En-Route to a Better Care Delivery: RFID and Mobile App Data Analytics

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Data Analytics in Healthcare
ASQ Long Island 303 - Hofstra University Symposium
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Care Delivery vs. IT

- During doctor visits
  - Process efficiency
  - Data analytics on RFID-enabled process data

- Between doctor visits
  - Self-care quality
  - Data analytics on consumer data collected by mobile apps
RFID-enabled Data Analytics of Process Analysis in Ambulatory Care
Motivation

- **Ambulatory care** setting handles most of the healthcare delivery all over the world
- High **variability** negatively impacts process **efficiency**

- Radio Frequency Identification (RFID) technology can collect detailed movement and location data precisely and unobtrusively
- **Data analytics** can help identify potential solutions before actually implementing changes
Project Goal and Objectives

- Analyze patient flow process in ambulatory care to improve process efficiency
  - Understand the performance of the current process
    - Analysis of patient waiting time and process variability
  - Identify feasible solutions to reduce patient waiting time
    - Patient scheduling: discrete even simulation
    - Standardized care delivery sequence: Markov decision process
Study Site and Data Collection

Study Site: An outpatient specialty clinic affiliated with a major academic medical center

- Clinicians: 6 MDs, 1 PA, 3 MAs
- Radio Frequency Identification (RFID) Technology
  - Monitors were deployed in each room in the clinic
  - Tags were worn by patients and clinicians
  - Communication between RFID monitors and tags generate time and location stamped data for each individual every few seconds

- RFID data supplemented by observations and interviews
Floor Layout

- Procedure Room
- OT Room
- Waiting Room
- Exam Rooms
- Corridor
- Check-In/Out
Example Flow 2

- Procedure Room
- OT Room
- Waiting Room
- Exam Rooms
- Corridor
- Check-In/Out
Data Description

- 19 business days
- 389 visits
- 327 unique patients
- One RFID record every two seconds for each pair of monitors and tags!
### RFID-enabled Data Collection

#### Raw Data

<table>
<thead>
<tr>
<th>Date</th>
<th>Appt. Time</th>
<th>Tag Id</th>
<th>Room Id</th>
<th>Staff/Patient Id</th>
<th>Entered Time</th>
<th>Exited Time</th>
</tr>
</thead>
<tbody>
<tr>
<td>02/09</td>
<td>08:00 AM</td>
<td>1118</td>
<td>157</td>
<td>2283</td>
<td>08:18 AM</td>
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<td>165</td>
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<td>10:05 AM</td>
</tr>
<tr>
<td>02/09</td>
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<td>165</td>
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<td>09:05 AM</td>
<td>09:23 AM</td>
</tr>
<tr>
<td>02/09</td>
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<td>10:13 AM</td>
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</table>

An example of the sequence: ITWEMEDJMYCO

![Diagram of patient movement through different locations]
During the 67 minutes in the clinic on average, patients spend 42 minutes (63%) in waiting, and are able to receive about 13 minutes (19%) of care.

In the 42 minutes of waiting, patients spend 19 minutes (45%) waiting in the encounter room. This has been ignored by prior studies which include waiting time in the exam room in total service time!
Current Performance: Process Variability

<table>
<thead>
<tr>
<th>Location</th>
<th>Check-in</th>
<th>Intransit</th>
<th>Waiting room</th>
<th>Exam room</th>
<th>Corridor</th>
<th>Check-out</th>
</tr>
</thead>
<tbody>
<tr>
<td>Patient</td>
<td></td>
<td></td>
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<td>MD</td>
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<td>E</td>
<td>M</td>
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<tr>
<td>MA</td>
<td>IT</td>
<td></td>
<td></td>
<td>E</td>
<td>M</td>
<td>DJ</td>
</tr>
</tbody>
</table>

- 204 completed visits yield 204 flow sequences
- 157 unique clinic visit patterns. Ex. IWTWMEMTO
- 90 unique encounter patterns. Ex. MED

The large variability in care delivery process results in an inefficient process
Potential Solutions

Sources of variability

- Variable patient arrival rate
  - Changing patient scheduling policy
    - Discrete event simulation
- Variable patterns of care delivery
  - Changing care delivery sequence
    - Markov decision process
Discrete Event Simulation

- A technique to imitate the actual system and to evaluate possible outcomes of various decisions without physical implementation
- Uncertainties are taken into account
- Built upon a pre-defined process model
Simulation Schema

Replication length: 1 day

**Initial Condition**
Monday, 8:00am
7 exam rooms are available.
The clinic is empty.

**Expected Patient Arrival**
Arrival rate ~ Non homogenous Poisson, driven by scheduling policy

**Check In**
No Show?

**Renege?**

**Enter Exam Room**

**Post Visit**

**Intransit?**

**Check Out**

**Meet w/ 1st set of clinicians**
Dress Up

**Post-Visit?**

**Intransit?**

Yes

No
A good schedule can reduce patient waiting time before encounters

<table>
<thead>
<tr>
<th>Interventions</th>
<th>Wait b/f</th>
<th>Wait d/r</th>
<th>Total Wait</th>
<th>P-Value</th>
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<td></td>
<td>15.41</td>
<td>21.19</td>
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<td>21.82</td>
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<td></td>
<td>12.18</td>
<td>20.98</td>
<td>33.37</td>
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<tr>
<td></td>
<td>10.95</td>
<td>20.56</td>
<td>31.70</td>
<td>&lt; .0005</td>
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</table>
Markov Decision Process

- An analytical model to find the best policy in a discrete-time dynamic system when the outcome is uncertain
- Uncertainties are taken into account
- Built upon a pre-defined state space
Markov Decision Process: Step 1

Stage 1

0 Enter

Step 1

0.46 (25)
0.02 (0)
0.05 (0)
0.45 (0.5)
0.02 (0)

Stage 2

2 MD
3 MD 1MA
6 2MA
10 1MA
11 3MA

Expected Patient Waiting
Time in Step 1: **11.79**
Markov Decision Process: Step 2

Expected Patient Waiting
Time in Step 2: 6.88
Markov Decision Process: Step 3

Expected Patient Waiting Time in Step 3: 1.72
Markov Decision Process: Step 4

Expected Patient Waiting Time in Step 4: 0.51
Markov Decision Process: Step 5

Expected Patient Waiting Time in Step 5: 0.14
Markov Decision Process: Step 6
Markov Decision Process: Step 7

Stage 1 | Stage 2 | Stage 3 | Stage 4 | Stage 5 | Stage 6 | Stage 7 | Step 7 | Stage 8
---|---|---|---|---|---|---|---|---
0 | Enter | 2 MD | 2 MD | 2 MD | 2 MD | 6 | 2MA | 0.5
6 | 2MA | 3 MD | 1MA | 3 MD | 1MA | 10 | 1MA | 0.5
10 | 1MA | 6 | 2MA | 8 MD | 2MA | 6 | 2MA | 1
11 | 3MA | 10 | 1MA | 10 | 1MA | 10 | 1MA | 1
11 | 3MA | 11 | 1MA | 11 | 1MA | 10 | 1MA | 1
1 | Exit | S.1 | 11.8 | S.2 | 6.9 | S.3 | 1.7 | S.4 | 0.5 | S.5 | 0.1 | S.6 | 0.1 | Exit

Step 7 0.00
Markov Decision Process: Step 8
Markov Decision Process: Step 9

Stage 1  Stage 2  Stage 3  Stage 4  Stage 5  Stage 6  Stage 7  Stage 8  Stage 9

<table>
<thead>
<tr>
<th></th>
<th>S.1</th>
<th>S.2</th>
<th>S.3</th>
<th>S.4</th>
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<td>6</td>
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<tr>
<td>11</td>
<td>3MA</td>
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<td>0.1</td>
<td>0.1</td>
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</table>

Expected Total Waiting Time: 21.12
**Some MDP Results for MD6**

<table>
<thead>
<tr>
<th>Policy</th>
<th>The possible states in the first stage</th>
<th>Corresponding Probabilities</th>
<th>( \mathbb{E} ) (Waiting Time)</th>
</tr>
</thead>
<tbody>
<tr>
<td>( \pi_0 )</td>
<td>1MA, MD, PA, MDMA, 2MA</td>
<td>.66, .21, .05, .04, .04</td>
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<tr>
<td>( \pi_1 )</td>
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<td>.66, .21, .05, .04, .04</td>
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</tr>
<tr>
<td>( \pi_2 )</td>
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<td>( \pi_3 )</td>
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<td>.66, .21, .05, .04, .04</td>
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<td>.66, .21, .05, .04, .04</td>
<td>16.70</td>
</tr>
</tbody>
</table>
### Some MDP Results for MD8

**Diagram:**
- **Decision 1:** Enter
- **Step 1:** Tran. Prob. 1, Cost 1
- **Step 2:** Tran. Prob 2, Cost 2
- **Step 3:** Tran. Prob 3, Cost 3
- **Time 1:** Enter
- **Time 2:** MD1MA, 1MA
- **Time 3:** MD; 1MA
- **Time 4:** Exit

**Table:**

<table>
<thead>
<tr>
<th>Policy</th>
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<th>Corresponding Probabilities</th>
<th>$\mathbb{E}$ (Waiting Time)</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\pi_0$</td>
<td>MD, 1MA, 2MA, 3MA, MDMA</td>
<td>.46, .45, .05, .02, .02</td>
<td>21.12</td>
</tr>
<tr>
<td>$\pi_1$</td>
<td>1MA, 2MA, 3MA, MDMA, MD</td>
<td>.46, .45, .05, .02, .02</td>
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<tr>
<td>$\pi_2$</td>
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<td>.46, .45, .05, .02, .02</td>
<td>15.79</td>
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<tr>
<td>$\pi_5$</td>
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<td>.46, .45, .05, .02, .02</td>
<td>15.56</td>
</tr>
</tbody>
</table>

**Patient waiting time can be reduced by 50% if MA, rather than MD, initiates the visit**
Conclusions

- RFID technology enables the unobtrusive analyses of the flow of patients and clinicians; a limitation - can result in missing data.

- Analyses of RFID data help improve process efficiency.
Acknowledgements

- **UPMC (University of Pittsburgh Medical Center)**
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  - Gideon Naim (CFO)
  - Israel Amir (CTO)
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  - Dr. Robert Hampshire

- **General Electric Global Research Center**
  - Dr. Bahar Biller
Evaluating m-Health Services for User Engagement and Health Promotion

A Mobile App for Healthy Eating
Smartphones have great potential to change people’s behaviors. What about influencing people’s eating behaviors?
An app for promoting healthy eating which makes users’ tasks easier and behavioral outcomes better?
Capabilities of Smartphone Apps

- Information processing
  - Graphic representation
- Communication
  - Personalization
- Analysis
  - Continuous and objective data collection
- Convenience
  - Anywhere, anytime
  - Taking and sending images, videos, or audios at fingertips
Popularity of Smartphone Apps

>100,000 mHealth apps (NEJM 2014) !!!
Current Solutions and Limitations

Dietary Tracking

- **Essential** (Baker and Kirschenbaum 1993; Burke et al., 2011)
- **Burdensome and hard to sustain** (Thompson et al. 2010; Glanz et al. 2006)
- **Portion size misperceived** (Lechner et al. 1997; Mahabir et al. 2005; Subar et al. 2003)
- **Behavior undesired** (Chandon and Wansink, 2006)
Current Solutions and Limitations

2 Professional Support

- **Effective** (Morrison et al. 2012)
  - Email (Alexander et al. 2010), telephone (Spring, 2012), in-person sessions (Herman, 2012)

- Text messages or forums

- Feedback suboptimal (Byrd-Bredbenner and Schwartz, 2004)

- Calibration impossible (eHealth Initiative 2013)
Current Solutions and Limitations

Peer Support

- Effective in online communities (Yan et al., 2014; Susarla et al., 2012; Rishika et al., 2013)
- Uncertain effects on health behaviors (Maher et al. 2014)
Our Mobile-device Enabled Intervention

1 Dietary Tracking

Mobile-based Visual Diary

**Operations**
- Take a picture
- Visually estimate the portion size

**Expected Effects**
- Mobile: increased adherence (Burke et al. 2011; Shapiro et al. 2008)
- Visual:
  - Objective reference
  - Effective decision making (Chandon and Wansink 2006)

(Drawn by Iris Yang, 2014)
Our Mobile-device Enabled Intervention

2 Professional Support
Our Mobile-device Enabled Intervention

Professional Support

Image-based Dietitian Support

Operations
• Calibration on specific meals
• Feedback on meal patterns

Expected Benefits
• Increased engagement (Brouwer et al. 2011; Tate et al. 2006)
• Improved eating behaviors (Wright et al. 2011; Pomerleau et al. 2005)
Private Social Media

Operations
• “Join” or “create” social groups
• “Like/dislike” posts
• “Reply” to posts
• “Post” images, texts, and ratings

Expected Benefits
• Scientific evidence
• Peer support
• Peer * Dietitian

Our Mobile-device Enabled Intervention

Peer Support
## Experiment Design

- **Continuous App usage data** (summarized as monthly measures)
- **Monthly survey data** (1 baseline + 4 post-intervention): demographics and behavioral constructs

<table>
<thead>
<tr>
<th>Mobile App</th>
<th>Arm 1</th>
<th>Arm 2</th>
<th>Arm 3</th>
<th>Arm 4</th>
</tr>
</thead>
<tbody>
<tr>
<td>Food Diary</td>
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<td></td>
<td></td>
</tr>
<tr>
<td>(Web-visual)</td>
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<td>(Mobile-visual)</td>
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<tr>
<td>Dietitian Support</td>
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<td>Peer Influence</td>
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Experiment Design

<table>
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<th>Mobile App</th>
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<th>Arm 2</th>
<th>Arm 3</th>
<th>Arm 4</th>
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</thead>
<tbody>
<tr>
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<td>✓</td>
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Experiment Design

<table>
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<tr>
<th>Mobile App</th>
<th>Arm 1</th>
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<th>Arm 4</th>
</tr>
</thead>
<tbody>
<tr>
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<td>✔</td>
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<td>2 Dietitian Support</td>
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<td>3 Peer Support</td>
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## Experiment Design

### Data:
- Continuous App usage data (summarized as monthly measures)
- Monthly survey data (1 baseline + 4 post-intervention): demographics and behavioral constructs

### Mobile App

<table>
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<th>Mobile App</th>
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</table>

### Web

- Arm 4
- Arm 5
## Experiment Design

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<tr>
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<td>3. Peer Support</td>
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</tbody>
</table>

- **Data:**
  - Continuous App usage data
  - Monthly survey data (1 baseline + 4 post-intervention): demographics and supplementary information
Participants

- Inclusion Criteria
  - Age \( \geq 18 \)
  - Android smartphone users
  - Living in the US
  - Not currently following specialized diets or diets that require severe restrictions

- Recruitment
  - 425 subjects from March to June in 2014 (85/arm on average)

- Analysis
  - 239 technology users (48/arm on average)
## Users

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<tr>
<th></th>
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<th>Arm 1</th>
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<th>Arm 3</th>
<th>Arm 4</th>
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Data Collected

- **Mobile app**
  - 77,381 screen views with 19 seconds per screen
  - Diary
    - 15,671 food ratings
    - 12,580 food images
    - 306 meal comments by 82 users
  - Dietitian support
    - 160 messages by 45 users
  - Social support
    - 791 posts/replies by 34 users
    - 156 like/dislikes by 27 users
    - 505 memberships of 8 social groups

- **Web app**
  - 1,935 detailed diaries

- **Surveys**
  - Repeated measures
    - Usage behaviors unobservable from the intervention tools
    - Reasons not utilizing
    - Perceived healthiness of eating for the month
    - Self-report weight
    - Behavioral constructs
  - One-time measures
    - Perceived importance of theoretical features
    - Satisfaction of implemented features
    - Suggestions for improvement
Mobile-based visual diary does not work for Asian users

Odds of NOT Recording

**Asian Users**
- Web: 100%
- Mobile: 575%

**White Users**
- Web: 100%
- Mobile: 18%

*p < .0001*
Dietitian support significantly improves engagement

**Odds of NOT Recording**

- No Dietitian: 100% (p=0.02)
- Has Dietitian: 59%

**Number of Recorded Meals**

- No Dietitian: 100%
- Has Dietitian: 159% (p=0.003)
Dietitian support is effective on F&V intake for users with higher BMI.
Peer support facilitates disengagement

![Graph](image)

- Number of Recorded Meals
- No peer vs. Has peer
- P < .0001
- Month 1 to Month 4
Conclusions

**Mobile apps**
- Deliver advanced behavioral interventions
- Allow better data collection for deeper analyses

**Mobile-based visual diary**
- Needs to be tailored according to different meal types

**Image-based dietitian support**
- Is operationally feasible and effective

**Peer support**
- Should be provided with caution
- Needs further investigation
Acknowledgement

- Technical support
  - Paul Sandberg, CEO, PHRQL Inc.
  - Kumaril Bhattacharya, CTO, PHRQL Inc.
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  - Paula Martin, RD, University Health Services, CMU
  - 4 professors, University of Pittsburgh
- Funding support
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  - Dr. Ramayya Krishnan
  - Dr. Rema Padman
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- Beta testing
  - 18 friends
Thank you!
Questions?

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