
  - Covariate-constrained randomization
Baseline covariate imbalance
Example: 8 schools (clusters)

Baseline malaria prevalence

20%
0%
Baseline covariate imbalance
Example: 8 schools (clusters)

Baseline malaria prevalence

**Question:** Why do we care about getting balance between treatment arms on school-level malaria prevalence?

**It might be related to prevalence in future!**
Baseline covariate imbalance

Example: 8 schools (clusters)

Example of extreme baseline imbalance using simple (i.e., regular) randomization
Baseline covariate imbalance
Possible design solution 1: pair-matching
Baseline covariate imbalance
Possible design solution 1: pair-matching

One example of pair-matched randomization to control & intervention arms

Important: account for paired design in the analysis (eg, paired t-test or Wilcoxon signed rank test for cluster-level analysis or matched regression model)
Efficacy of iron-supplement bars to reduce anemia in urban Indian women: a cluster-randomized controlled trial $^{1,2}$

Rajvi Mehta, $^{3}$ Alyssa C Platt, $^{4,6}$ Xizi Sun, $^{4}$ Mukesh Desai, $^{7}$ Dennis Clements, $^{5,6}$ and Elizabeth L Turner $^{4,6,*}$

$^{3}$Duke University School of Medicine, Departments of $^{4}$Biostatistics and Bioinformatics and $^{5}$Pediatrics, and $^{6}$Duke Global Health Institute, Duke University, Durham, NC; and $^{7}$Department of Hematology and Immunology, B.J. Wadia Hospital, Mumbai, Maharashtra, India

Baseline covariate imbalance
Example: 8 schools (clusters)
Baseline covariate imbalance
Possible design solution 2: stratification

Baseline malaria prevalence

Stratum 1  Stratum 2
Baseline covariate imbalance
Possible design solution 2: stratification

An example of stratified randomization to control & intervention arms

Important: account for stratified design in the analysis
(eg, stratified permutation test or fixed effect for strata in model-based analysis)
Stratification in practice
Example from my research: published CRT protocol paper

Turner et al. Trials (2016) 17:442

STUDY PROTOCOL

The effectiveness of the peer delivered Thinking Healthy Plus (THPP+) Programme for maternal depression and child socio-emotional development in Pakistan: study protocol for a three-year cluster randomized controlled trial

Elizabeth L. Turner¹,², Siham Sikander³, Omer Bangash³, Ahmed Zaidi³, Lisa Bates⁴, John Gallis¹,², Nima Ganga¹, Karen O'Donnell¹, Atif Rahman⁵* and Joanna Maselko⁶*
Baseline covariate imbalance
Possible design solution 3: Constrained randomization

- Previous examples – only one school-level covariate
  - i.e., baseline malaria prevalence
- Often have multiple school-level covariates
  - Categorical & continuous
  - Pair-matching & stratification cannot easily handle this
- Need more general form of restricted randomization
  - Covariate-constrained randomization
Baseline covariate imbalance
Possible design solution 3: Constrained randomization

Example: balance two continuous cluster covariates
Baseline covariate imbalance
Possible design solution 3: Constrained randomization

An example of simple randomization to control & intervention arms

Baseline malaria prevalence

Not well-balanced on baseline malaria prevalence but reasonable balance on bednet use
Baseline covariate imbalance

Possible design solution 3: Constrained randomization

Neither randomization has good balance of both covariates across trial arms.

Solution: only allow randomizations that are “balanced enough” as measured by a “balance score” i.e., use covariate-constrained randomization
Baseline covariate imbalance
Possible design solution 3: Constrained randomization

This randomization could be “balanced enough”

Must account for constrained randomization design in the analysis
Covariate constrained randomization
Example from my research - methods
Covariate constrained randomization
Example from my research – software implementation

The Stata Journal (yyyy) vv, Number ii, pp. 1–23

cvcrand and cptest: Efficient design and analysis of cluster randomized trials

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Covariate constrained randomization by Raab and Butcher (2001) doi:10.1002/1097-0258(20010215)20:3<156::AID-CPH4>3.0.CO;2-Q Motivated from Li, et al. (2016) doi:10.1002/sim.7410, the package baseline values of cluster-level covariates and cluster permutation test on the individual-level outcome...
Cluster randomized trials

Design challenge: baseline imbalance

Solution:
use restricted randomization
Cluster randomized trials

Stepped-wedge designs
Parallel CRT vs. SW-CRT

Examples with 8 clusters: 1-year intervention

Parallel CRT vs. SW-CRT

Examples with 8 clusters: 1-year intervention

- **Parallel design**
- **Complete stepped-wedge design**
- **Incomplete stepped-wedge design**

CRT analysis: treatment effects

Estimated (primarily) using between-cluster information

Estimated using both **vertical** & **horizontal** (ie, within-cluster) information

Parallel design

Complete SW design

SW-CRT design and analysis
Examples from my research

Sample size determination for GEE analyses of SW-CRTs
Li F, Turner EL, Preisser J. Under review.

Optimal allocation of clusters in cohort SW designs

Covariate constrained randomization for the design of parallel and SW-CRTs
- Invited session at Society of Clinical Trials Annual Meeting, May 2018
- Joint work with Karla Hemming (University of Birmingham), Andrew Copas (University College London) and Fan Li (Duke)
Summary

Evaluation of Public Health Interventions: Recent Developments in Cluster Randomized Trials and Related Designs
Summary

• Recent developments in CRTs

1. Motivating example
2. Clustering
3. Small # clusters & baseline covariate imbalance
4. Stepped wedge designs
References - Statistical

- Campbell MK, Grimshaw JM, Elbourne DR (2004). Intracluster correlation coefficients in CRT: empirical insights into how they should be reported *BMC Medical Research Methodology* 4:9
References – Motivating example


