Learning at Scale in a Collaborative Chronic Care Network: Insights from a Discrete Choice Experiment

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Innovation in Healthcare Delivery Systems: Engaging Patients & Families to Transform Care
A McCombs Healthcare Initiative Symposium

THE UNIVERSITY OF TEXAS AT AUSTIN
McCOMBS SCHOOL OF BUSINESS
Background

Collaborative improvement networks have emerged in health care systems as a means to support quality improvement and research with cycles of discovery, development, and dissemination.
Background

While network models are beginning to impact health system paradigms, network design and management approaches remain experimental.

PCORI's national vision: a network of networks
Lessons from the Field

Research and practical wisdom from pioneering networks suggest that sustained participant engagement affords greater leverage for getting results.
Motivation

- Understanding how to structure networks for sustained engagement is essential to ensure and accelerate translation of evidence into practice.

- Challenge: maintain effectiveness and efficiency alongside an innovative spirit of collaboration as networks grow in size and scope.

- Novel approaches are needed to manage variation in capabilities and create conditions for collaboration.
Research Objectives

1. Explore how scalable collaboration mechanisms may support continuous learning for teams in inter-organizational networks.
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1. Explore how scalable collaboration mechanisms may support continuous learning for teams in inter-organizational networks.

2. Present the discrete choice experiment as an efficient and inclusive approach to support dynamic design in improvement initiatives.
Research Setting
ImproveCareNow Results: IBD Remission Rates

Since network inception, IBD remission rates at ImproveCareNow care centers have improved from a baseline 55% to current 78%.
ImproveCareNow Network Trailblazers

2007: 8 enterprising care centers
Network Growth

2015: 73 sites in 34 states and in England
Network Growth

Individuals Chart with exponential-growth centerline:
Increase in number of ImproveCareNow care centers, 2006 - 2014
Getting to Scale

- Network growth presents both exciting opportunities and new practical challenges.

- It is increasingly complex to monitor and respond to learning needs of participants as they increase in number and diversity.

- The innovative spirit of close-knit collaboration may also be in jeopardy as networks expand, although these sort of cooperative dynamics may well have contributed to initial success and attracted others to participate.

- This paradox motivated ImproveCareNow to search for innovative techniques to facilitate the onboarding of new teams and to continually engage established teams.
Approach

- We explored previous research on group learning in the management and organization science literatures.

THREE MAJOR RESEARCH STREAMS:

- Task Mastery
  - Transactive Memory System
  - Role differentiation
  - Schema agreement / collective mind
  - Social and cognitive forces (e.g., collaborative inhibition, mutual enhancement)
  - Expertise (stability, diversity)
  - Higher-order learning processes: Enrollment, preparation, trials, reflection
    - Experimentation, reflective communication, knowledge codification
  - Cumulative experience
  - Delivery of learning content; instructional approach

- Learning Curve
  - Nature of knowledge transferred (Tacit vs. codified)
  - Feedback and evaluation
  - Teamwork (coordination, communication, cooperation)
  - Management of learning process

- Group Process
  - Leadership behavior (approach to: decision-making, power distance, goal clarification)
  - Team climate (psychological safety, autonomy, emotional intelligence)
  - Knowledge management (team reflexivity, system for codification)
  - Team identity (shared mental models, faultlines, management of uncertainty)
  - Learning orientation (incremental, radical, local, distal, experiential, vicarious, contextual)
  - Boundary spanning

EXPLANATORY VARIABLES

- Complexity, accuracy, agreement, validation, convergence
- e.g., collaborative inhibition, mutual enhancement

BACKGROUND VARIABLES

- Turnover
- Educational similarity
- Training as team
- (mediated by TMS)
- Individual effort
- Organizational context: dynamic vs. stable
- Collegiality
- Task / curriculum complexity
- Team size
- Team recruitment
- Team composition
- Team structure
- Learning objectives
- Strategic alignment with organization
- Managerial approach
- Framing of learning, objectives
- Resource / technology availability

S. Provost 2013
Approach

- We interviewed network leaders, staff, and participants to gain insight from their personal experiences.
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- We identified 3 focal mechanisms for management of network-based collaborative learning:
  1. Micro-communities to promote small-group interaction,
  2. Orientation to improvement curricula and network interventions
  3. Team-to-team mentoring.
Approach

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▶ We identified 3 focal mechanisms for management of network-based collaborative learning:

1. Micro-communities to promote small-group interaction,
2. Orientation to improvement curricula and network interventions
3. Team-to-team mentoring.

▶ We conducted a discrete choice experiment to examine relative preferences for these 3 strategies within the network itself.
Methodology: Discrete Choice Experiment (DCE)

- Examines individual choices of discrete alternatives.
- Uses experimental design to assess the relative importance that individuals place on different attributes of a given product, service, or scenario.
- Also known as conjoint analysis and used frequently in marketing studies and for design of products and services.

This choice set asks customers to choose between TVs with different bundles of features:
Discrete Choice Methods in Health Care

- Discrete choice methods are increasingly used in health economics and health policy studies.
- DCE are also useful to elicit patient and provider preferences for health services configurations.

*Quality in Health Care 2001;10(Suppl I):i55–i60*

Use of discrete choice experiments to elicit preferences

M Ryan, A Bate, C J Eastmond, A Ludbrook

The use of discrete choice experiments to inform health workforce policy: a systematic review

Mandeville et al. BMC Health Services Research 2014, 14:367

*Improving the quality of health care*

Methods for incorporating patients’ views in health care

Michel Wensing, Glyn Elwyn

BMJ VOLUME 326 19 APRIL 2003

*Esther W. de Bekker-Grob*

Discrete choice experiments in health care

Theory and applications

HEALTH ECONOMICS

Health Econ. 18: 951–976 (2009)

EXPLORING THE SOCIAL VALUE OF HEALTH-CARE INTERVENTIONS: A STATED PREFERENCE DISCRETE CHOICE EXPERIMENT

COLIN GREEN and KAREN GERARD

Learning at Scale in a C3N: Insights from a Discrete Choice Experiment

April 10, 2015
DCE Attributes

Our selection of experimental attributes came from the three group learning mechanisms that we had identified:

1. Micro-communities (aka “Learning Labs”)
2. Network curriculum
3. Team Mentoring

Alternative levels for each attribute represent distinct approaches to implementation of these strategies.

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<th>(1) Learning Lab Composition (LL)</th>
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<th>(2) ICN Curriculum (CR)</th>
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<th>(3) Team Mentoring (TM)</th>
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DCE Scenarios

- Experimental treatments are combinations of attribute levels, or scenarios, as seen here in this experimental design matrix.

- Individual decision-makers in our study were asked to consider a series of choice sets each presenting two of these scenarios.

<table>
<thead>
<tr>
<th>Scenario</th>
<th>(1) &quot;Learning Lab&quot; Composition</th>
<th>(2) Network Curriculum</th>
<th>(3) Team Mentoring</th>
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DCE Choice Sets

- We designed our experiment to maximize statistical efficiency and to minimize respondent burden.
- We wanted to estimate 3 main attributes and their interactions.
- Orthogonal design – *each pair of attribute levels appeared with equal frequency across the 8 choice sets* – maximized information gain.

<table>
<thead>
<tr>
<th>Efficient Design DCE Choice Sets</th>
<th>Scenario A</th>
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Does the Number of Choice Sets Matter?

While research suggests that DCE respondents are capable of managing up to 17 choice sets, we considered 8 choice sets to be appropriate in this context.
DCE Survey Instrument

- Sampling frame: active ImproveCareNow team members as identified by their respective care centers.

- Our DCE was distributed via online survey.

- 149 multidisciplinary network participants from 63 sites responded during June – September 2014.

- 65% response rate

- Respondents answered 3 questions about their professional role, network tenure, and home organization.

- We randomized the order in which the 8 choice sets were presented as well as the order of attributes within choice sets.
Sample Choice Set

Please read the following scenarios describing different learning experiences for care teams that have recently joined the ImproveCareNow Network. Based on your opinion and/or your own experiences with ImproveCareNow, please select one of the two scenario options, choosing the scenario that describes the experience most conducive to learning and improvement.

Scenario:
- New teams are matched with an assigned, permanent mentor team that will serve as a guide through different stages of the ICN curriculum.
- The curriculum will introduce all ICN content simultaneously; teams can select which intervention(s) is/are most appropriate for them and can work on it/them in depth.
- New care center teams will join a subset of more experienced ICN teams in a Learning Lab to facilitate knowledge sharing and small-group collaboration.

Scenario:
- New teams are matched with mentor teams that may change over time based on their current focal topic, for example, pre-visit planning.
- The curriculum will introduce all ICN content simultaneously; teams can select which intervention(s) is/are most appropriate for them and can work on it/them in depth.
- New care centers teams will join a subset of other novice ICN teams in a Learning Lab to facilitate knowledge sharing and small-group collaboration.
Discrete Choice Analysis

- Observations resulting from survey data were a full set of choice scores for each attribute level.
- We evaluated preferences for the 3 main attributes as well as their interactions.
Discrete Choice Analysis

- Observations resulting from survey data were a full set of choice scores for each attribute level.

- We evaluated preferences for the 3 main attributes as well as their interactions.

- We measured preferences as probabilities that a given participant would select a specific group learning alternative, for example *assigned* mentoring versus *ad hoc* mentoring.

- We developed conditional logit models which utilize both selected and rejected scenarios to estimate choice probabilities (in contrast with binary logistic regression, which uses selected scenarios only).
Conditional Logit Model

- We used the Multinomial Discrete Choice Procedure with SAS/STAT® software.

- Probability that individual $i$ chooses alternative $k$ is

$$\Pi_{ik} = \frac{\exp(\theta^T Z_{ik})}{\sum_{a=1}^{m} \exp(\theta^T Z_{ia})}$$

- $\theta$ is the vector of regression coefficients and $Z$ are the explanatory variables.

| Parameter          | Estimate (logit) | P > |t| | P(+) LL 95% CI | P(choice +) | P(+) UL 95% CI |
|--------------------|------------------|-----|---|-----------------|-------------|-----------------|
| Learning Lab       | -0.33            | < 0.001 | 0.38 | 0.42            | 0.46        |
| Curriculum         | 0.17             | 0.05  | 0.51 | 0.55            | 0.59        |
| Team Mentoring     | 0.43             | < 0.001 | 0.59 | 0.62            | 0.65        |
Main Attribute Results

Participants preferred:

- 42% MIXED micro-communities were chosen with 58% probability (p < 0.001)
Main Attribute Results

Participants preferred:

- **SEQUENTIAL Curriculum** (p = 0.02) with 55%
- **MIXED micro-communities** were chosen with 58% probability (p < 0.001) at 42%
Main Attribute Results

Participants preferred:

- **SEQUENTIAL Curriculum** (p = 0.02)
- **AD HOC Mentoring** (p < 0.001)

- MIXED micro-communities were chosen with 58% probability (p < 0.001)

- Learning Labs: 42%

- Curriculum: 55%

- Team Mentoring: 62%
Attribute Interactions

- Interactions between main attributes (e.g. LL × CR) were not significant.
- Participants felt similarly about Learning Lab, Curriculum, and Team Mentoring alternatives regardless of how the other attribute alternatives were presented.

| Parameter          | Estimate (logit) | P > |t|   | P(+) LL 95% CI | P(choice +) | P(+) UL 95% CI |
|--------------------|------------------|-----|----|----------------|-------------|---------------|
| Learning Lab       | -0.42            | 0.003 |    | 0.33           | 0.40        | 0.46          |
| Curriculum         | 0.26             | 0.06  |    | 0.50           | 0.56        | 0.63          |
| Team Mentoring     | 0.38             | 0.007 |    | 0.53           | 0.59        | 0.66          |
| LL × CR            | -0.05            | 0.69  |    | 0.43           | 0.49        | 0.55          |
| LL × TM            | 0.23             | 0.20  |    | 0.47           | 0.56        | 0.64          |
| CR × TM            | -0.12            | 0.49  |    | 0.39           | 0.47        | 0.56          |
Subgroup Analysis

- We wanted to explore how choice probabilities varied amongst respondent subgroups (segmented by professional role, individual time in network, and care center characteristics such as patient population size).

- We used Mixed Logit models to incorporate respondent- and organization-level covariates.

- We assessed all readily identifiable subgroup predictors in an iterative fashion, retaining those predictors which best explained variation in preferences.
Mixed Logit Model

- Recall that the conditional logit model specified the probability of individual $i$ choosing alternative $k$

$$\Pi_{ik} = \frac{\exp(\theta^T Z_{ik})}{\sum_{a=1}^{m} \exp(\theta^T Z_{ia})}$$

- Mixed logit model includes both characteristics of the individual and the alternatives

$$\Pi_{ik} = \frac{\exp(\beta_k^T X_i + \theta^T Z_{ik})}{\sum_{a=1}^{m} \exp(\beta_a^T X_i + \theta^T Z_{ia})}$$

- $\theta$ is the vector of regression coefficients and $Z$ are the explanatory variables for the alternatives. $\beta_k$ is the coefficient specific to alternative $k$, and $X_i$ are the attributes of the $i$th individual.
Subgroup Preferences

We observed attribute choice probabilities modified significantly by several respondent and organizational characteristics:

Overall, participants preferred:
- SEQUENTIAL Curriculum: 55% (p = 0.02)
- AD HOC Mentoring: 62% (p < 0.001)

Subgroup preferences:
- MIXED micro-communities: 42% (p < 0.001)
- Network novices (< 2 years) chose MIXED micro-communities with 67% probability (p < 0.001)

Learning at Scale in a C3N: Insights from a Discrete Choice Experiment
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  - **AD HOC Mentoring**: 62% (p < 0.001)

- **Subgroup preferences**:
  - Nurses and Nurse Practitioners: 70% (p = 0.02)

- **Network novices (< 2 years)**: chose **MIXED micro-communities** (33%) with 67% probability (p < 0.001)

- **Learning Labs**: 42% (p < 0.001)

- **Curriculum**: MIXED micro-communities

- **Team Mentoring**: AD HOC mentoring

- **Novice x LL**: AD HOC mentoring

- **Nurse x TM**: AD HOC mentoring

- **LargePop x TM**: AD HOC mentoring
Subgroup Preferences

We observed attribute choice probabilities modified significantly by several respondent and organizational characteristics:

- **Overall, participants preferred:**
  - **SEQUENTIAL Curriculum**
    - 55%
    - $p = 0.02$
  - **AD HOC Mentoring**
    - 62%
    - $p < 0.001$

- **Subgroup preferences:**
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    - 70%
    - $p = 0.001$
  - **Network novices (< 2 years)** chose **MIXED micro-communities** with 67% probability
    - 33%
    - $p < 0.001$

Participants from larger care centers (> 346 patients)

Learning at Scale in a C3N: Insights from a Discrete Choice Experiment
Variation in Preferences for Micro-community Composition

We also observed that the choice probability for Cohorted Learning Labs increased as a function of remission rates at participant care centers.
Discussion

- Once time-bound and limited to synchronous participation, collaborative improvement and research efforts are now enduring and expanding.

- We have examined collective learning preferences of participants in one network. Overall, mixed micro-communities, sequentially-delivered curricula, and ad hoc, topical team mentoring were preferred.

- We observed clear and significant preferences, yet no overwhelming majorities. We found interesting variation in choices across subgroups.
Discussion

▶ Once time-bound and limited to synchronous participation, collaborative improvement and research efforts are now enduring and expanding.

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▶ We observed clear and significant preferences, yet no overwhelming majorities. We found interesting variation in choices across subgroups.

▶ Application of our findings may present practical limitations for improvement networks in that discrete attributes are not well-suited to compromise... But sometimes solutions may be segmented or even customized.

▶ Attribute interactions were not important to our respondents, implying that one or more of the strategies could be implemented in isolation.
Are DCE for me?

- We recommend the discrete choice experiment as a rigorous and relevant method to distill insights from large groups of dispersed stakeholders.

- End-user feedback can help improvement leaders to navigate a shifting managerial landscape at different levels of scale. However a scalable method is required to solicit feedback in growing initiatives.
Are DCE for me?

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- Methodological advantages of DCE include:
  1. Neutralized threats from social desirability bias relative to Likert rating scales
  2. Capacity to explore a new design space; products/scenarios may well be hypothetical.
  3. Statistical efficiency
  4. Bundling of attributes maps to how we make real decisions under uncertainty, picking up on implicit tradeoffs which are hard to capture when choice components are disaggregated.
Limitations

- Preferences of ImproveCareNow participants could reflect a distinctive community culture and may be less generalizable to other network contexts.

- While selection of our three experimental attributes was informed by research and practice, other potentially potent group learning mechanisms were not examined in this study.

- We included data from care centers with incomplete enrollment which could impact reported remission rates.
Contributions

- We have identified group learning preferences that could inform efforts of health care improvement networks to support and connect participants.

- We demonstrated the discrete choice experiment as a straightforward and scalable means to solicit feedback from multidisciplinary health care professionals.
Conclusions

- As improvement networks scale up, it is not enough to do more of the same in a bigger way...

- The use of formal discrete choice methods to engage network participants in evaluating managerial alternatives is feasible and informative. This method merits broader consideration as networks and other large-scale multi-organizational improvement platforms become more widespread.

- Future research on this front should include empirical testing to identify network-based group learning mechanisms which are not only preferred by participants, but also conducive to improvements in care processes and patient outcomes.
Thank you. What questions are there?
Study Population

- We wanted to learn from self-identifying members of ImproveCareNow improvement teams at 62 pediatric gastroenterology care centers.

- We used a population-based sample with sampling frame of active network contributors via their respective care centers.

- A contact database was used to collect 296 email addresses associated with ImproveCareNow QI team members. We worked with network staff to identify eligible participants based on the sampling frame.

- The institutional review board of Cincinnati Children’s Hospital Medical Center approved the study.
Sample Characteristics

▶ Of 149 respondents, 44% were physicians, 30% nurses, 15% Research Coordinators, and 11% occupied other roles (including dietitians, parent advisors, QI specialists, and social workers).

▶ Role distributions were independent of survey response status ($\chi^2 = 6.3368, p = 0.7862$)

▶ Of 149 respondents, 20% had participated in ImproveCareNow for less than 1 year, 22% for 1-2 years, 14% for 2–3 years, 18% for 3–4 years, and 26% for more than 4 years.

▶ We assessed IBD patient population size (median 243, IQR 255) at respondents’ care centers.

▶ The difference in means of respondents’ and non-respondents’ associated patient populations was not significantly different than 0.
Multiple Imputation (MI)

- We had survey data from 17 partial respondents who completed between 1 - 7 of the 8 choice sets.

- Randomization in the survey design showed that choice data were missing completely at random, justification for MI.

- MI was implemented in SAS and used to fill in missing choice values.

- We simulated plausible values multiple times for missing choice variables to complete 20 copies of the data set; each copy was analyzed and estimation results pooled.

- MI estimates were substantially similar with estimates calculated from the subset of full respondents’ data.
SAS Orthogonal Design

SAS Orthogonal Design Summary

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<th>Saturated</th>
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<th>Final Results</th>
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* - 100% Efficient design can be made with the MktEx macro.
S - Saturated Design - The smallest design that can be made.