Institute for Data Science & Informatics
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INTERDISCIPLINARY DATA ANALYTICS AND SEARCH

APEA: A Type 1 Diabetes Self-Management Ambient-AI Assistance Tool that Bridges Trajectory Prediction, Interactive Explanation, and Just-in-Time Adaptive Intervention Action

Kun-Yi Chen[1], MS, Erin M. Tallon[1,2,3], PhD, RN, Chi-Ren Shyu[1], PhD, FACMI

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Disclosure of Relevant Financial Relationships

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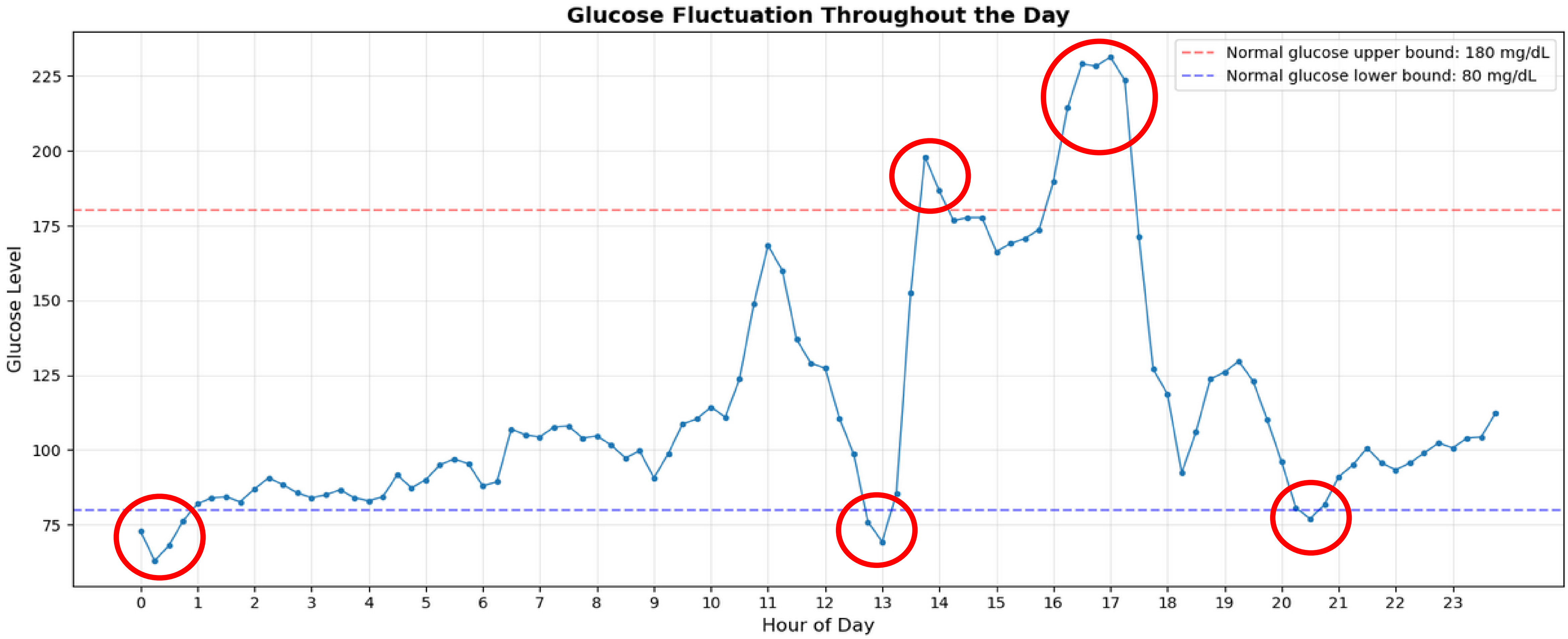
- Kun-Yi Chen
- Erin M. Tallon
- Chi-Ren Shyu

The Challenge of Chronic Disease Self-Management

- Real-time physiological fluctuations demand continuous decisions
  - **A T1D pediatric patient's daily glucose fluctuation**



The Challenge of Chronic Disease Self-Management

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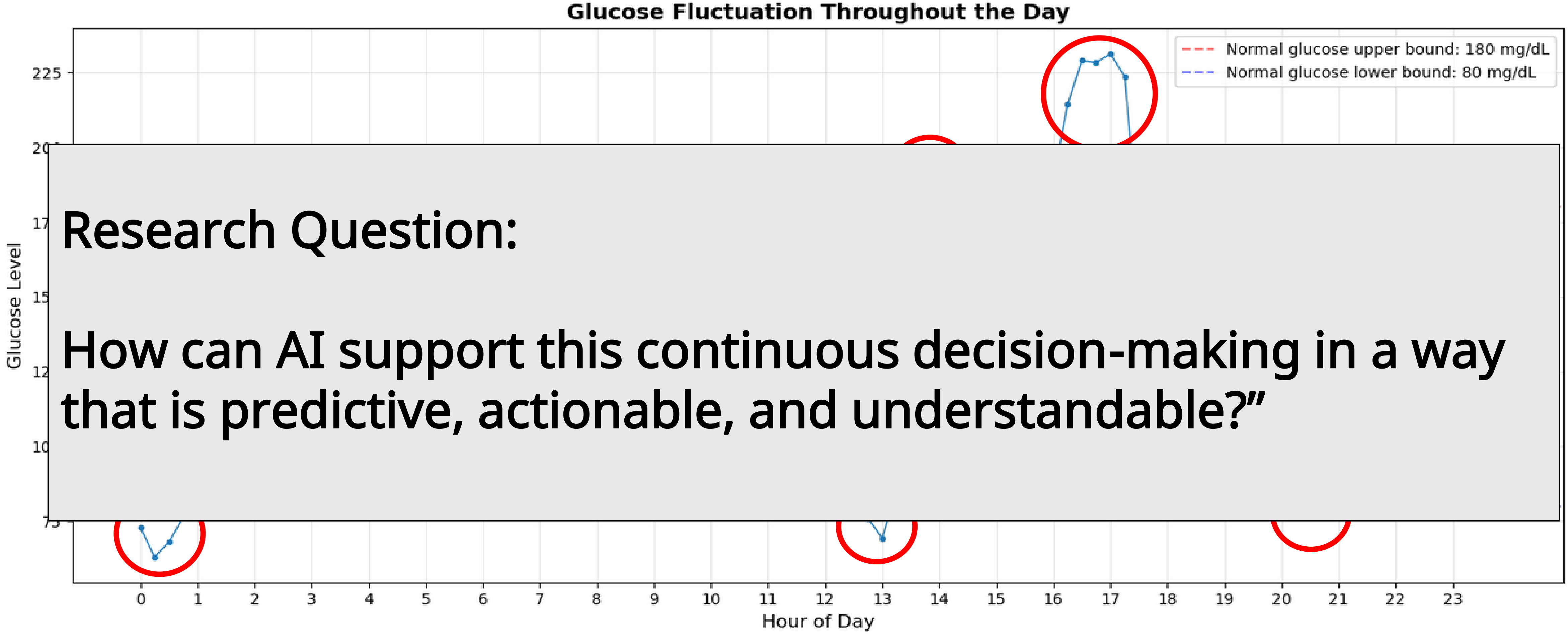

Research Question:

How can AI support this continuous decision-making in a way that is predictive, actionable, and understandable?"

Three Critical Gaps in Healthcare AI for Clinical Decision Support System Adoption

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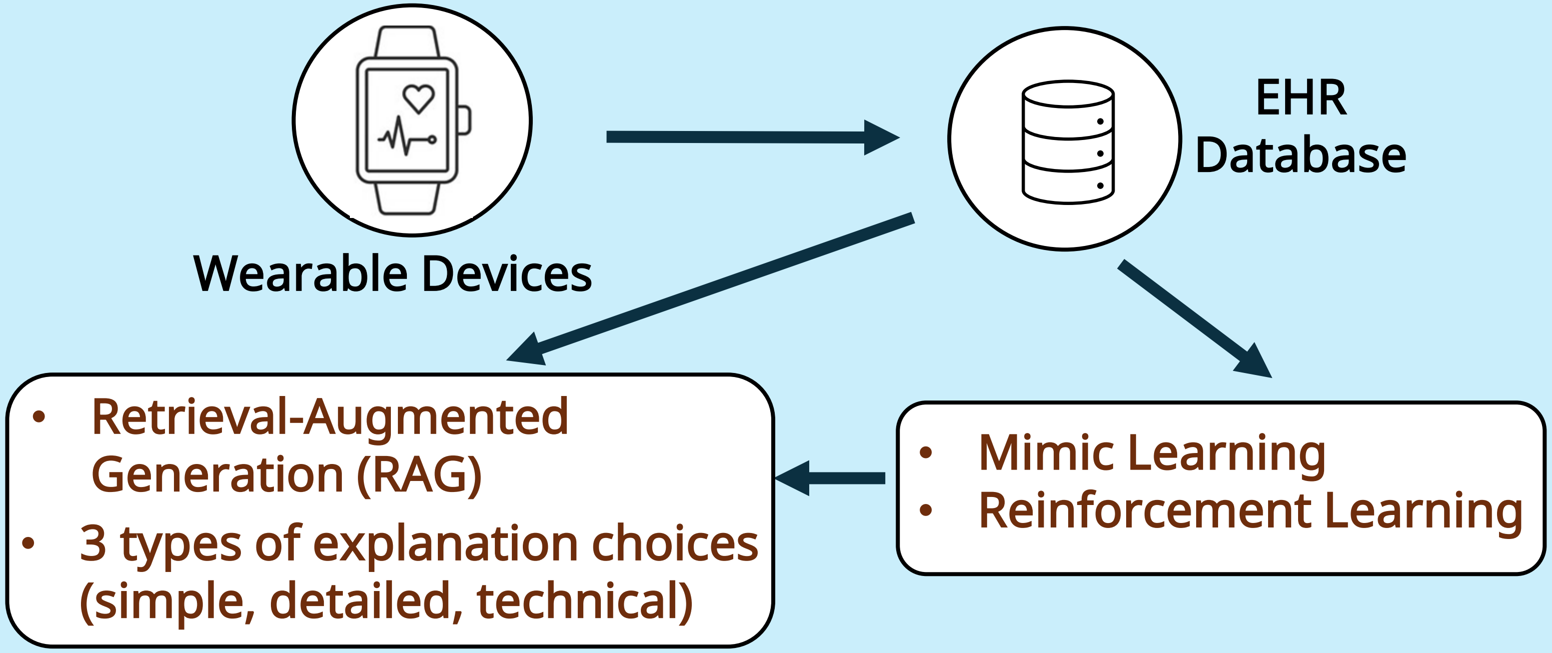
- Gap 1: Trajectory Prediction Gap
  - AI models generally predict endpoints, not dynamic trajectories
  - Missing multiple potential scenarios prediction based on different interventions
- Gap 2: Intervention Action Gap
  - AI predictions rarely suggest specific interventions
  - ML intervention prediction methods: single-intervention focus
- Gap 3: Explanation Gap
  - XAI methods: feature importance, lack integration with guidelines or patient context
  - Current XAI-LLM based methods: missing the link from explanation to actionable recommendations

APEA Framework for T1D Self-Management

- Bridging:

- **Ambient** sensing
- Multi-trajectories **Predictions**
- **Explain** ML results by LLM-based contextualized explanations
- **Actionable** & personalized intervention guidance



APEA Framework for T1D Self-Management

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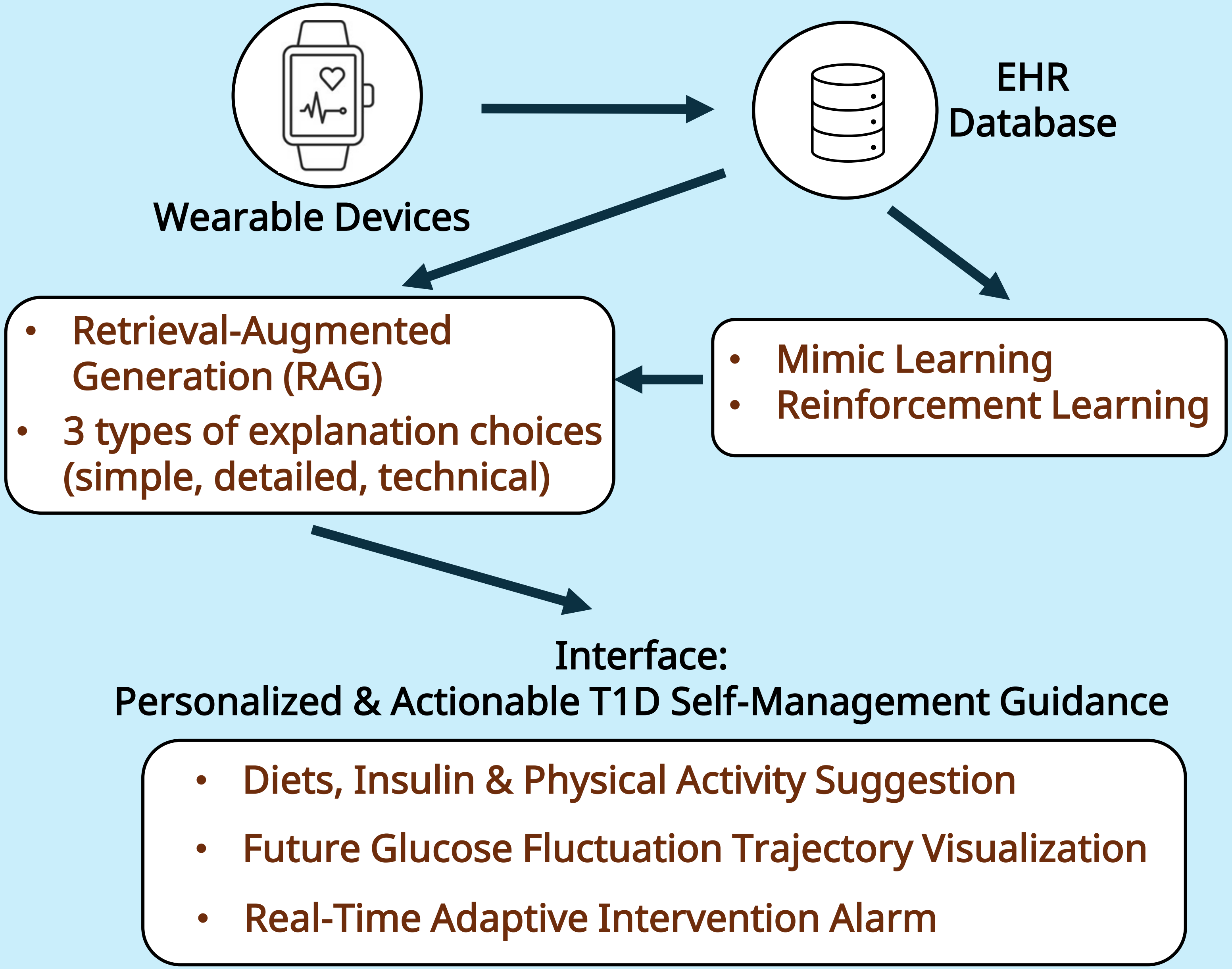

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Wearable Devices

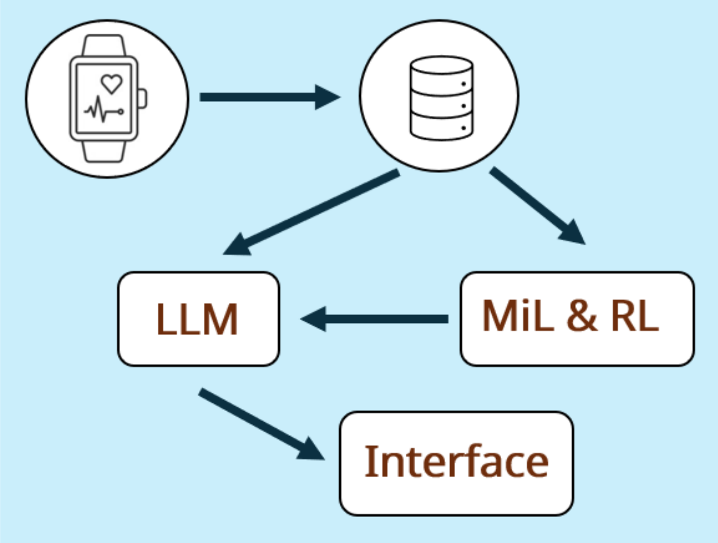
EHR Database

- Retrieval-Augmented Generation (RAG)
- 3 types of explanation choices (simple, detailed, technical)

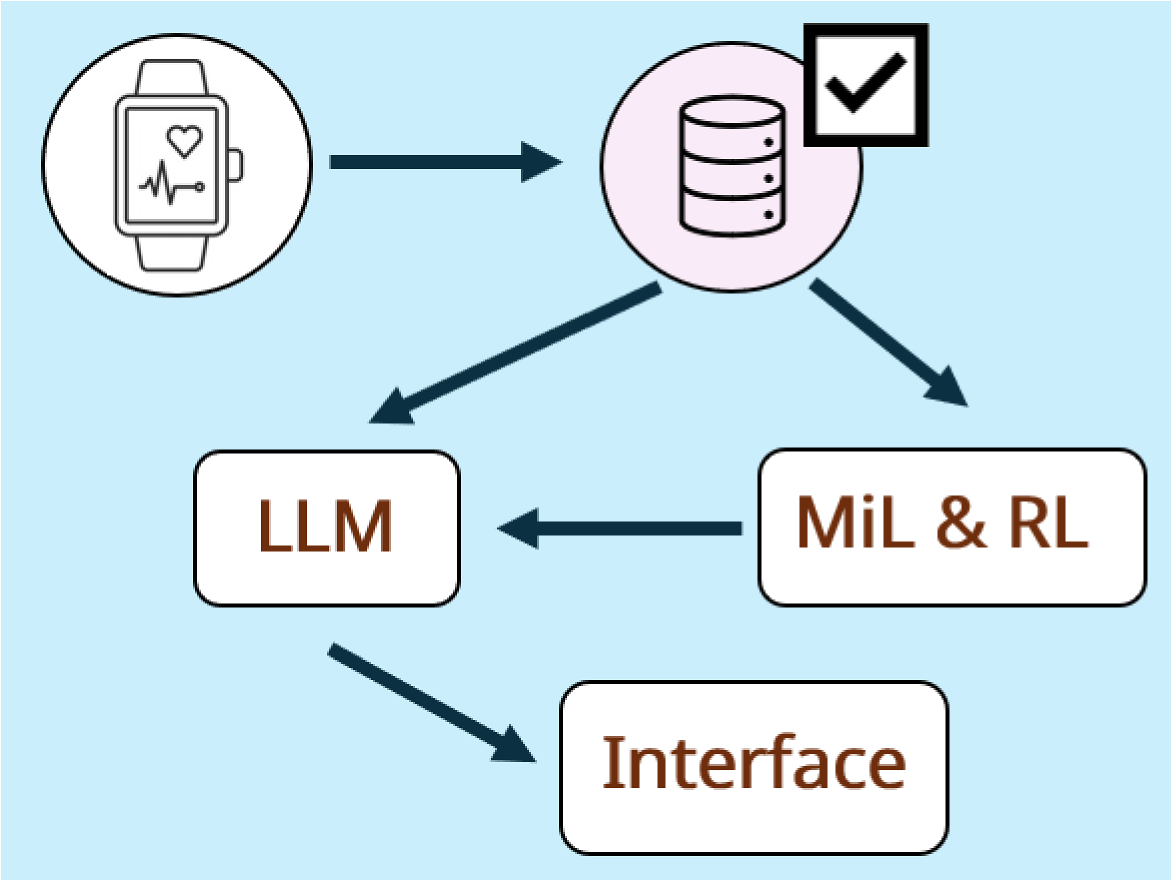
- Mimic Learning
- Reinforcement Learning

Interface:
Personalized & Actionable T1D Self-Management Guidance

- Diets, Insulin & Physical Activity Suggestion
- Future Glucose Fluctuation Trajectory Visualization
- Real-Time Adaptive Intervention Alarm



APEA Framework: Module 1 - T1D Pediatric Dataset[1,2]



1. Riddell MC, Gal RL, Bergford S, Patton SR, Clements MA, Calhoun P, et al. The acute effects of real-world physical activity on glycemia in adolescents with type 1 diabetes: The type 1 diabetes exercise initiative pediatric (T1DEXIP) study. Diabetes Care. 2024;47(1):132-9.
2. Data Contributor: Jaeb Center for Health Research Foundation, Inc. The data is accessed through the platform provided by Vivli, Inc..

APEA Framework: Module 1 - T1D Pediatric Dataset[1,2]

- 262 pediatric T1D patients (aged 12-17) across multiple U.S. clinical sites
  - Human-managed group:
    - patients using **<u>manual insulin injections</u>**
  - Insulin pump-managed group:
    - patients using **<u>insulin pump (IP) systems</u>**
- Time series data (10 days), 29 features including:
  - Demographics, physiological measurements, physical activity (PA), carbohydrate (CHO) intake, and insulin (IU) dosing

1. Riddell MC, Gal RL, Bergford S, Patton SR, Clements MA, Calhoun P, et al. The acute effects of real-world physical activity on glycemia in adolescents with type 1 diabetes: The type 1 diabetes exercise initiative pediatric (T1DEXIP) study. Diabetes Care. 2024;47(1):132-9.
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APEA Framework: Module 1 - T1D Pediatric Dataset[1,2]

- ML Prediction: 1 continuous & 3 categorical variables
  - Glucose fluctuation values in 3 hrs. (12 time points)
  - Physical activity:
    - No activity, Activity
  - Carbohydrates intake (calorie):
    - No intake, 1-50 calorie, > 50 calorie
  - Insulin dosing rate (units/hr.):
    - No dosing, low dosing (0, 0.5] (0.1%), moderate dosing (0.5, 1], high dosing (1, 200)

APEA Framework:
Module 2 - Trajectory Prediction & Intervention Optimization

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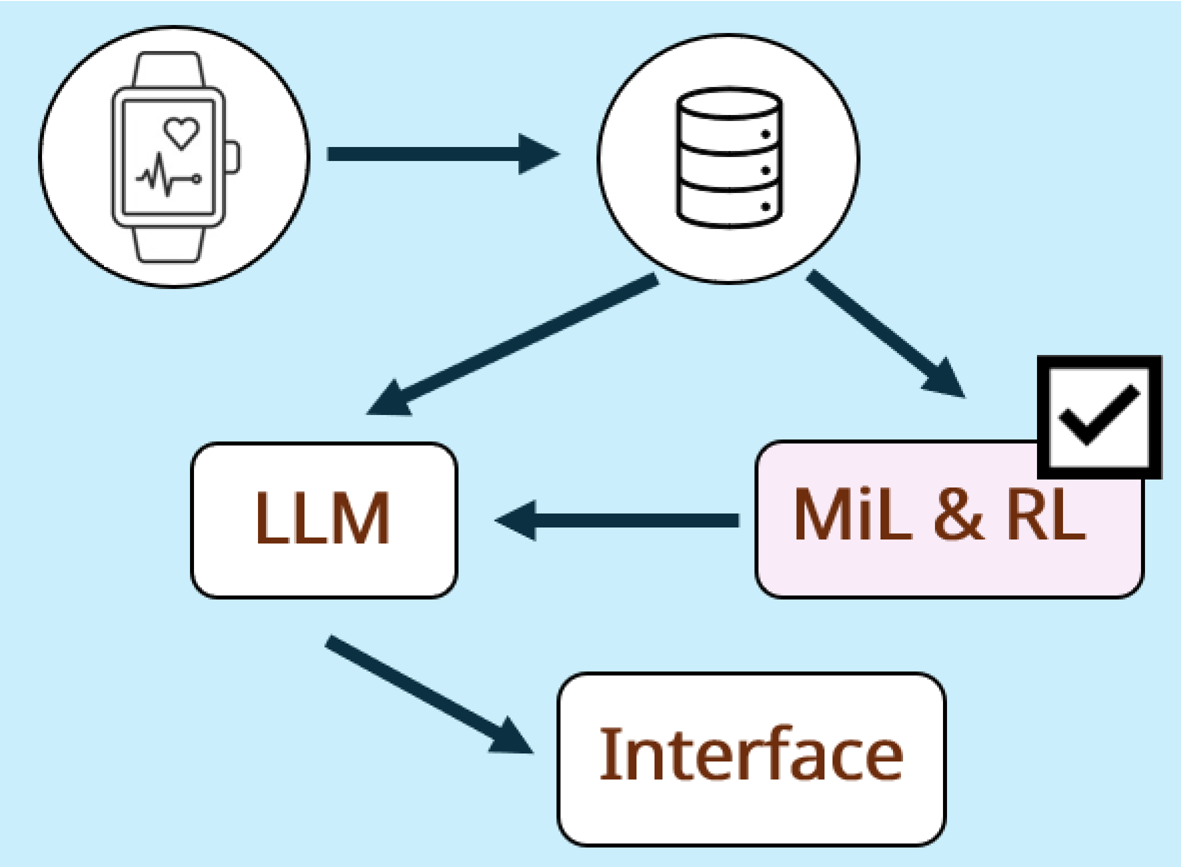
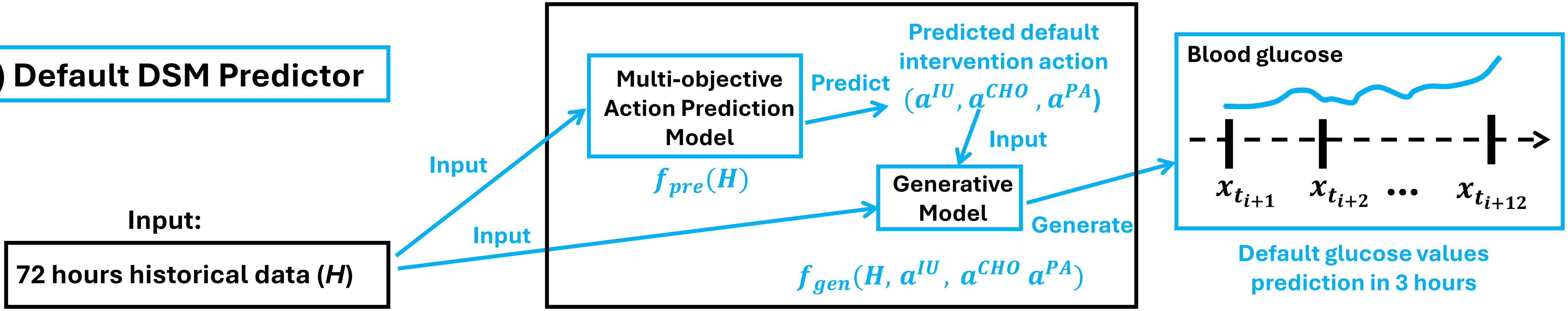


APEA Framework:
Module 2 - Trajectory Prediction & Intervention Optimization

- 1st Component: Default DSM Predictor
  - Motivation:
    - Learning human glucose management behavior directly
  - ML method: mimic learning
- 2nd Component: Alternative DSM Optimizer
  - Motivation:
    - Human behavior of glucose control are not always optimal
    - Learning glucose optimal control strategy from suboptimal data with clinically inspired reward function
  - ML method: Offline deep Q-learning with multi-objective RL

APEA Framework:
Module 2 - Trajectory Prediction & Intervention Optimization

(1) Default DSM Predictor



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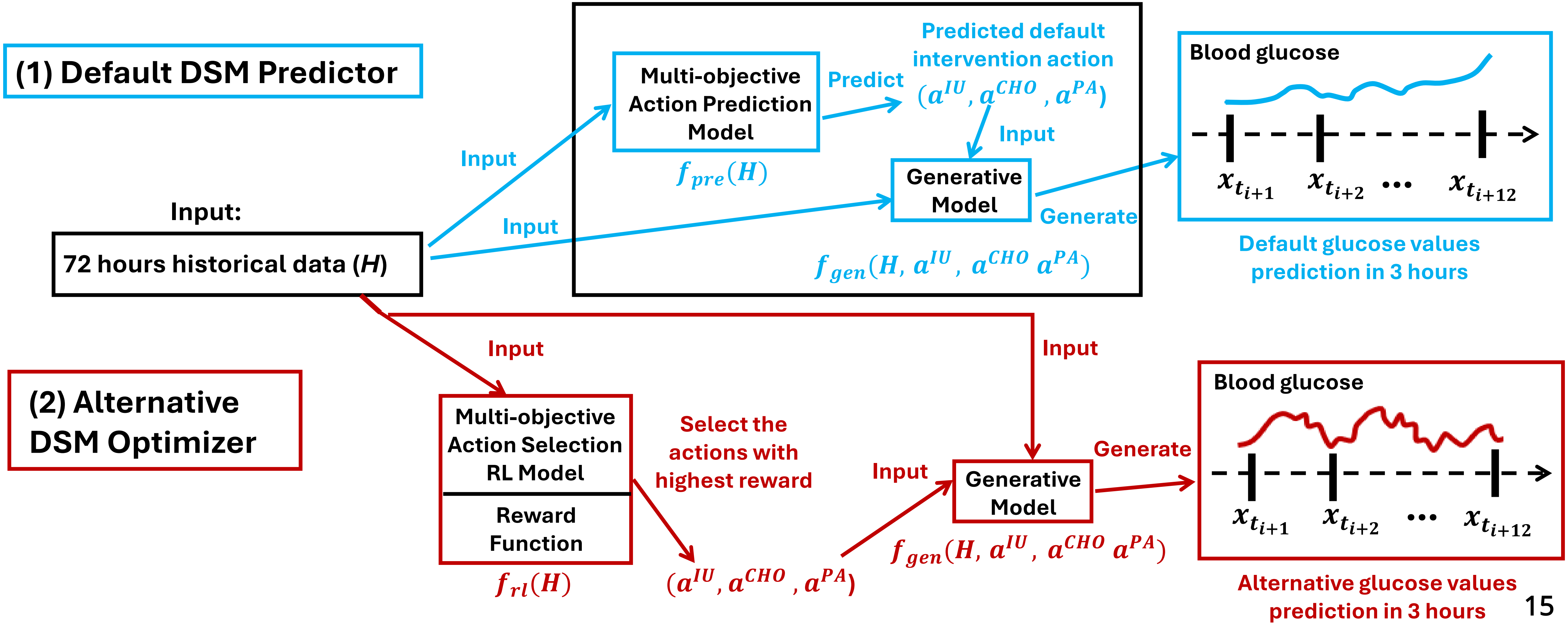
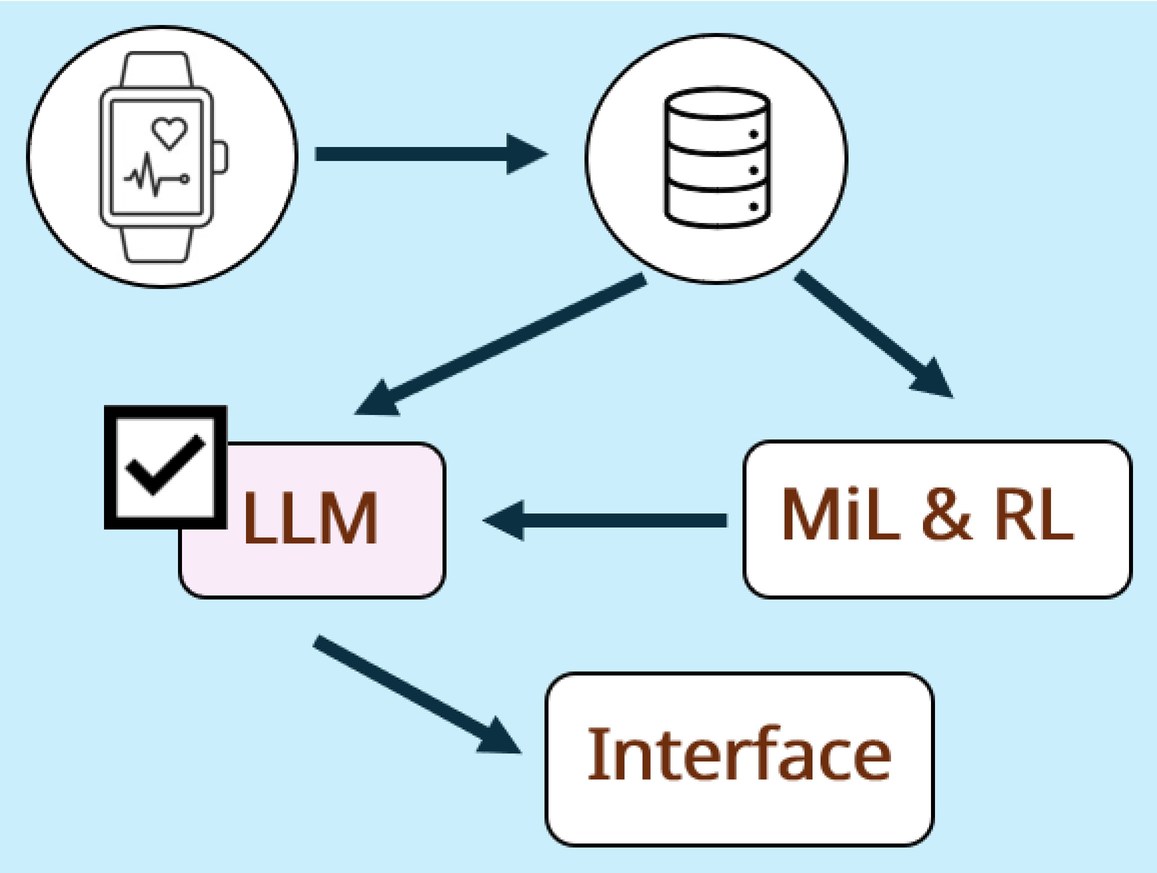


APEA Framework:
Module 2 - Trajectory Prediction & Intervention Optimization

- RL Training Strategy:
    - Reward function
        - Percentage of in-range glucose values over 3 hours
        - +1 if > 50% timestamps of predicted glucose is within-range [80,180]; -1 otherwise

APEA Framework:
Module 3 - LLM-Enhanced Explanation



APEA Framework: Module 3 - LLM-Enhanced Explanation

- **Purpose:**

  Translate ML model results into understandable, personalized & clinically relevant guidance

- **3 Layers:**
  - ML Model Output Aggregation Layer
    - Aggregates ML model results
  - Knowledge Enrichment Layer
  - Explanation Generation layer

APEA Framework:
Module 3 - LLM-Enhanced Explanation

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(1) ML Model Output Aggregation Layer

- ML recommended intervention actions
- Model confidence level of recommend actions (prediction probability)
- Predicted glucose fluctuation values

APEA Framework: Module 3 - LLM-Enhanced Explanation

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    - Enriches with patient context & clinical knowledge via RAG method
  - **Explanation Generation layer**

APEA Framework: Module 3 - LLM-Enhanced Explanation

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- ML recommended intervention actions
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(2) Knowledge Enrichment Layer (RAG)

- Knowledge repository database
  - Relevant clinical knowledge (e.g., clinical guidelines)
- Contextual retrieval
  - Similarity function: relationship between patient data & clinical literature
  - Select top 3 clinical literature

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  - **Explanation Generation layer**
    - Generates explanations with prompt engineering template

APEA Framework:
Module 3 - LLM-Enhanced Explanation

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(3) Explanation Generation layer

- Combine outputs from 1st & 2nd layers
- LLM prompting template with 3 explanation types (simple, detailed, technical)

APEA Framework: Module 3 - LLM-Enhanced Explanation

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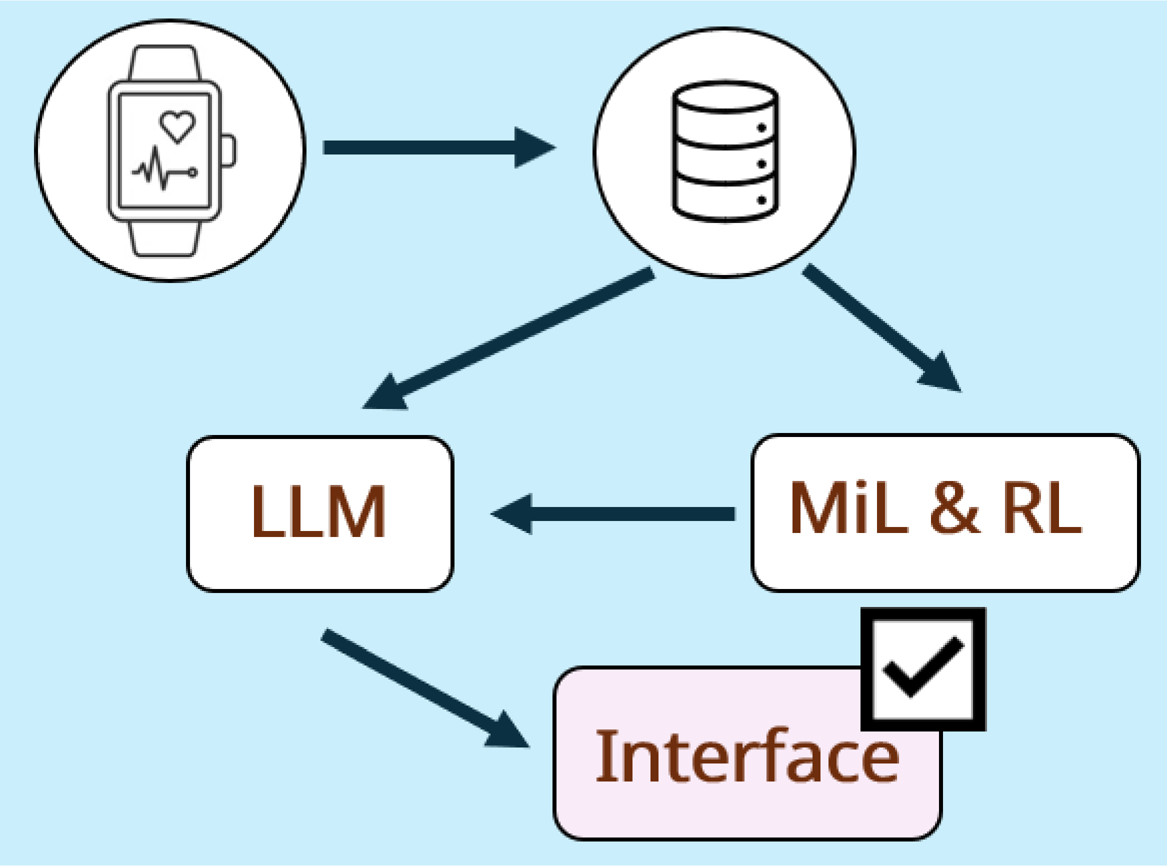
- LLM prompting template with 3 explanation types (simple, detailed, technical)

- LLM models:
  - Tokenization: all-MiniLM-L6-v2[1]
  - Prompting: BioMistral-7B-DARE model[2]

1. Labrak Y, Bazoge A, Morin E, Gourraud P-A, Rouvier M, Dufour R. Biomistral: A collection of open-source pretrained large language models for medical domains. arXiv preprint arXiv:240210373. 2024.
2. Wang W, Wei F, Dong L, Bao H, Yang N, Zhou M. Minilm: Deep self-attention distillation for task-agnostic compression of pre-trained transformers. Advances in neural information processing systems. 2020;33:5776-88.

APEA Framework: Module 4 - Interface



APEA Framework: Module 4 - Interface

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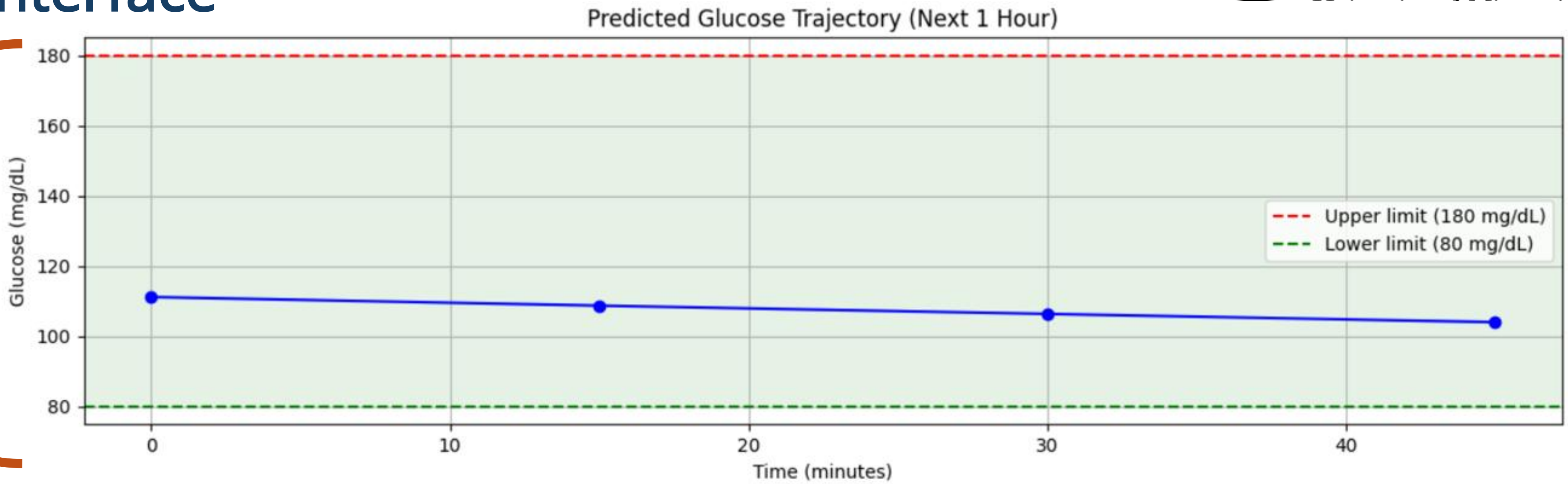
Visualization of future glucose fluctuation prediction



Explanation of ML outputs via LLM

AI-Generated Explanation:

Hello! Based on your current glucose level of 136 mg/dL, our system predicts that you will have consistently good glucose levels today. Your glucose trajectory shows that it'll be around 103.9 - 111.09 mg/dL today. That means you're doing great and don't need to make any changes at this time. Keep up the excellent work managing your diabetes!

Explanation of future glucose fluctuation & patient current condition

Recommended Interventions:
- **Insulin: No insulin adjustment needed**
- **Diet: No dietary change**
- **Activity: Physical activity recommended**

Action suggestion

ML Results Evaluation Methods

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- Evaluate RL performance over human & IP performance
  - The comparative improvement of model over human performance:

$$\frac{[RL\ success\ rate\ -\ human\ (or\ IP)\ success\ rate]}{human\ (or\ IP)\ success\ rate} \times 100\%$$

- Alert Delivery:
  - Deliver alert if > 1/3 predictions of glucose values are out-of-range [80, 180]
  - Alert accuracy evaluate :
    - Comparing ML model decision against whether >1/3 of the corresponding actual future glucose values are out of range

Main Results

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➢ In average, with 5-fold cross-validation

- ML models: LSTM[1], TCN[2] (temporal CNN), Transformer[3]

↑ 45%
RL vs. Human

↑ 69%
RL vs. IP Pump

8
Alerts/Day

80%
Alerts delivery accuracy

1. Hochreiter S, Schmidhuber J. Long short-term memory. Neural computation. 1997;9(8):1735-80.
2. Bai S, Kolter JZ, Koltun V. An empirical evaluation of generic convolutional and recurrent networks for sequence modeling. arXiv preprint arXiv:180301271. 2018.
3. Vaswani A, Shazeer N, Parmar N, Uszkoreit J, Jones L, Gomez AN, et al. Attention is all you need. Advances in neural information processing systems. 2017;30.

Conclusion

- **Limitations:**
  - LLM reliability requires ongoing validation
  - Incorporating more clinical insights into RL reward function design

- APEA shows potential to improve glycemic control by providing optimized multi-intervention suggestions and contextual explanations

Take-Home Message

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- **Informatics Impact: An Unified Ambient–Predict–Explain–Act architecture**

  APEA address current healthcare AI implementation gaps by bridging what might happen, what can be done about it, and why it makes clinical sense

- **Clinical Impact: Generalizability to other clinical applications**

  APEA offers a blueprint for AI systems in other chronic diseases requiring continuous monitoring and personalized intervention

- **Code on GitHub:**

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- Computational resources were provided by the Research Support Services High-Performance Computing infrastructure at the University of Missouri–Columbia (DOI: 10.32469/10355/97710)
- This work also made use of T1DEXIP data accessed through Vivli