# DATA-DRIVEN BEHAVIOR MODELING

# Human-in-the-Loop CPS

## Medicine

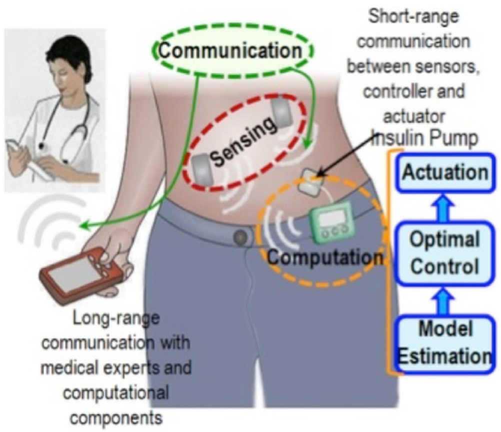


Image from http://ceng.usc.edu/cps/assets/001/92779.jpg

## Robotics

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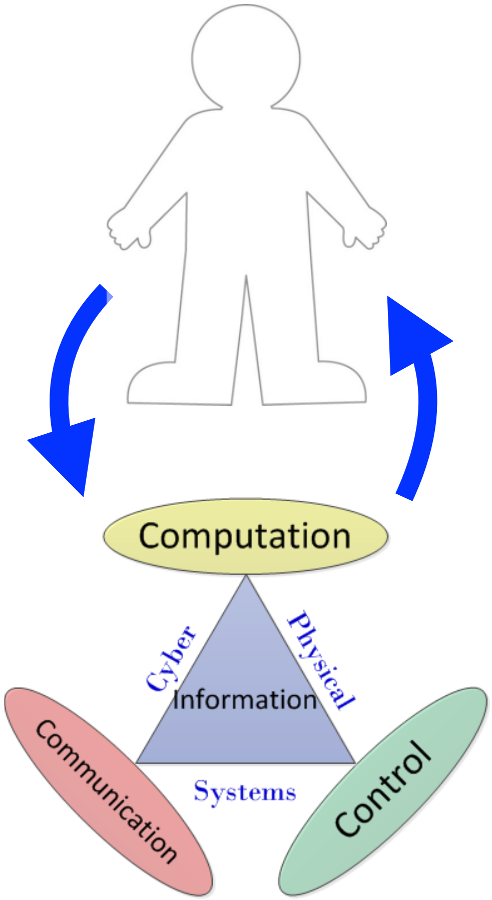


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## Transportation

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## Energy

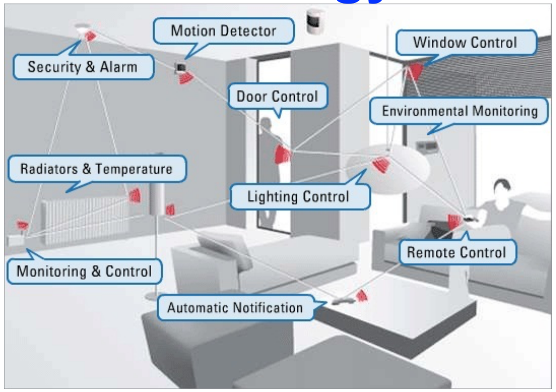
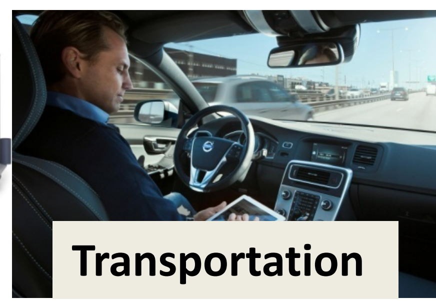



Image from http://www.skymics.com/sites/default/files/styles/portfolio_item/public/bms3_1.jpg?itok=1UFXjBIA

# Challenge: Operator Modeling

- Human-operated CPS
  - CPS operators are integral part of CPS applications
  - Uncertainty due to complex human-automation interaction
  - Needs to be taken into account in controller design and safety analysis
  - Behavior changes over time



# Behavioral Modeling in MCPS/IoMT

- Human-in-the-loop MCPS/IoMT
  - Clinicians and/or patients operate and coordinate medical devices
  - Analysis of safety and effectiveness needs to take operator behavior into consideration
    - How much the operator trusts the system
    - When and how operator interferes with automation
- Case study: patient-operated insulin pump
  - Smart pump suggest doses
    - Patients input carb intake
    - Patients can accept or adjust dose
  - How does behavior affect treatment?

# A Data-Driven Behavior Modeling and Analysis Framework for Diabetic Patients on Insulin Pumps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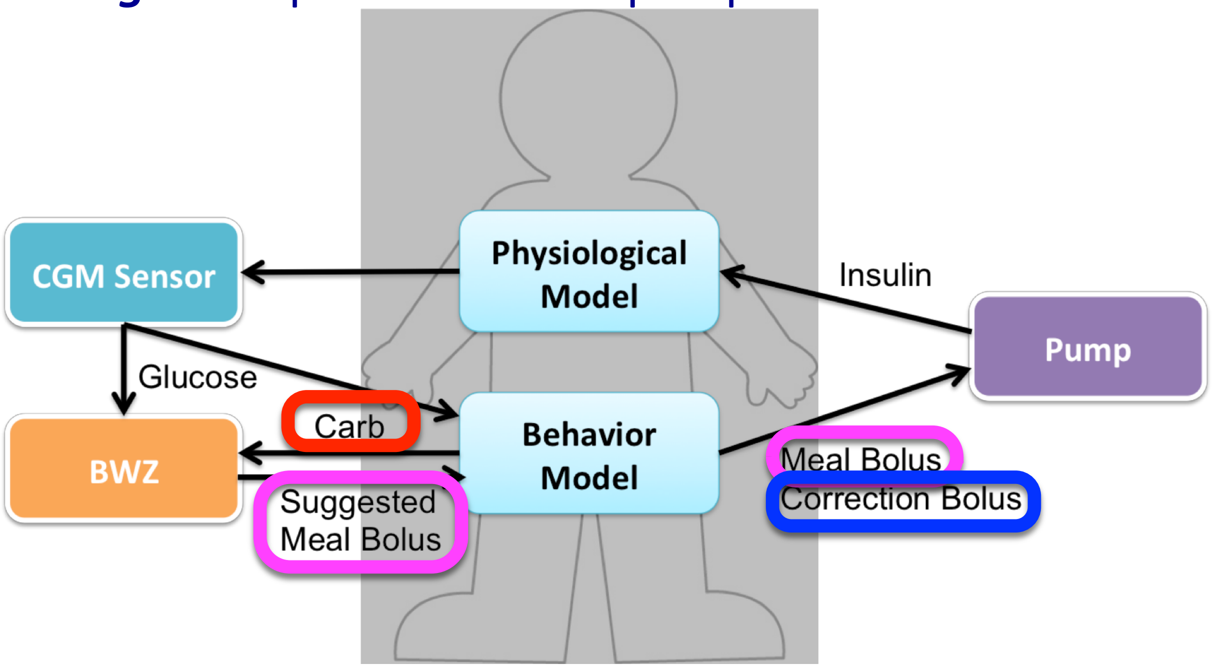
# Type 1 Diabetics (T1D) on Insulin Pumps

- Sensor-augmented subcutaneous insulin therapy
  - 30% - 40% T1D patients in the US use insulin pumps
  - Requires user supervision
    - Input meal information, approve pump-suggested boluses, give non-mealtime boluses, calibrate CGM sensor
  - American Association of Clinical Endocrinologists report highlights critical needs for better understanding the ***physiological and psychological*** impacts of insulin pumps on diabetic users

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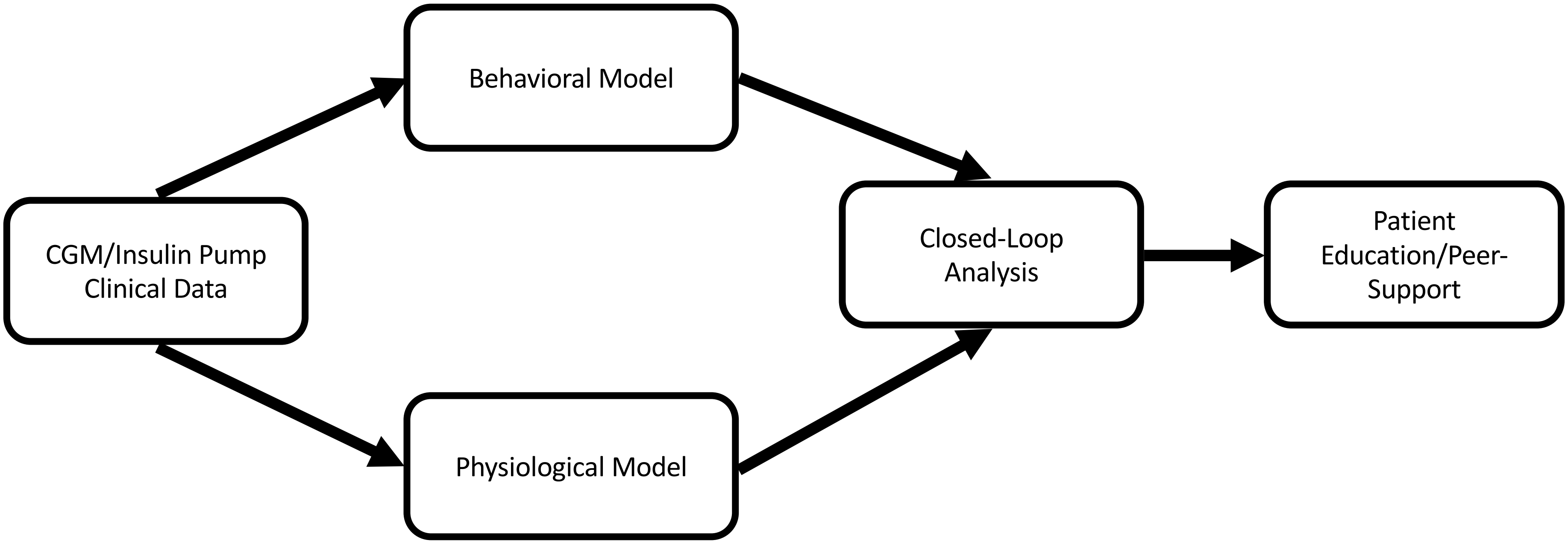
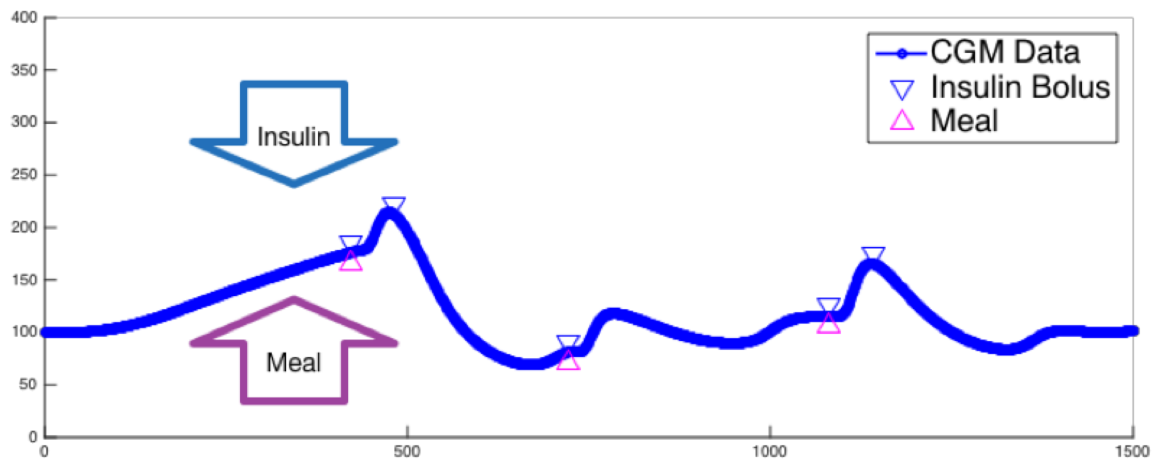
# Overview of our Approach

- Behavioral modeling: unsupervised learning
- Physiological modeling: fitting a standard physiological model
- Closed-loop analysis: probabilistic model checking
- Patient education/peer-support: how behaviors affect outcomes



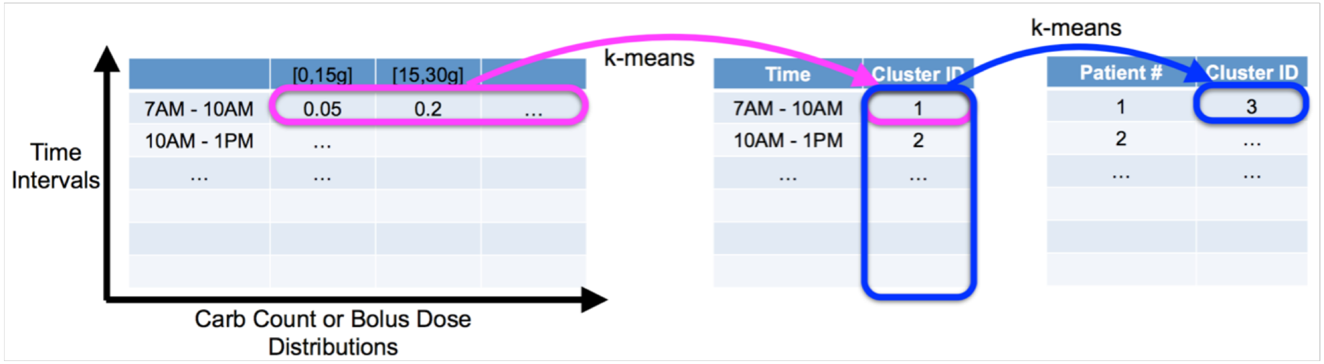
# Clinical Dataset

- Sensor-augmented insulin pump data
  - CGM readings, mealtimes & carb counts, pump suggested boluses, user-selected boluses
- 55 T1D patients at the UPenn Hospital (age 45.7 ± 15.3, body weight 79.2 ± 21.9 kg)
  - Average time duration 31 days
  - The majority of 84 patients expected to use sensor-augmented insulin pumps
    - 932 T1D patients seen at the UPenn Hospital last year, 60% use insulin pumps, 15% use CGM sensors



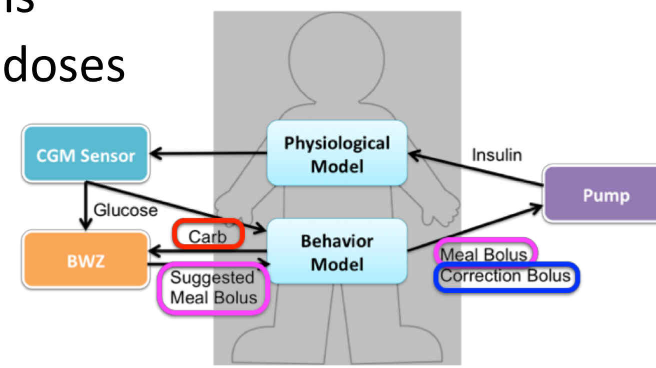
# Data-Driven Behavior Modeling

- Three behavioral sub-models
  - **Eat**: distributions of mealtime and carb counts
  - **Trust**: the likelihood of following pump-suggested boluses and distributions of dose adjustments
  - **Correct**: distributions of correction-bolus frequencies and doses
- Two-tier clustering heuristic
  - 1st stage: Probability Table —> Vector of Row Cluster ID
  - 2nd stage: Vector of Row Cluster ID —> Patient Cluster ID

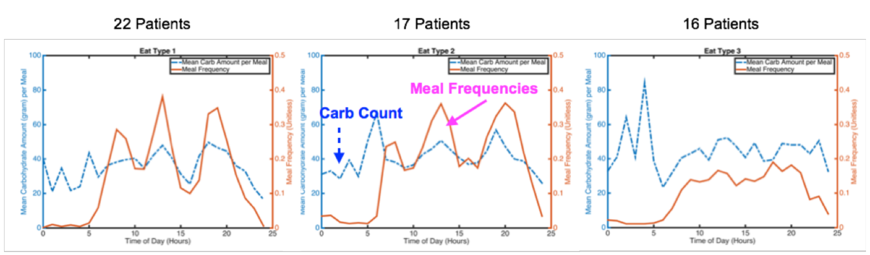


# Behavioral Modeling in MCPS

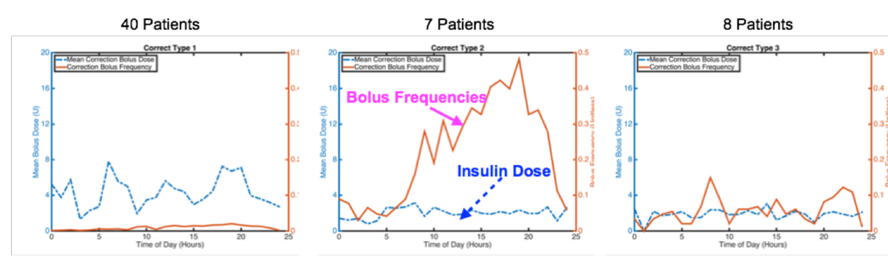
- "Eat-Trust-Correct" model
  - Distributions of  mealtime and carb counts
  - The likelihood of following pump suggestions
  - Distributions of correction frequencies and doses
  - – Constructed from actual patient data
  - – Identified a set of behavior types




- Combine behavioral and physiological models to assess expected outcomes
  - – Immediate implications for patient education




"Eat" patient types

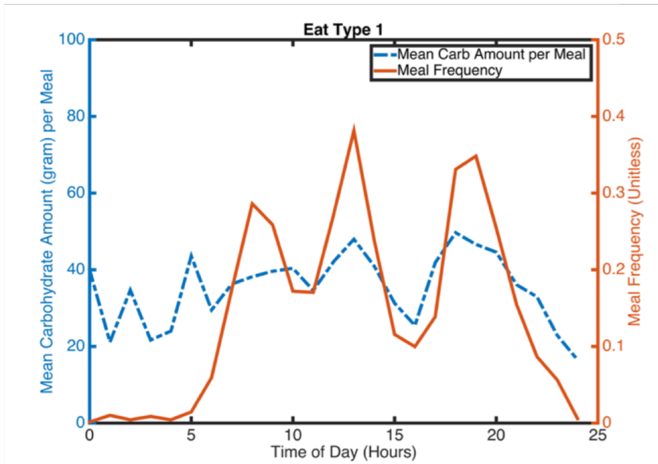



"Trust" patient types

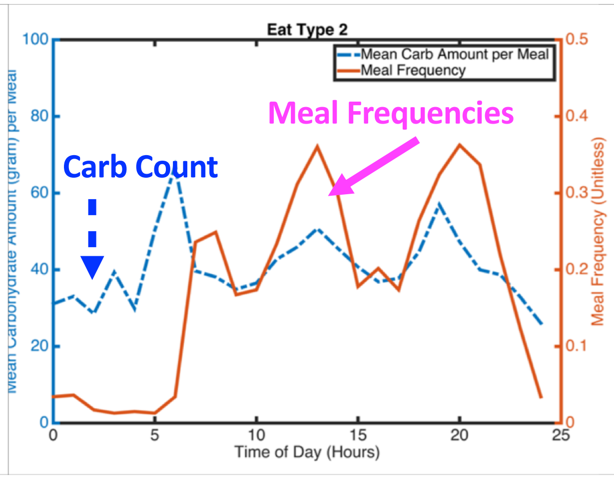
# Eat Clusters

- Eat Type 1: 3 regular meals with low-carb inter-meal snacks
- Eat Type 2: 3 regular meals with moderate-carb inter-meal snacks
- Eat Type 3: no regular meal times

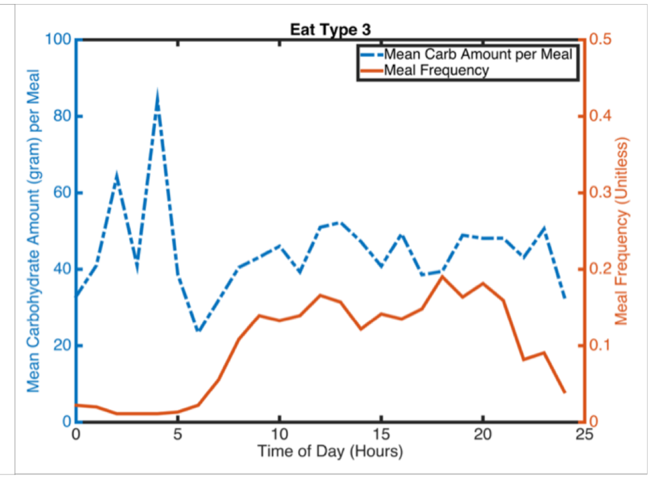
22 Patients




17 Patients




16 Patients

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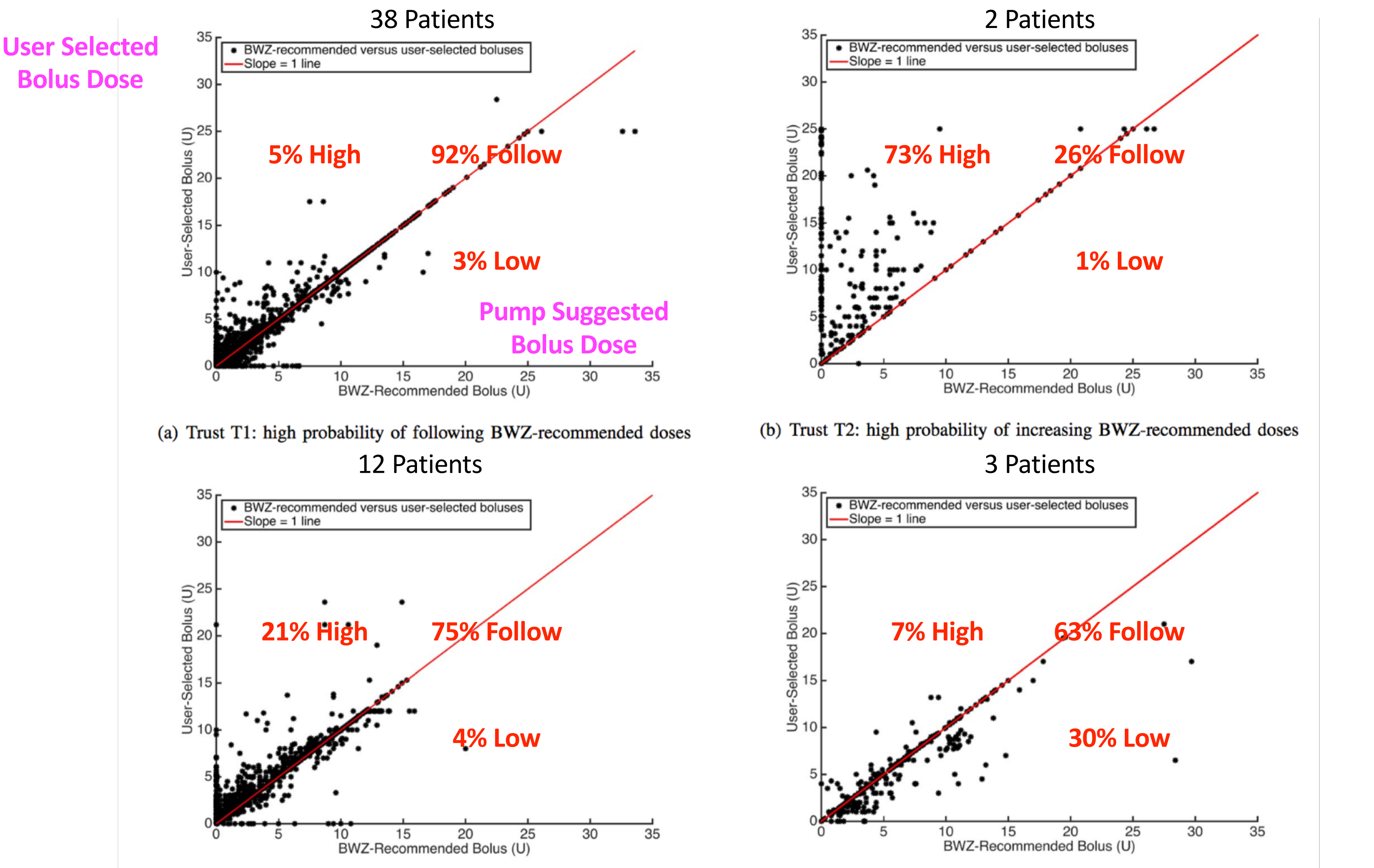
# Trust Clusters




(a) Trust T1: high probability of following BWZ-recommended doses

(b) Trust T2: high probability of increasing BWZ-recommended doses

(c) Trust T3: moderate probability of increasing BWZ-recommended doses

(d) Trust T4: high probability of decreasing BWZ-recommended doses

# Physiological Model

- Bergman model: compartmental physiological model

$$\frac{d}{dt}\begin{bmatrix} G(t) \\ g(t) \\ m(t) \\ x(t) \\ I(t) \end{bmatrix} = \begin{bmatrix} p1 & 0 & 1 & 0 & p2 \\ 0 & \frac{-1}{t_G} & 0 & 0 & 0 \\ 0 & \frac{1}{t_G} & \frac{-1}{t_G} & 0 & 0 \\ 0 & 0 & 0 & -k_a & 0 \\ 0 & 0 & 0 & \frac{k_a}{V_d} & -k_e \end{bmatrix}\begin{bmatrix} G(t) \\ g(t) \\ m(t) \\ x(t) \\ I(t) \end{bmatrix} + \begin{bmatrix} p_3 \\ \frac{A_G}{t_G} D_G(t) \\ 0 \\ u(t) \\ 0 \end{bmatrix}$$

Plasma Glucose

Plasma Insulin

Meal Input

Insulin Input

- Fit the parameters to reproduce the key glycemic statistics
  - Ranges of parameters are given in clinical literature

Population Statistics

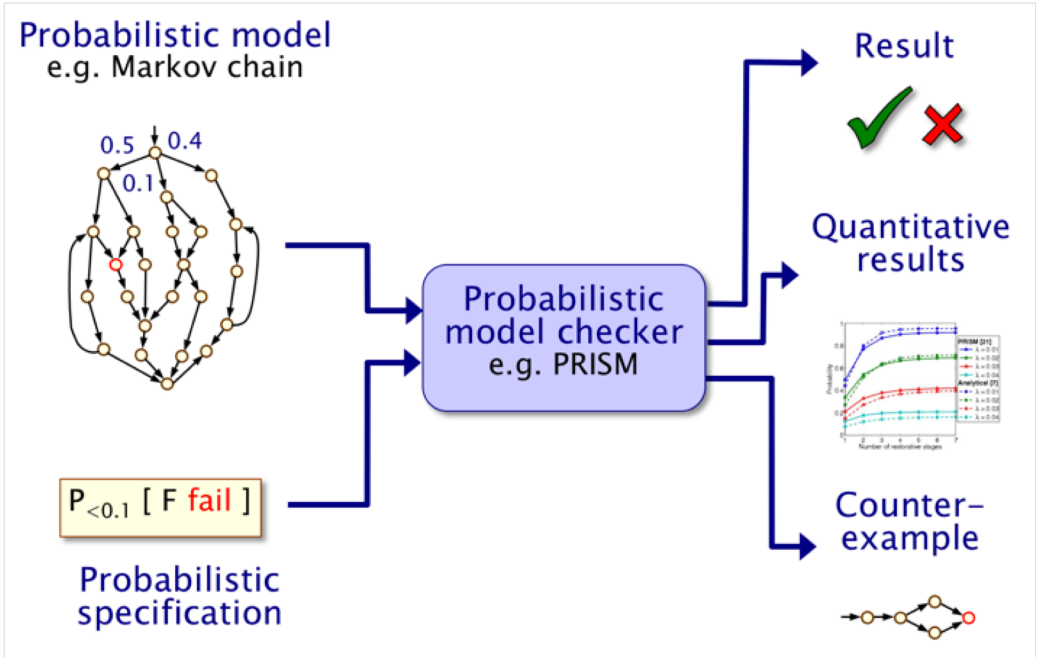
| | CSII Dataset BG | Model Simulated BG |
|---|---|---|
| Mean BG | 163 | 159 |
| Max BG | 365 | 379 |
| Min BG | 50 | 49 |
| BG > 180 | 35% | 30% |
| BG < 70 | 3% | 3% |
| BG in [70,180] | 62% | 67% |

Per-Subject Statistics

| Metric | Value |
|---|---|
| Mean Difference of Per-Patient Mean BG | 14 mg/dL |
| Mean Difference of Per-Patient BG > 180 Percentage | 5% |
| Mean Difference of Per-Patient BG < 70 Percentage | 1% |
| Mean Difference of Per-Patient BG in [70,180] Percentage | 6% |

# Probabilistic Model Checking

- The PRISM model checker
  - The coupled system can be expressed as discrete-time Markov chains
  - Exhaustively checks all execution paths of a model against probabilistic specifications



# Closed-Loop Analysis

- PRISM model checker
  - Support probabilistic transitions
  - Enables exhaustive check all execution paths of a model
- Integrate individualized physiological model and behavioral models
  - Explore how changing behavior types may impact outcomes
  - Hypoglycemia: % of CGM readings < 70 mg/dL
  - Hyperglycemia: % of CGM readings > 180 mg/dL

| | ETC Type | Hypoglycemia Rate (%) | Hyperglycemia Rate (%) |
|---|---|---|---|
| Actual type | E3T2C1 | **6.93** | 8.43 |
| Change E subtype | E1T2C1 | 6.20 | 12.78 |
| | E2T2C1 | 5.99 | 13.72 |
| Change T subtype | E3T1C1 | 0.02 | 10.33 |
| | E3T3C1 | 0.04 | 10.09 |
| | E3T4C1 | 0.02 | 11.05 |
| Change C subtype | E3T2C2 | 7.04 | 6.30 |
| | E3T2C3 | 6.95 | 7.93 |
| Change multi-subtypes | E2T1C1 | 0.04 | 16.46 |
| | E2T2C1 | 5.99 | 13.72 |
| | E3T1C3 | 0.10 | 9.76 |
| | E2T1C3 | 0.08 | 15.42 |

| | ETC Type | Hypoglycemia Rate (%) | Hyperglycemia Rate (%) |
|---|---|---|---|
| Actual type | E1T1C1 | 0 | **43.92** |
| Change E subtype | E2T1C1 | 0 | 44.38 |
| | E3T1C1 | 0 | 41.62 |
| Change T subtype | E1T2C1 | 0 | 39.13 |
| | E1T3C1 | 0 | 43.46 |
| | E1T4C1 | 0 | 45.31 |
| Change C subtype | E1T1C2 | 0 | 41.59 |
| | E1T1C3 | 0 | 43.47 |
| Change multi-subtypes | E1T2C2 | 0 | 37.22 |
| | E3T2C1 | 0 | 35.45 |
| | E3T1C2 | 0 | 38.01 |
| | E3T2C2 | 0 | 32.56 |

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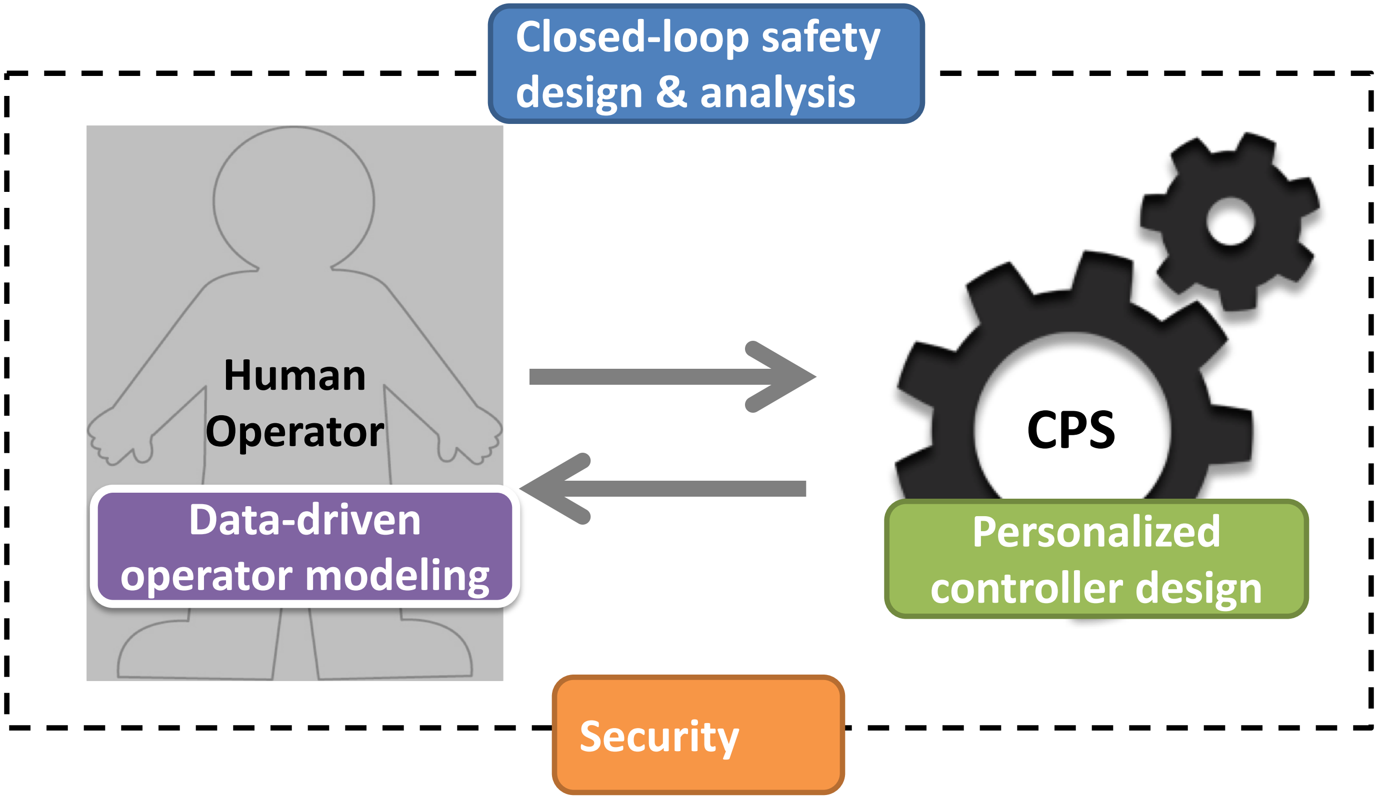
# Conclusion

- "Eat, Trust, and Correct" behavioral modeling framework for T1D on insulin pumps
- Learn ETC behavioral clusters from clinical data
- Closed-loop analysis suggests switching behavioral types may improve glycemic control outcomes
  - More effective patient education and peer-support
- Future work
  - Testing on larger clinical datasets
  - Further development and validation of learning techniques
  - Plug in other physiological models

# Challenges

## Human-in/on-the-loop CPS/IoT: Modeling, design and analysis




# Resources

- References
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  - Medical Cyber-Physical Systems, I. Lee, et al., Book Chapter, June 2016.
- Publications
  - http://www.cis.upenn.edu/~lee/home/publications/area.shtml#01
- PRECISE Center
  - https://precise.seas.upenn.edu/
- Medial Device Club
  - https://rtg.cis.upenn.edu/meddevclub/
- Penn Health Tech
  - https://healthtech.upenn.edu/

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