Help Clients Overcome Diabetes Data Smog: Perspectives from a CEO with Diabetes

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• PWD – Type 1 for 20 years
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What is “Diabetes Data Smog”?
• 25 billion blood glucose data points collected annually
• MOST tools present back all the data with little value-added insight
• MOST people do not have the time to analyze all this data
• MOST people do not have the clinical acumen to make sense of the data

Topics to be covered
• What is “Diabetes Data Smog”?
• Specific diabetes data analysis challenges
• What technologies can help cut through the smog
• Criteria for evaluating and using new diabetes data analysis technologies

Disclosure to Participants
Notice of Requirements For Successful Completion
Please refer to learning goals and objectives
Learners must attend the full activity and complete the evaluation in order to claim continuing education credit/hours
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But wait, doesn’t diabetes software solve this problem?

Q1: What do you think of this diabetes software?
* I love it. The software is visually stunning and colorful *

Q2: How do you use software to extract insight?
* Well … extracting insight from diabetes software is often more art than science *

The impact of diabetes data smog

- Wong et al study:
  - Survey of 155 adults and 185 caregivers of children
  - People who have ever downloaded meter data
    - Adults=31% Caregivers=56%
    - People who are “Routine Downloaders” (4+ times in last year)
      - Adults=20% Caregivers=49%
    - People who are “Routine Reviewers” (Reviewed data most of the time when downloaded)
      - Adults=12% Caregivers=27%

What kind of art are we talking about?

The impressionist view

Data acquisition issues

- Causes of data dysintegration
  - Lack of meter downloading standardization
  - Gaps in data due to multiple meters
  - Date / time issues
  - Lack of food / medication / activity data

Logging data is ... Hard.
Issues with diabetes data analysis

- Too much data being presented
  - The log book
  - The spot chart
- Lack of context
  - What does a standard deviation of 50 really mean?
- The software does not answer important clinical questions

Unanswered Clinical Questions

- When am I at risk for hypoglycemia or severe hypoglycemia?
- Where do I have persistent daily patterns that, if mitigated, will improve my glycemic control and quality of life?
- Where do I stand in terms of my overall risk of acute complications?
- How can I improve my basal insulin profile?
- What are my meal time bolus issues?

But there is hope . . .

In Theory . . .

MORE WORK DONE BY COMPUTER
LESS WORK DONE BY YOU / PATIENT
BETTER INSIGHT / CONTROL = BETTER OUTCOMES
Does Theory = Reality?

Not always . . .
Different forms of DM insights can have significantly different levels of utility

What is a “good” TPMS alert?
- Accurate estimation of tire pressure
- Even more NB: Warning is predictive of danger

Possible Scenarios:
- Accidents are 3x more likely after a tire pressure warning
- Accidents are 10x more likely after a tire pressure warning

Diabetes control is like driving a car
- Try to stay between the lines (i.e. highs and lows)
- If you don’t you can get in an accident (i.e. severe lows, ketoacidosis)
Why do we use HbA1c?

They say it’s predictive, so it must be useful, right?

Eg: “Gluco Savant predicts 80% of blood glucose highs.”

IMPORTANT QUESTIONS
What information did it need to predict 80%?
• Only food, insulin, glucose, heart rate, insulin sensitivity, and BMI

In what population?
• Diverse population or only red-headed 14 year olds.

Independent validation or fitting to a specific dataset?
How many times did it flag or warn?
• What is the positive predictive value?

Frequency of warnings/alerts is critically important

Scenario 1:
Predicts 50% of severe lows
Makes a prediction 1 x per day on average
Assume 100 severe lows and 2000 days of data
\( \frac{1}{40} \) chance of a severe low every warning
(2.5% chance)

Assume 100 severe lows and 2000 days of data
\( \frac{1}{8} \) chance of a severe low every warning
(12.5% chance)

Scenario 2:
Predicts 25% of severe lows
Makes a prediction 1 time every 10 days on average

The “predictive” acid test works across the spectrum of data analysis tools

• Control systems
  – Constantly trying to predict future glucose and course correct
• Alert systems
  – A CGM should be able to accurately predict lows and highs
• Daily Patterns
  – An identified pattern of highs should be predictive of future highs
  – If uncorrected
• Measures of Diabetes Control
  – A measure of variability should be predictive of glucose excursions

Receiver Operator Characteristic
Other insight utility considerations

- Education is imperative
- Make sure you have the right tool for the job
- Coaching and support can help
- **Ultimately, clinical outcomes are the ultimate barometer of utility**
  - But make sure it is efficacious AND people will use it.

The right tool for the job

Example – measuring glycemic variability
- Knowing glycemic variability is important, but how do we measure it?
- Most people use Standard Deviation
- Is Standard Deviation the right tool for the job?

Timeliness

- When you receive insight often determines . . .
  - How actionable it is
  - Whether you will pay attention at all

Personalization

- Some people like lots of messages / alerts, some don’t
  - Push messages should have frequency / sensitivity and off settings
- Personal glucose targets
- Diet / Lifestyle considerations
Lifestyle Obtrusiveness
• Actually, some of us will not be assimilated

Lots of devices
• Complexity and learning curve
• Lack of discretion
• Hassle
  – Data entry
  – Calibration
  – HCP interaction (sorry)

Accessibility concerns
• Affordability
• Availability
• Lack of support tools

Summary – what to look for
• **Useable:** Look for DM software interfaces that are Glanceable, Push Alerts, or Control systems
  
  • **Useful:** Predictive, right balance of alert frequency vs sensitivity, validated, the right tool for the job, timely feedback

For **everyone:** Personalized, discreet, low hassle, affordable

Smog busting enablers
• Pattern recognition
• Predictive algorithms
• Expert systems
• Machine learning
• Control systems engineering

These technologies can help us move along the Glanceable / Push / Control system spectrum

Summary
See through the smog, and help your patients be diabetes data rock stars