Responsive and Adaptive Design for Survey Optimization across the Pacific

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- **Challenges and Opportunities Remaining for RAD**
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Introduction

- A rapidly changing survey environment requires a nimble, flexible design
- Birth of responsive and adaptive survey design (Groves and Heeringa 2006; Wagner 2008)
- RAD is being evolved (Chun, Schouten, Wagner 2017, 2018)

Triple Phenomena to Watch

- Evidence-driven policy makers as well as survey researchers have renewed their attention to administrative records (Chun 2009; Chun et al., forthcoming)
- Computerization of survey data collection enables real-time analysis of paradata, or process data (Couper, 1998)
- Methods from fields as diverse as machine learning, operations research, and Bayesian statistics are found to be useful (Early, Mankoff and Fienberg, 2017)

Reflections on RAD

- Birth of responsive and adaptive design is a natural reaction to the basic rationale of survey design that addresses response and measurement errors in population subgroups
- Systematic approach to adaptive design evolved (Schouten et al. 2013)
- Evolution of RAD is due to:
  - increasing pressure on response rates,
  - use of paradata,
  - IT-driven data collection methods

Responsive vs. Adaptive

- Responsive survey design originates from settings with less auxiliary data, long data collection periods and detailed quality-cost constraints
- Adaptive survey design comes from settings with richer auxiliary data, short data collection periods and structural variation

What is RAD?

RAD = Wonderful, extraordinary!

(Youth slang)

What is RAD?

- RAD is essentially a form of adjustment by *design* in the data collection as opposed to adjustment by estimation, i.e., adjustment introduced in the design and data collection stage in contrast to adjustment in the estimation stage.

What is RAD?

- RAD is a data-driven approach to controlling survey design features in real-time data collection by monitoring explicit costs and errors of survey estimates that are informed by auxiliary information, paradata, and multiple sources of data
- As a such, RAD works toward a goal of survey optimization based on cost-error tradeoff analysis and evidence-driven design decisions, including the most efficient allocation of resources to survey strata.

Four Pillars of RAD

Four Pillars of RAD

- Use of Paradata and Auxiliary data
- Design features/interventions to adapt treatment
- Explicit quality and cost metrics
- Quality-cost optimization

1. Use of Paradata and Auxiliary data

- Paradata and auxiliary data should relate to nonresponse and other sources of survey errors under investigation, as well as to the key survey variables.
- Between 2000 and 2015, there was **renewed interest in paradata**, or auxiliary data coming from the data collection process (e.g. Kreuter 2013).
- For example, call record data, audit trails, and interviewer observations were increasingly used in dashboards to monitor data collection. This might have resulted from increasing digitization of communication.
- The real-time paradata were instrumental to developing evidence -driven models to understand the process of response and nonresponse and to creating statistical interventions to control for potential nonresponse bias.

2. Design features/interventions to adapt treatment

- Design features should be effective in reducing survey errors for the relevant strata.
- Survey design features obviously go as far back as surveys themselves. There has been renewed interest in mixed-mode surveys with the emergence of online devices (e.g. Dillman et al. 2014; Klausch 2014).
- The survey mode appears to be the strongest quality -cost differential of all design features.
- Between 2005 and present, various papers have been published about indicators for nonresponse (e.g. Chapter 9 in Schouten et al. 2017).

2. Design features/interventions to adapt treatment (Continued)

- It has been declining response rates that drove the development of alternative indicators, not necessarily to replace response rates but to supplement them and to provide a more comprehensive picture of data quality.
- Notable in data quality metrics is the development of **response propensity measure** (e.g., Chun 2009; Schouten, Cobben, Bethlehem, 20009; Chun and Kwanisai 2010; Toureangeau et al. 2016).

2. Design features/interventions to adapt treatment (Continued)

<u>RAD Employes Unequal Efforts</u>

- Change/vary modes
- Change/vary incentive levels
- Vary level of effort for different cases or subgroups (e.g., multiple calls)
- Two-phase sampling and focus effort (e.g., sub-sampling)

3. Explicit quality and cost metrics

- Quality and cost functions quantifying effort and errors should be properly defined and measurable, but, above all, should be accepted by the stakeholders involved.
- It is unfortunate that efforts to develop and implement cost metrics remain quite limited - probably due to practical constraints of quantifying or modelling cost parameters.

4. Quality-cost optimization

- The quality-cost optimization strategy should be transparent, reproducible, and easy to implement.
- Optimization strategies remain an underexplored area. This may be, in part, because they are the final step of RAD. In other words, they require that choices in the other elements have been made and implemented.

4. Quality-cost Optimization (Continued)

- For instance, a consensus is necessary on quality and cost indicators. We observe that it is also because optimization requires accurate estimates of survey design parameters, such as response propensities and survey costs.
- Survey cost metrics are multi-dimensional like data quality; optimization strategies, therefore, remain incomplete as long as cost estimates as input variables are neither reliable nor valid indicators of survey costs.

4. Quality-Cost Optimization (Continued)

The optimization problem can now be formulated as

$\max_p Q(p)$ given that $C(p) \leq C_{max}$ (1.1)

$\min_p C(p)$ *given that* $Q(p) \geq Q_{min}$, (1.2)

where C_{max} *represents the budget for a survey and* Q_{min} *for minimum quality constraints.*

Problems (1.1) and (1.2) are called dual optimization problems, although the solutions to both problems may be different depending on the quality and cost constraints.

Parables of RAD across the Pacific: 2013 - 2016

1. SRI 2015 Census Pilot Survey Paradata
2. SRI Concurrent Mixed Mode Pilot Survey
3. SRI Sequential Mixed Mode Pilot Survey
4. SRI Adaptive Mixed Mode Pilot Survey

Studies on RAD: 2013 - 2016

▶ **2015 Census pilot survey paradata (2013)**

- Lim & Park, 2013

▶ **Concurrent mixed mode pilot survey (2014 – 2016)**

- Lim, 2014
- Shim & Baek, 2015
- Baek & Min, 2016

▶ **Sequential mixed mode pilot survey (2015 – 2016)**

- Baek, Min, & Shim, 2015
- Shim & Na, 2016

▶ **Adaptive mixed mode pilot survey (2016)**

- Shim, Jung, & Baek, 2016

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2015 Census Pilot Survey Paradata

▶ **Design : 2015 Census Pilot -** Urban 816 households, Rural 264 households, Total 977 households

▶ **Response :** Urban 718 households(88.0%), Rural 259 households(98.1%), Total 874 households(89.5%)

▶ Feature

Region	Visits (average)	How many visits (response)		No Contact (1st visit)	Average survey time (min:sec)		
		1st	Up to 2nd		total	weekday	weekend
Urban	3.14	24.1%	46.0%	67.9%	16:16	16:19	18:00
Rural	1.56	72.2%	84.9%	28.8%	17:29	18:06	14:35
Total	2.76	41.1%	62.9%	64.5%	16:36	17:06	15:12

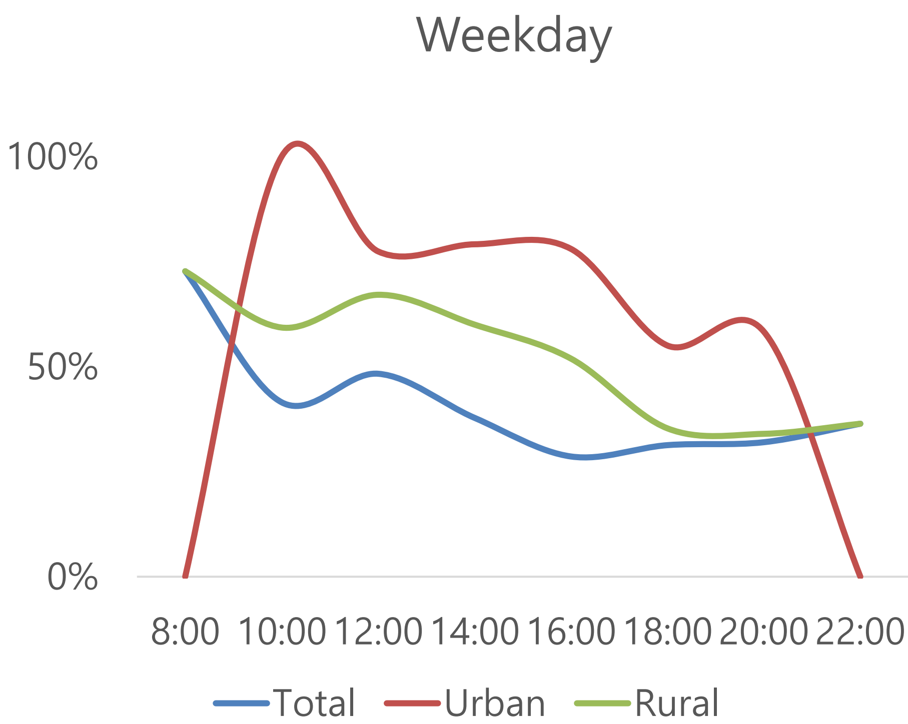
▶ Attitude

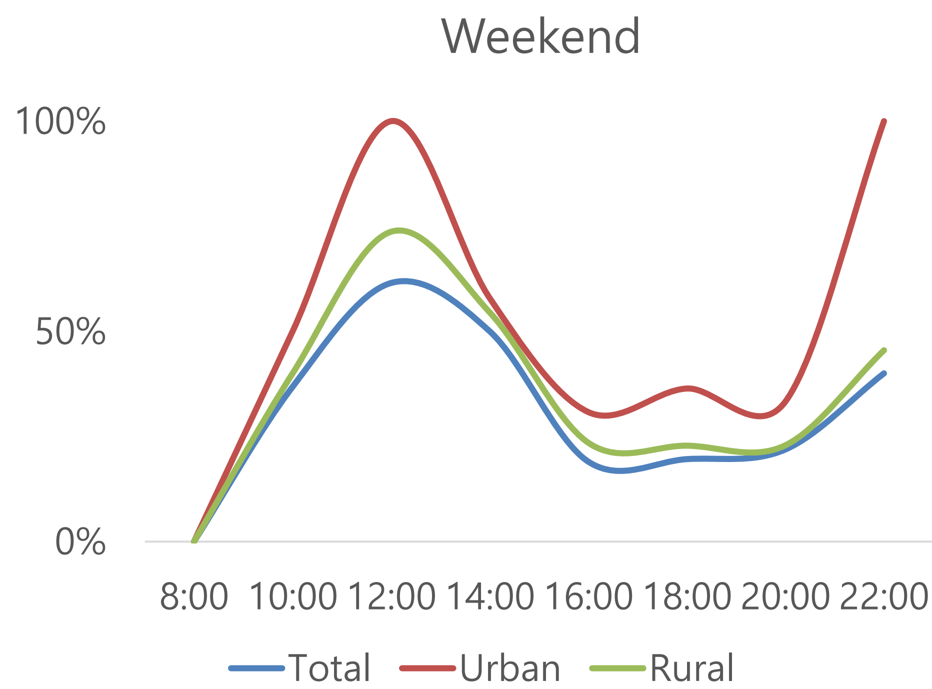
Region	Negative (at visit)				Positive (at visit)			
	1st	2nd	3rd	4th	1st	2nd	3rd	4th
Urban	19.5%	23.0%	27.6%	45.9%	34.9%	20.3%	16.8%	17.1%
Rural	4.3%	9.7%	6.9%	14.3%	55.9%	68.8%	65.5%	57.1%
Total	11.6%	20.5%	24.8%	44.1%	45.9%	28.8%	23.4%	19.5%

Lim & Park (2013)

Hourly Response & Strategy

▶ **Hourly Response**





Lim & Park(2013)

Hourly Response & Strategy

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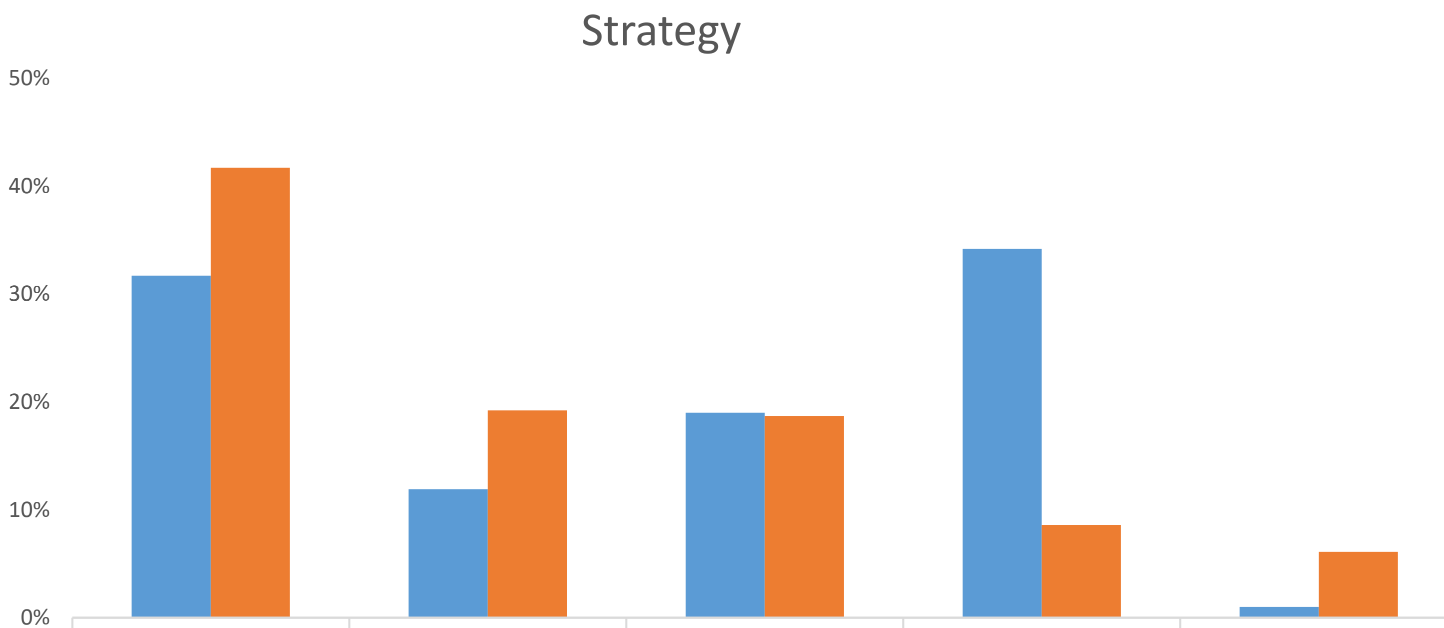
▶ Strategy



	Survey guide distribution	Survey guide tel./SMS	Visit persuasion	Many callbacks	Village community
Urban	31.70%	11.90%	19.00%	34.20%	1.00%
Rural	41.70%	19.20%	18.70%	8.60%	6.10%

Lim & Park (2013)

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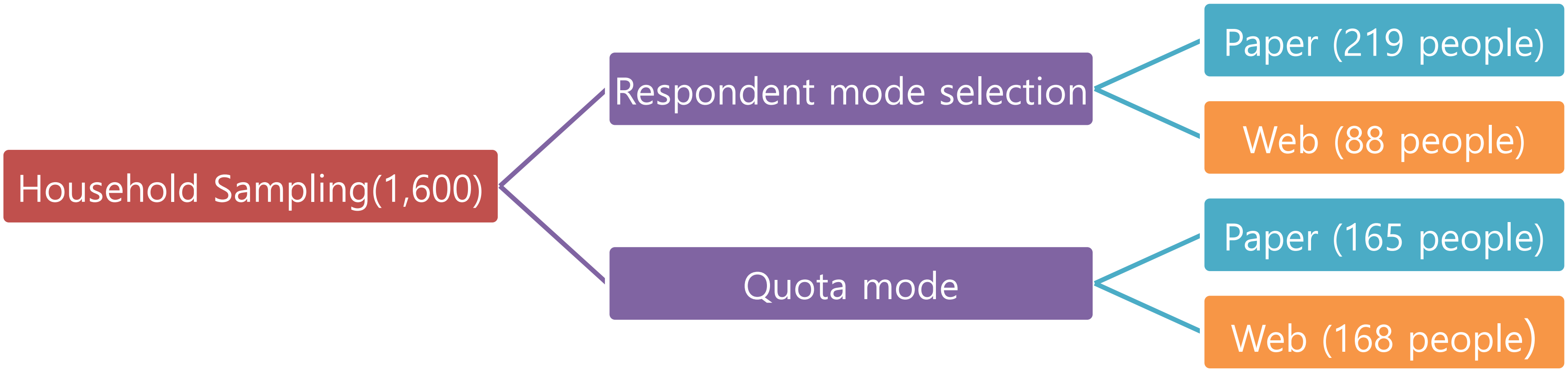
Concurrent Mixed Mode Pilot Survey 2014 - 2016

Design & Feature

▶ **Design: Randomized Controlled Design to Test Concurrent Mixed Mode**



Lim (2014)

▶ **Response**

	Total	Respondent mode selection			Quota mode		
			Paper	Web		Paper	Web
R-indicator	0.6631	0.5214	0.613	0.6557	0.7295	0.6525	0.8107

1st	2nd	3rd
0.6629	0.8356	0.7942

Shim & Baek (2015)

Mode effect

▶ **Survey Measurement : Social Survey**

- Life satisfaction, Attitude about family, Social safety, Labor, Welfare, Income, and Expenditure

▶ **Mode effect in web survey compared to paper survey (selection vs. quota)**

	Tendency	Life satisfaction	Social safety	Family-oriented culture
Selection	(web)Under 40 years old (paper)Over 40 years old	Negative	Negative	Negative
Quota		Positive	Positive	Positive

Baek & Min(2016)

▶ **Mode effect in selection mode (web vs. paper)**

	Family-oriented culture	Life satisfaction	Economic activity	Divorce	Adoption
Web	Negative	Negative	Over estimate	**Positive**	Negative
Paper	Positive	Positive	-	**Negative**	Positive

Baek & Min(2016)

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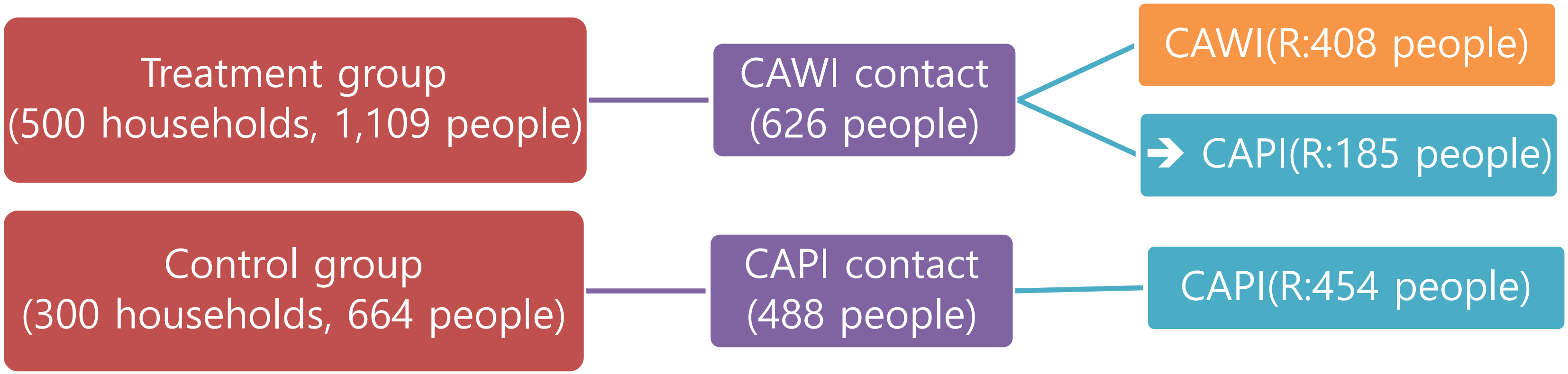
Sequential Mixed Mode Pilot Survey 2015

Design & Feature

▶ Design – Sequential Mixed Mode



Baek, Min, & Shim (2015)

▶ Feature

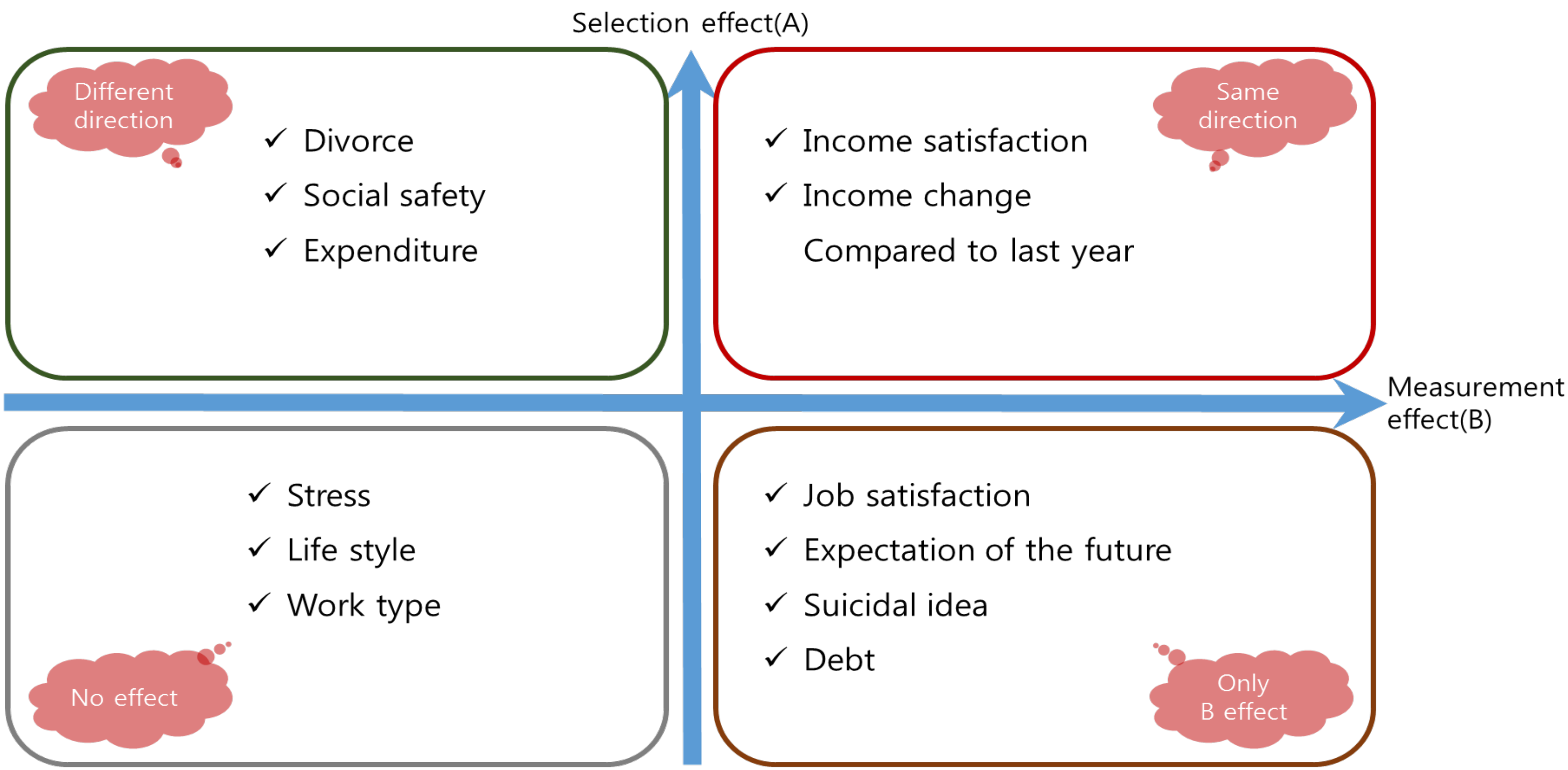
	Total	Treatment group			Control group
			CAWI	CAPI	CAPI
R-indicator	0.9409	0.9549	0.9307	0.8934	0.9632

- After 5th week, mode change

	3rd week	4th week	5th week	6th week
R-indicator	0.9822	0.9430	0.9131	0.9409

Shim & Na (2015)

▶ Mode effect



Baek, Min, & Shim (2015)

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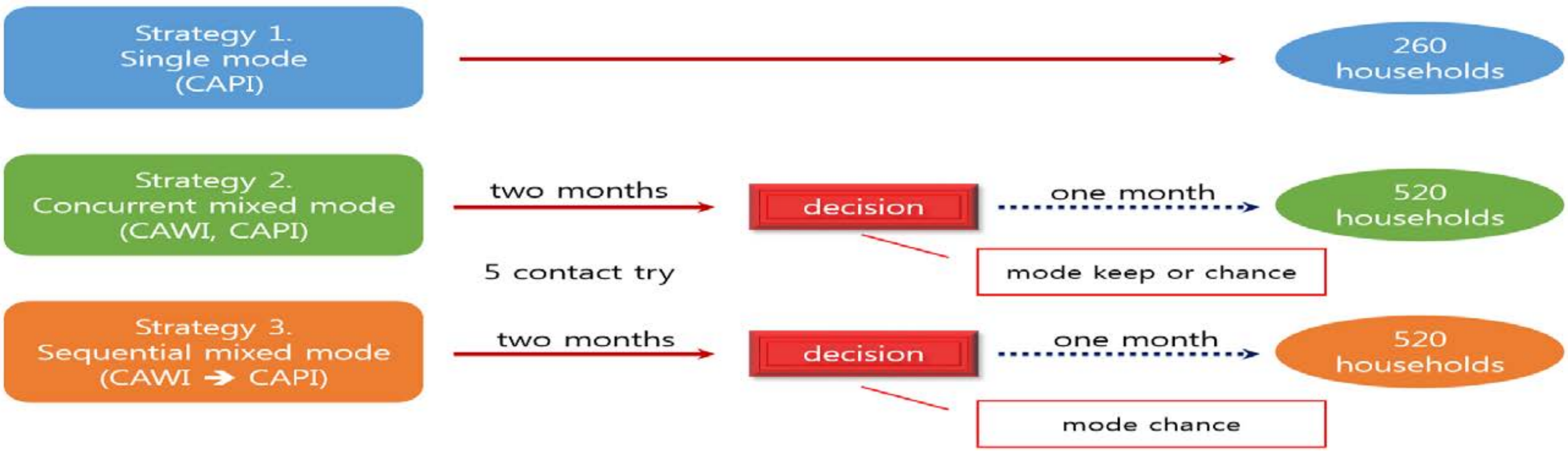
Adaptive Mixed Mode Pilot Survey 2016

▶ Design – Adaptive Mixed Mode

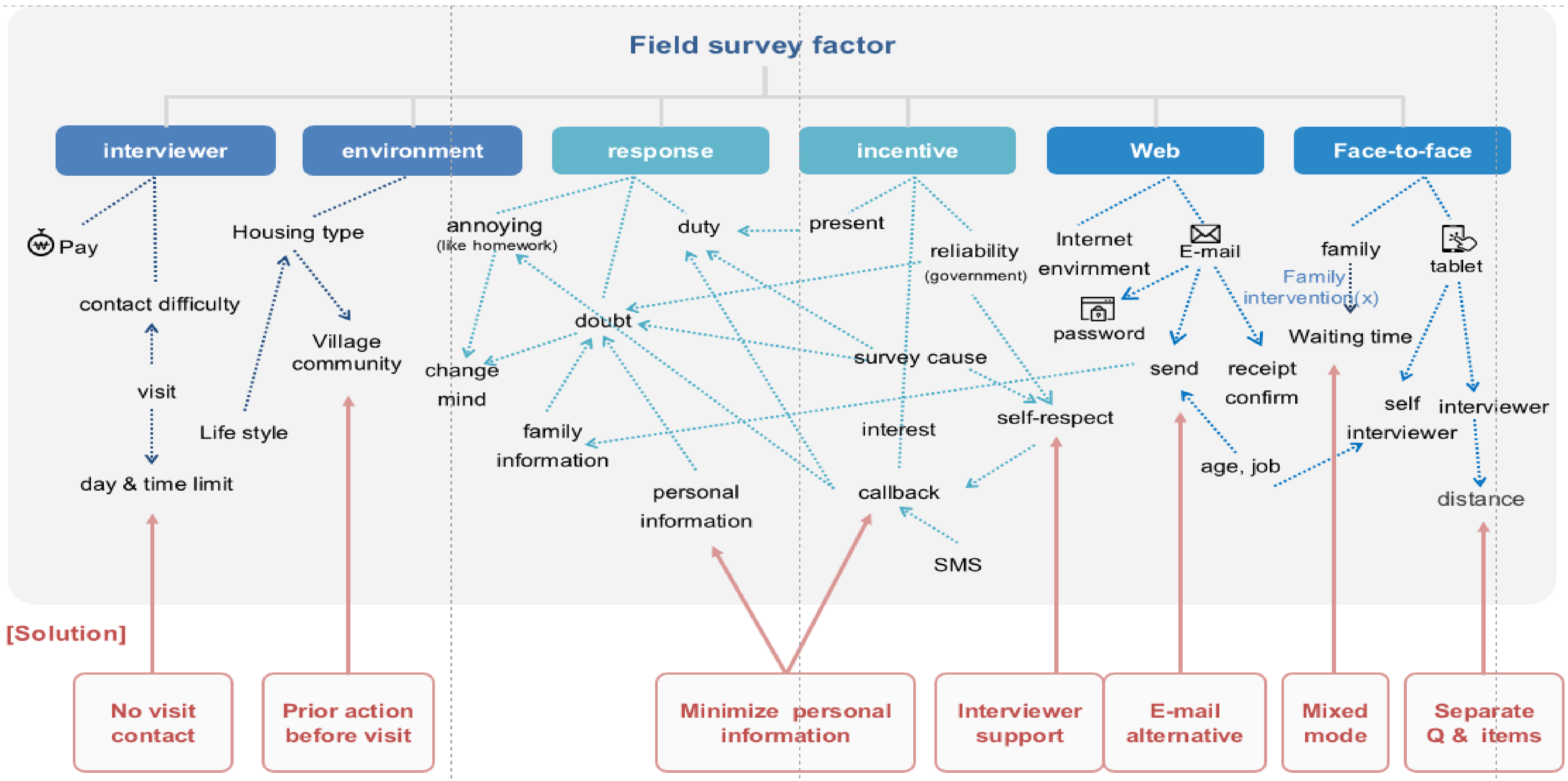


▶Feature

	Single mode (CAPI)	Concurrent mixed mode	Sequential mixed mode
Contact ➞ Response	585 ➞ 473 (80.8%)	1,245 ➞ 977 (78.5%) (CAPI 915, CAWI 62)	1,140 ➞ 614 (53.9%) (CAWI 379 ⇒ CAPI 235)
R-indicator	0.83	0.84	0.91

Shim, Jung, & Baek (2016)

▶ Contact strategy



Shim, Jung, & Baek (2016)

Innovations Featured in the Journal of Official Statistics Special Issue on RAD:2017, 2018

Edited by

Asaph Young Chun,
Barry Schouten, James Wagner

Key Questions to Ask in RAD

- What approaches can be used to guide the development of cost and quality metrics in RAD and their use over the survey life cycle?
- Which methods of RAD are able to identify phase boundaries or stopping rules that optimize responsive designs?
- What would be best practices for applying RAD to produce high quality data in a cost-effective manner?

Innovations Featured by JOS Special Issue on RAD (‘17, ‘18)

- What cost-quality tradeoff paradigm can be operationalized to guide the development of cost and quality metrics and their use around the survey life cycle?
- Under what conditions can administrative records or big data be *adaptively* used to supplement survey data collection?
- How are paradata in multiple mode of data collection conceptualized, pretested and collected to inform survey design decisions?

Switching and Stopping Rules in JOS Special Issue on RAD (‘17, ‘18)

- What indicators of data quality can be combined to monitor the course of the data collection process?
- Under what scenarios can the rules of switching from one mode to another be cost-effective?
- What stopping rules of data collection can be used across major phases of the survey life cycle?

Experiments and Simulations Tested in the JOS Special Issue on RAD (‘17, ‘18)

- How could adaptive design be effectively designed and executed, especially in surveys involving multiple data sources and mixed modes of data collection?
- How could adaptive design guide web surveys while controlling for multiple sources of survey errors, such as nonresponse, measurement errors, and sampling errors?

Revisiting the JOS Special Issues on RAD (Chun, Schouten, Wagner 2017, 2018)

- Several papers provide formalized rules for adaptation.
- A few papers examine the impact of responsive and adaptive designs on the quality of estimates
- Some papers consider adaptive design tailored to panel surveys
- A few papers examine RAD for establishment surveys

Rules for adaptive design

- **Paiva, T., Reiter, J.**
  Stop or Continue Data Collection: A Nonignorable Missing Data Approach for Continuous Variables
- **Lewis, T.**
  Univariate Tests for Phase Capacity: Tools for Identifying When to Modify a Survey's Data Collection Protocol
- **Early, K., Makoff, J., Fienberg, S.**
  Dynamic question ordering in online surveys.
- **Vandenplas, C., Loosveldt, G., Beullens, K.**
  Fieldwork Monitoring for the European Social Survey: an illustration with Belgium and the Czech Republic in Round 7
- **Burger, J., Perryck, K., Schouten, B.**
  Robustness of adaptive survey designs to inaccuracy of design parameters

Impact of RAD on the Quality of Estimates

- **<u>Lundquist, P., Särndal, C.</u>**
  Inconsistent regression and nonresponse bias: Exploring their relationship as a function of response imbalance

- **<u>Brick, M., Tourangeau, R.</u>**
  Responsive survey designs for reducing nonresponse bias

RAD tailored to Panel Surveys

- **Shlomo, N., Plewis, I.**
  Using Response Propensity Models to Improve the Quality of Response Data in Longitudinal Studies
- **Lynn, P., Kaminska, O.**
  The implications of alternative allocation criteria in adaptive design for panel surveys
- **Durrant, G., Maslovskaya, O., Smith, P.**
  Using prior wave information and paradata: Can th ey help to predict response outcomes and call seq uence length in a longitudinal study?

RAD for Establishment Surveys

- **Thompson, K.J., Kaputa, S.**
  Investigating Adaptive Nonresponse Follow-up Strategies for Small Businesses through Embedded Experiments
- **McCarthy, J., Wagner, J., Sanders, H.**
  The Impact of Targeted Data Collection on Nonresponse Bias in an Establishment Survey: A Simulation Study of Adaptive Survey Design

Three Critical Perspectives on RAD

- **Perspective A** presents key points by leveraging the four pillars of RAD.
- **Perspective B** articulates five key elements of RAD, or variants of the four pillars of RAD, to make a coherent discussion.
- **Perspective C** focuses on elaborating on cost measures and cost modeling, the missing half of cost-quality tradeoff analysis and optimization strategy, as tied to the third and fourth pillars of RAD.

Perspective C

- The litmus test of RAD success depends heavily on the extent to which the third and fourth pillars of RAD are properly assembled and tested against the pressure of total survey errors and total survey costs – both anticipated and unanticipated.
- The critical gap remaining in these two pillars of RAD is more due to under-development of the framework of cost metrics and lack of its implementation in real-world survey applications.

Perspective C (Continued)

- Costs and errors are reflections of each other; increasing one tends to reduce the other (Groves 1989).
- Thus cost-quality optimization strategies would be neither feasible nor complete unless there is rigorous development and examination of the cost functions of various survey designs that offer error properties (Groves 1989; Chun 2012; Mulry 2012).

Cost Model

- Total Cost = Fixed Costs + Variable Stratum Costs

$$C = C_0 + \sum_{1}^{H} c_h n_h$$

- Fixed costs are costs that remain fairly constant in a survey, such as costs for survey system design, IT, and survey management.
- Variable costs are costs that vary as a function of the sample cases in various strata. Variable costs may include costs of frame construction, interviewing, nonresponse followup, data entry, and editing, which incur over the survey life cycle.

Perspective C (Continued)

- In practice, the pragmatic cost models need to be inclusive of *nonlinear, discontinuous and stochastic* properties of survey costs (Fellegi and Sunter 1974; Groves 1989).
- Groves observes that existing cost models tend to be linear functions of survey parameters like the number of interviews, although nonlinear cost models often apply to practical survey administration.
- Most cost models are continuous in those parameters; however, he points out that discontinuities in costs often arise when administrative changes accompany certain design changes.
- While cost models tend to be deterministic, costs can vary extensively because of chance occurrences in probability sample selection, or choice of interviewers.

Perspective C (Continued)

- The cost models proposed by Groves remain useful and viable today
- Cases in point are the papers by Paiva and Reiter (2017) and Kaminska and Lynn (2017) in the 2017 JOS special issue and by Murphy and his colleagues in this special section.
- Using data from the 2007 U.S. Census of Manufactures, Paiva and Reiter showed how to compute and compares measures of cost for various sample sizes by applying the traditional cost model.
- Kaminska and Lynn provide and test explicit cost metrics to determine pros and cons of alternative methods for allocating sample elements to data collection protocols, particularly in a longitudinal survey setting.
- Extending the cost model by Groves, Kaminska and Lynn demonstrate how variants of adaptive and non-adaptive designs can be appraised in terms of relative costs as well as multiple measures of data quality for each proposed scenario of RAD.

Perspective C (Continued)

- In a discussion of adaptive, responsive, and tailored (ART) design principles, Murphy and his colleagues (2018) make a smart move of presenting relative cost per case by interview protocol.
- They also provided data visualization of percentage of cases requiring editing, one that is tailored to the nee ds of cost metrics in an energy consumption survey sponsored by the U.S. Energy Information Administration.
- None of these papers, however, has taken a major step yet towards nonlinear, discontinuous, and stochastic properties of cost modeling.

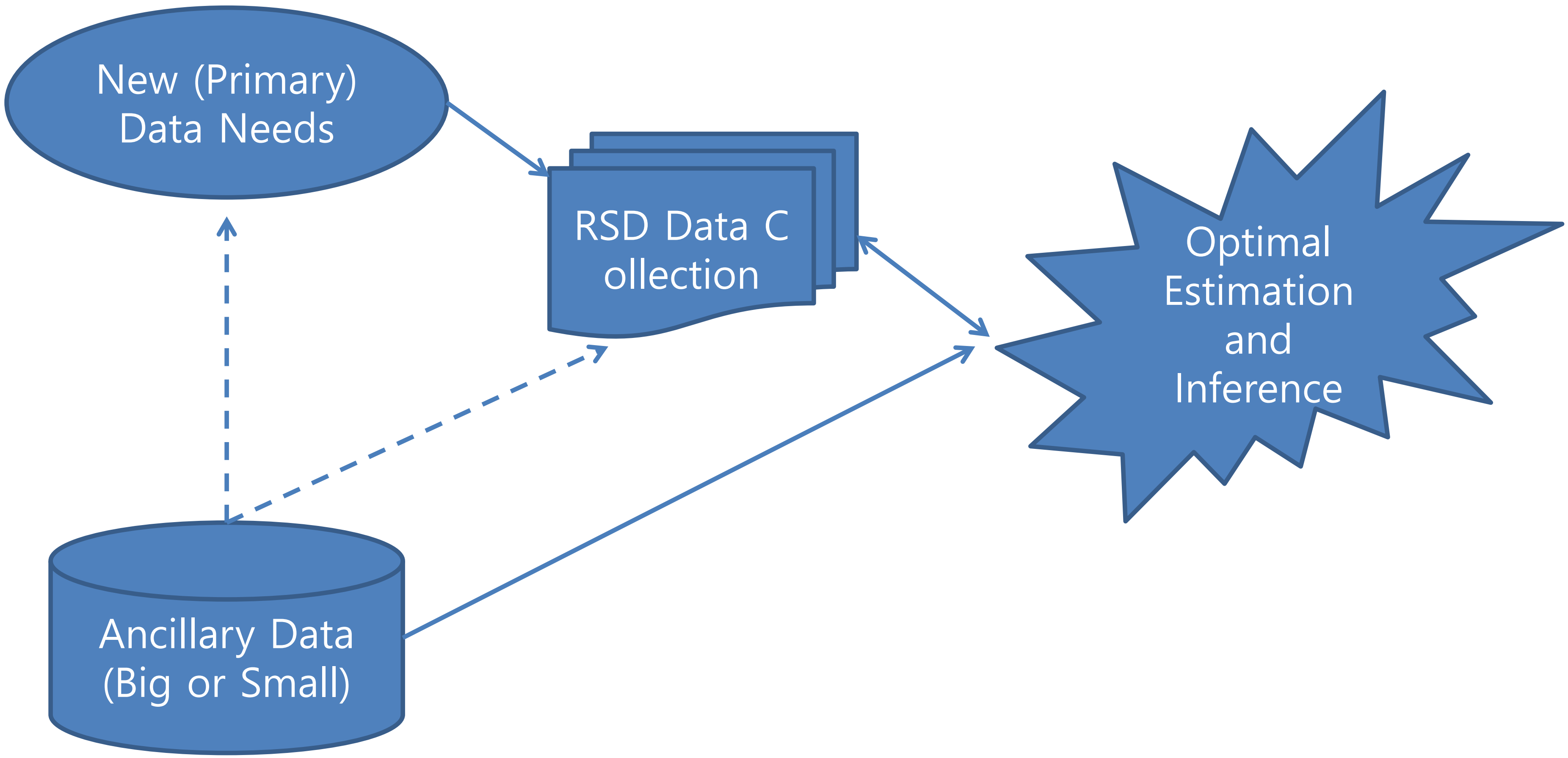
Impediments to Growth of RAD

- Literature tends to be produced by survey statisticians and not by survey managers.
- Survey designs demand for more complex monitoring and case management systems, as well as explicit cost-quality control
- Number of success stories is limited

Challenges and Opportunities for RAD

- Build the toolkit of evidence-based designs
- Learn more about deploying features & cost allocation differentially across pop subgroups
- Have survey managers work more closely with statisticians, survey methodologists, cost experts
- Develop rules of phase switching and of stopping data collection (e.g. AD in clinical trials)
- Design and test cost-quality tradeoff models (Groves, 1989)

RAD in Survey-assisted Applications



Source: Heeringa, 2018

Survey-Assisted Modeling

- **“Model training”** - providing timely estimates of models parameters relating the outcomes of interest to the covariate information available in <u>the big data systems</u>;
- **“Model refinement”** - by supplying more complete information on multivariate associations, mediating and moderating effects and chronological or spatial variation in <u>big data models</u>;
- **“Compensation”** - for population non-coverage, non-observation or missing data in the large data systems;
- **“Insight”** - into the error structure of large scale data systems that can only be obtained through direct survey measurement.

Conclusions

- RAD is evolving today.
- Further innovation and cross-fertilization is required.
- Use the JOS articles and other papers on RAD as a catalyst of further innovation and real-world applications.
- Advance RAD applications across culture

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Thank you!!!

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