

# Bridging the Gap Between Clinicians, Lived Experience Experts, and AI Systems for Glucose Regulation in Type 1 Diabetes

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**CAPSML**



Australian  
National  
University



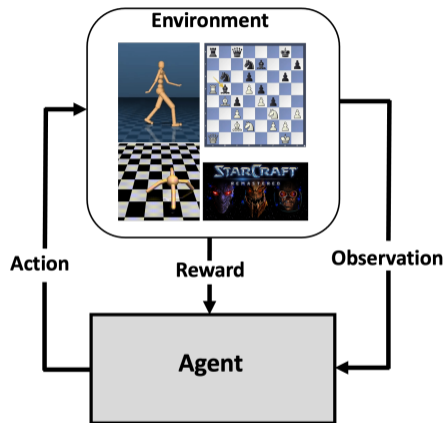
# Acknowledgement of Country



- 1 Background: Reinforcement Learning & Type 1 Diabetes
- 2 Introduction: What are we trying to solve?
- 3 Methods: Formulating the problem and experimental setup
- 4 CAPSML: How we integrate clinical and lived experience insights
- 5 Results: Progress & future work
- 6 Conclusion

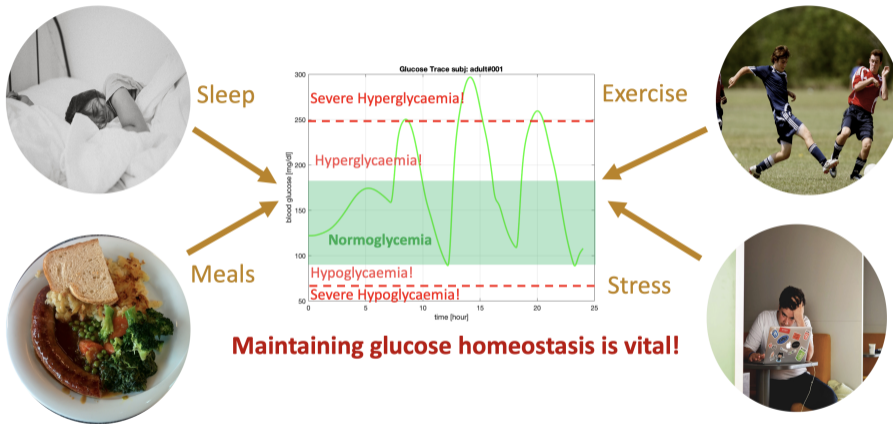
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# Reinforcement Learning (RL)



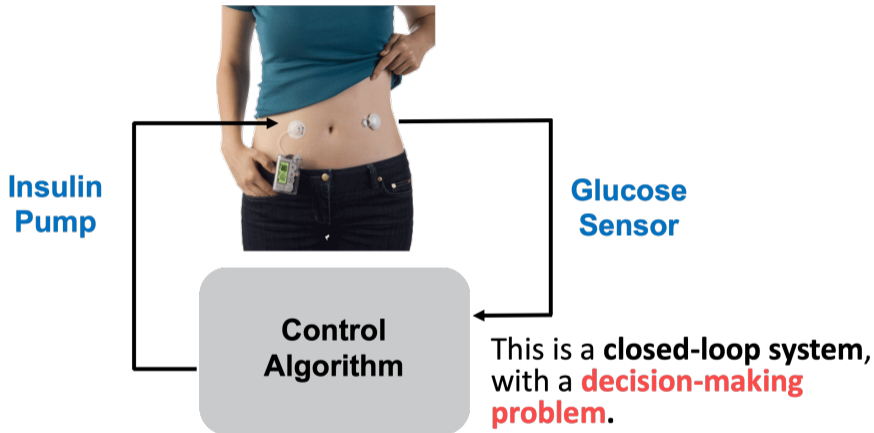
The “Law of Effect” in psychology introduced learning by trial and error, which described the effect of reinforcing events based on the tendency to select actions [Thorndike, 1911].

# The Glucoregulatory System & Type 1 Diabetes



**Clinical objective is to improve Time in Normoglycemic Range (TIR), while avoiding hypoglycemic & hyperglycemic risk.**

# Artificial Pancreas Systems (APS)



APS are **high-risk medical devices**. Existing commercial APS are **hybrid systems (manual decision-making required)**, and designed using classical control algorithms (PID & MPC).

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# Improve Performance & Eliminate Cognitive Burden



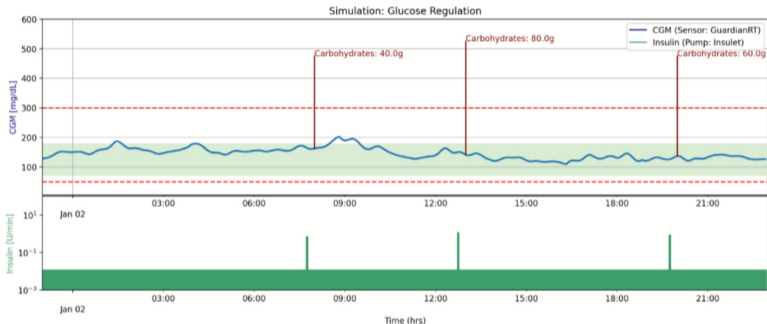
How much **Insulin**  
do I need?

Brew-Sam, et al. "Experiences of young people and their caregivers of using technology to manage type 1 diabetes mellitus: Systematic literature review and narrative synthesis", JMIR Diabetes, 2021.

Hettiarachchi, et al. "Integrating multiple inputs into an artificial pancreas system: Narrative literature review", JMIR Diabetes, 2022.

Brew-Sam, et al. "Toward Diabetes Device Development That Is Mindful to the Needs of Young People Living With Type 1 Diabetes: A Data-and Theory-Driven Qualitative Study", JMIR Diabetes, 2023.

# Existing Clinical Treatment (Basal-Bolus)



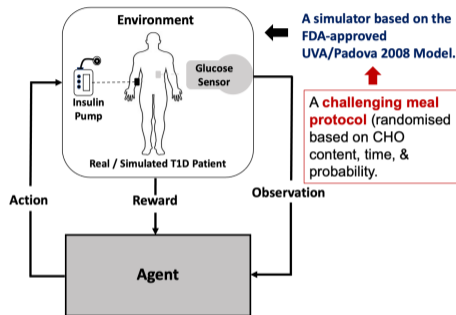
**Figure:** An ideal basal-bolus insulin treatment strategy without human error.

**Requires manual user input on meal announcements & carbohydrate estimation, which leads to errors & sub-optimal glucose regulation.**

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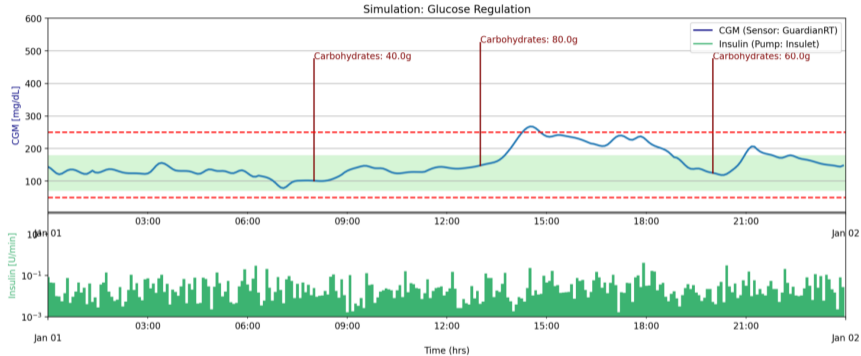
# Method: Problem Formulation & Experimental Setup



**A Partially Observable Markov Decision Process (POMDP).** Use the open-source Simglucose simulator, based on the **FDA-accepted UVA/PADOVA 2008 model** for **pre-clinical trials**.

Hettiarachchi, et al. "A Reinforcement Learning Based System for Blood Glucose Control without Carbohydrate Estimation In Type 1 Diabetes: In Silico Validation", EMBC2022.

Hettiarachchi, et al. "Non-linear continuous action spaces for reinforcement learning in type 1 diabetes", AJCAI2022. <img alt="Navigation icons" data-bbox="715 925 945 945"/> 12/35



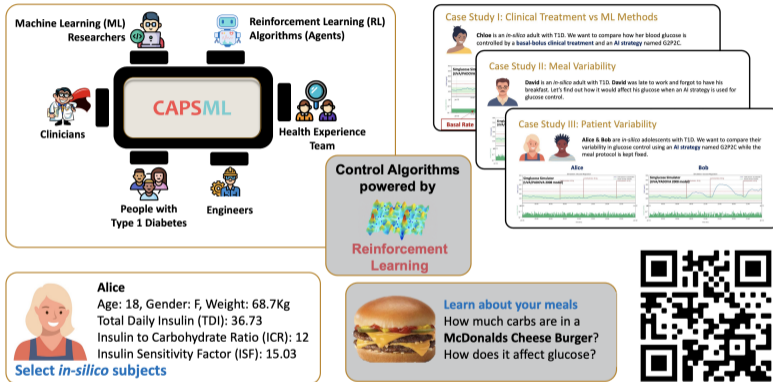
**No meal announcements.**  
**No meal carbohydrate (CHO) estimation.**

Hettiarachchi, et al. "A Reinforcement Learning Based System for Blood Glucose Control without Carbohydrate Estimation In Type 1 Diabetes: In Silico Validation", In 2022 44<sup>th</sup> Annual International Conference of the IEEE Engineering in Medicine & Biology Society (EMBC) 2022 Jul 11 (pp. 950-956). IEEE.

# Content


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# CAPSML: Co-creation & synergies when people and AI work together



Desborough, et al. "A Framework for Involving Coproduction Partners in Research About Young People with Type 1 Diabetes", Health Expectations, 2022.

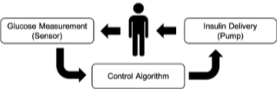
Hettiarachchi, et al. "CAPSML: Bridging the Gap Between Clinicians, Lived Experience Experts, and Artificial Intelligence Systems for Glucose Regulation in Type 1 Diabetes", 34<sup>th</sup> Medical Informatics Europe (MIE), 2023.



## Controlling Artificial Pancreas Systems through Machine Learning

### Abstract

Type 1 Diabetes (T1D) requires the administration of insulin externally to maintain glucose levels, which is crucial as both low and high glucose levels are detrimental. This is usually done through an insulin pump attached to the body. A continuous glucose sensor is also attached to measure the glucose levels so that a control algorithm can estimate the appropriate insulin dose. We design Reinforcement Learning (RL) algorithms for this control problem. The figure below summarises the main components of an Artificial Pancreas System (APS) to treat T1D.



Maintaining glucose levels is a life-long optimisation problem, complicated due to the disturbances associated with daily events (meals, exercise, stress... etc), delays present in glucose sensing and insulin action, partial observability, and safety constraints among others. Below you can see a simulated glucose control strategy of a RL algorithm.

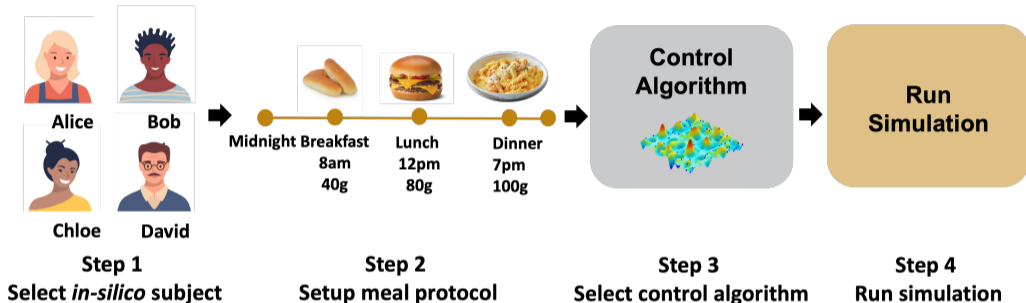
**Acknowledgement:** This research was funded by the Australian National University and the Our Health in Our Hands initiative; and by the National Computational Infrastructure (NCI Australia), and NCRIS enabled capability supported by the Australian Government.

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**Publicly available online** and released under the MIT license.

System demonstration: <https://youtu.be/J05MkPCuqCw>.

# Running a simulation...



**Four simple steps, on a desktop/mobile device without any specialized hardware.  
Previous simulation tools require technical knowledge & inaccessible to the public.**

# Sample simulation output

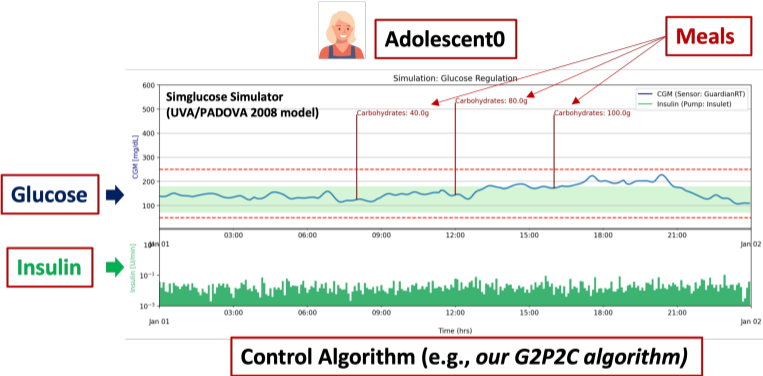


Table. Clinical performance metrics.

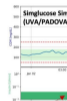
Metric	Value
0 Time Above Range (TAR) - Level2 (>250 mg/dL)	0.0%
1 Time Above Range (TAR) - Level 1 (180 - 250 mg/dL)	14.93%
2 Time In Range (TIR) (70 - 180 mg/dL)	85.07%
3 Time Below Range (TIR) - Level 1 (54 - 70 mg/dL)	0.0%
4 Time Below Range (TIR) - Level 2 (<54 mg/dL)	0.0%
5 Risk Index (RI)	4.21
6 Low Blood Glucose Index (LBGI)	0.44
7 High Blood Glucose Index (HBGI)	3.77

Simple visualizations & specialized clinical metrics / features for power users.

## Case Study I: Clinical Treatment vs ML Methods



**Chloe** is an *in-silico* adult with T1D. We want to compare how her blood glucose is controlled by a **basal-bolus clinical treatment** and an **AI strategy** named G2P2C.



Basal Rate

## Case Study II: Meal Variability



**David** is an *in-silico* adult with T1D. **David** was late to work and forgot to have his breakfast. Let's find out how it would affect his glucose when an AI strategy is used for glucose control.



## Case Study III: Patient Variability



**Alice & Bob** are *in-silico* adolescents with T1D. We want to compare their variability in glucose control using an **AI strategy** named G2P2C while the meal protocol is kept fixed.

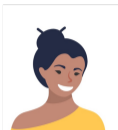
Alice



Bob

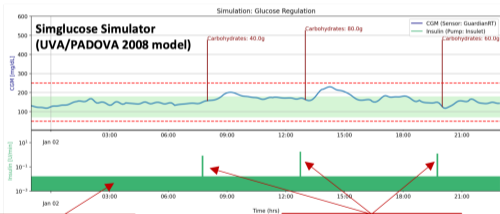


# Sample Case Study I: Clinical Treatment vs RL Methods



**Chloe** is an *in-silico* adult with T1D. We want to compare how her blood glucose is controlled by a **basal-bolus clinical treatment** and an **RL strategy** named G2P2C.

## Basal-bolus Treatment

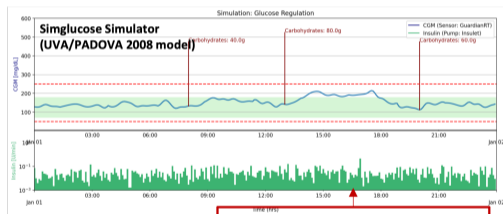


**Basal Rate**

**Bolus Insulin**

- Requires manual user input on **meal announcements & carbohydrate estimation**.
- Easy to understand.

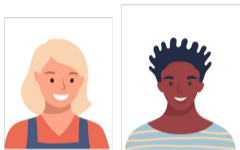
## RL Strategy



**Complex Insulin Infusion**

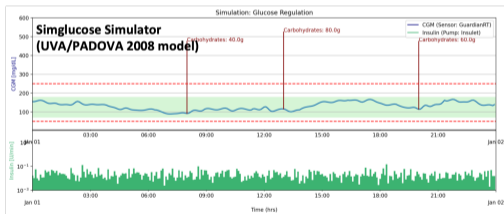
- The RL treatment strategy is more complex.
- Highlights the importance of collaboration & tools to improve explainability.

# Sample Case Study II: Patient Variability

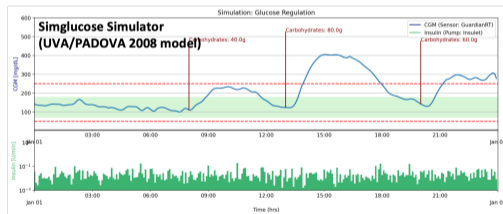


**Alice & Bob** are *in-silico* adolescents with T1D. We want to compare their variability in glucose control using an **RL strategy** named G2P2C while the meal protocol is kept fixed.

**Alice**



**Bob**



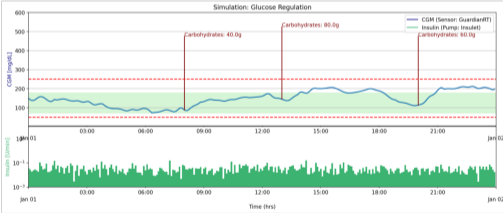
- Controlling blood glucose in Alice is easier compared to Bob.
- The RL strategies need to be carefully validated across all cohorts and subjects. CAPSML provides the capability to run simulations and visualise.

# Sample Case Study III: Meal Variability

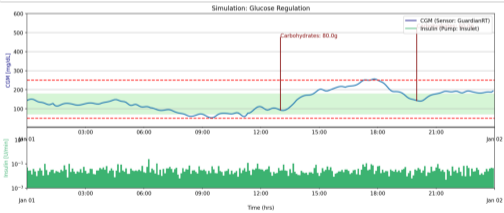


**David** is an *in-silico* adult with T1D. **David** was late to work and forgot to have his breakfast. Let's find out how it would affect his glucose when an RL strategy is used for glucose control.

## Normal Day



## Forgot to have breakfast



- Simulating real-life events to evaluate potential failures of RL strategies is important.

**CAPSML**

Home  
Quick Start  
Simulate  
**Clinical Analysis**  
Meal Analysis  
GluCoEnv  
RL Analysis  
Citation  
Publications  
Contact

**Clinical Analysis**

You can learn and simulate clinical treatment strategies such as basal bolus treatment. Customise the parameters of basal bolus treatment to run your simulations.

Please select an in-silico subject and setup the meal protocol.

Select Cohort	Select Subject	Breakfast Carbohydrates (g)	Breakfast Time (HH:MM, 24-hour)
Adult	0	40	8:00
	in-silico subject name: Adult0	Lunch Carbohydrates (g)	Lunch Time (HH:MM, 24-hour format)
	Age: 61.0	80	13:00
	Body Weight (BW): 102.32	Dinner Carbohydrates (g)	Dinner Time (HH:MM, 24-hour format)
	Total Daily Insulin (TDI): 50.42	60	20:00
	Insulin to Carb Ratio (ICR): 10.0		
	Insulin Sensitivity Factor (ISF): 8.77		

**Bolus Insulin Delivery:**

The meal bolus is delivered in advance to meals based on the meal announcement time specified.

Use Meal Bolus

Insulin to Carbohydrate Ratio (ICR)

The correction bolus is delivered together with the meal bolus with adjustments avoiding over corrections for previous meal.

Use Correcting Bolus

Insulin Sensitivity Factor (ISF)

**Acknowledgement:** This research was funded by the Australian National University and the Our Health in Our Hands initiative; and by the National Computational Infrastructure.

**A user friendly, accessible tool for analysing existing clinical treatment strategies.**  
**Current tools require programming knowledge (e.g., MATLAB, Python).**

# Feature Requests: People with T1D

**Home**  
Quick Start  
Simulate  
**Meal Analysis**  
GluCoEnv  
RL Analysis  
Publications  
Contact

## Analyse Effect of Meals

Simulate different meals and snacks to analyse the effect on glucose. The carbohydrate content of the meals are based on the Carbohydrate reference list provided by Diabetes UK.

Please select the required configuration for the simulation and press Run.

Select Cohort: Adult | Select Subject: 0 | Select Control Algorithms: BB

Breakfast: Snickers (Funsize) | Lunch: McDonalds Cheese Bu... | Dinner: Pasta Cooked (1 serve...)

Breakfast Portion Size: 1 | Lunch Portion Size: 1 | Dinner Portion Size: 1

Breakfast Time: 8:00 | Lunch Time: 13:00 | Dinner Time: 20:00

Run

Breakfast: | Lunch: | Dinner:

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Quick Start  
Simulate  
**Meal Analysis**  
GluCoEnv  
RL Analysis  
Publications  
Contact

## Meal Analysis

Breakfast: | Lunch: | Dinner:

Simulation Progress

Simulation: Glucose Regulation

Glucose (mg/dL) vs Time (hrs)

Carbohydrates: 11.0g | Carbohydrates: 31.0g | Carbohydrates: 73.3g

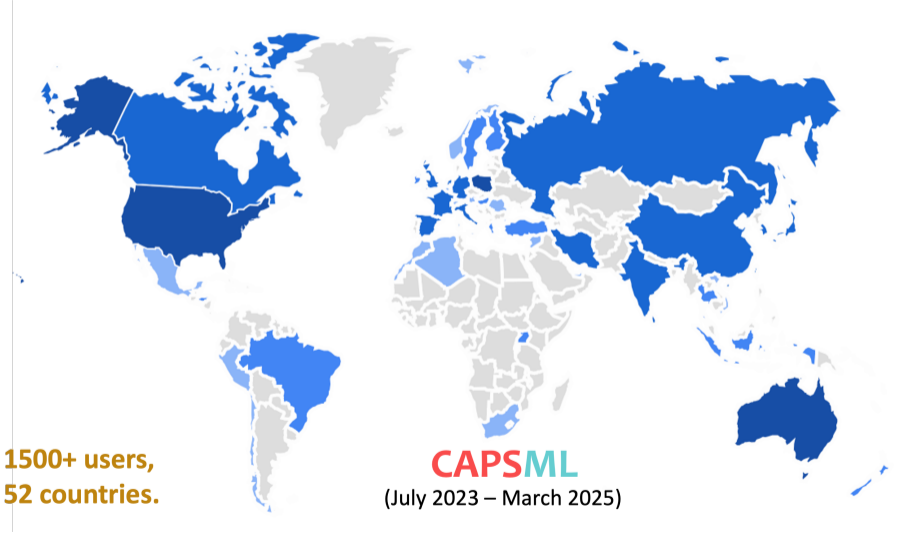
Metric	Value
Time Above Range (TAR) - Level2 (>250 mg/dL)	0.0%
Time Above Range (TAR) - Level1 (180 - 250 mg/dL)	18.41%

Acknowledgement: This research was funded by the Australian National University and the Our Health in Our Hands initiative; and by the National Computational Infrastructure (NCI Australia), and NCRIS enabled capability supported by the Australian Government.

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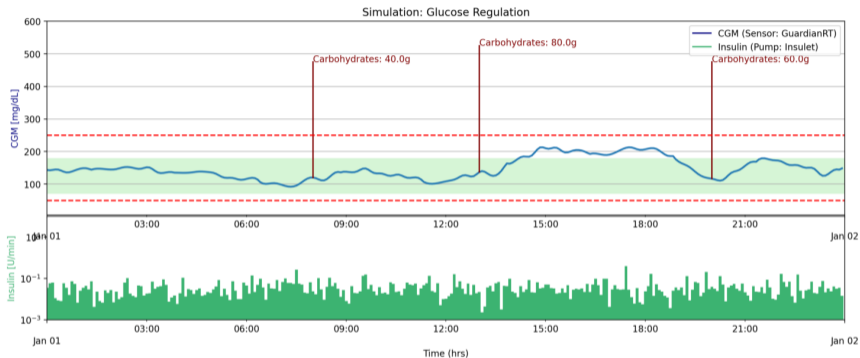
Learn about **glucose regulation & closed-loop AI systems**; **carbohydrate contents of different meals/food** and their effect on glucose regulation.

# CAPSML Usage & User Demographics



# Content

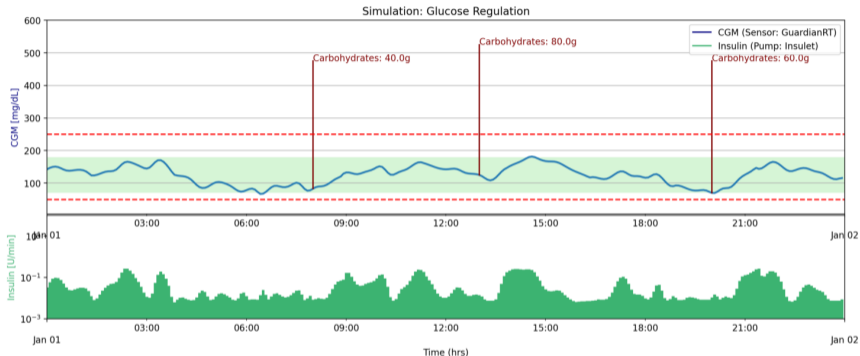
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## Auxiliary model learning & planning. Improved safety.

Hettiarachchi, et al. "G2P2C—A modular reinforcement learning algorithm for glucose control by glucose prediction & planning in T1D", Biomedical Signal Processing & Control, 90, p.105839, 2023.

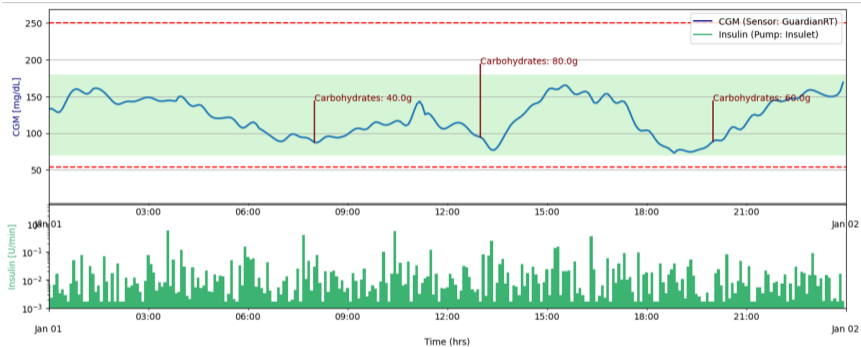
Hettiarachchi, Chirath. "Reinforcement Learning-based Artificial Pancreas Systems to Automate Treatment in Type 1 Diabetes", PhD Thesis, The Australian National University, 2023.



**Explored deterministic policies.  
Focus on explainability.**

Timms, David, et al. "Comparing Deterministic and Stochastic Reinforcement Learning for Glucose Regulation in Type 1 Diabetes", 20<sup>th</sup> World Congress on Medical and Health Informatics: MedInfo 2025 (Accepted).

Timms, David, et al. "Deterministic Policy Gradient Algorithms for Regulating Glucose in Type 1 Diabetes", (in-preparation).



**Explored constrained policies.  
Improved safety on hard subjects.**

External collaboration, University of Moratuwa, Sri Lanka.

Rakshitha, Dilshan; Lorensuhewa, Prasanjith; Anupama, Damika, et al. "Improving Safety in Reinforcement Learning based Artificial Pancreas Systems", (in-preparation).

# Other Current Projects

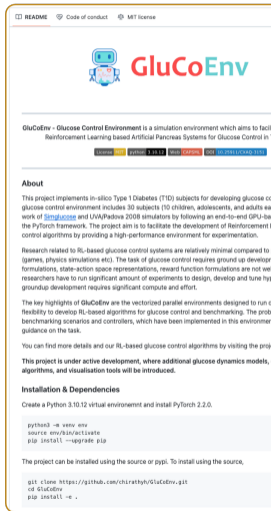
## Projects at ANU

- 1 Inverse Reinforcement Learning for Glucose Regulation, (*Honours Project: Jordan Trimming, 2024/25*).
- 2 Offline Reinforcement Learning for Automated Type 1 Diabetes Systems – Incorporating Clinical and Simulated Data, (*Honours Project: Samuel Price, 2025*).
- 3 A simulation dataset for machine learning applications in type 1 diabetes. Released Soon...
- 4 CAPSML: Co-creating a Deep Analytical Data Science Platform for Therapeutics Research and Education in Type 1 Diabetes. Open-opportunity HCI Applied Social Science
- 5 GluCoEnv: A GPU-based T1D Simulator. Open-opportunity ML Engineering

## Community Projects

- 1 Explainable RL methods: Integrated gradients, SHAP force plots, and explainability in policy space (*Malay Phadke, Preyes Parab*).
- 2 Integrating our current RL algorithm implementations into a mobile phone app.

# Open-source Resources: Codebase (GluCoEnv, G2P2C, RL4T1D)



**GluCoEnv**  
GluCoEnv - Glucose Control Environment is a simulation environment which aims to facilitate Reinforcement Learning based Artificial Pancreas Systems for Glucose Control in-silico.

**About**

This project implements in-silico Type 1 Diabetes (T1D) subjects for developing glucose control environment includes 30 subjects (10 children, adolescents, and adults) and work of [Sim glucose](#) and UVA/Padova 2008 simulators by following an end-to-end GPU-based PyTorch framework. The project aims to facilitate the development of Reinforcement Learning based control algorithms by providing a high-performance environment for experimentation.

Research related to RL-based glucose control systems are relatively minimal compared to (games, physics simulations etc). The task of glucose control requires ground up developer formulations, state-action space representations, reward function formulations are not well researched here to run significant amount of experiments to design, develop and tune hypoglycemia development requires significant compute and effort.

The key highlights of **GluCoEnv** are the vectorized parallel environments designed to run on GPU to develop RL-based algorithms for glucose control and benchmarking. The problem benchmarking scenarios and controllers, which have been implemented in this environment under the guidance of the task.

You can find more details and our RL-based glucose control algorithms by visiting the project page.

This project is under active development, where additional glucose dynamics models, algorithms, and visualisation tools will be introduced.

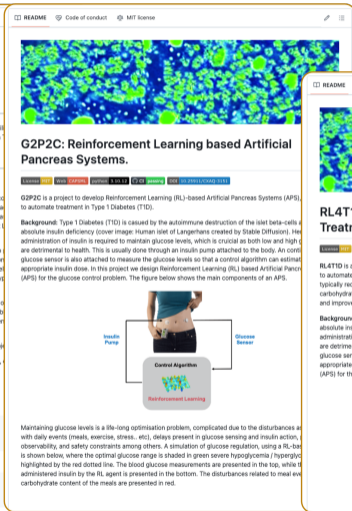
**Installation & Dependencies**

Create a Python 3.10.12 virtual environment and install PyTorch 2.2.0.

```
python3 -m venv env
source env/bin/activate
pip install --upgrade pip
```


The project can be installed using the source or pip. To install using the source,

```
git clone https://github.com/chirathy/GluCoEnv.git
cd GluCoEnv
pip install -e .
```



**G2P2C: Reinforcement Learning based Artificial Pancreas Systems.**

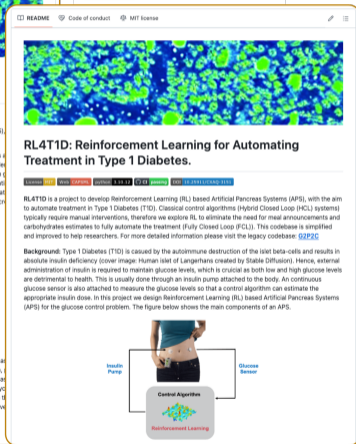
**Background:** Type 1 Diabetes (T1D) is caused by the autoimmune destruction of the islet beta-cells and absolute insulin deficiency (cover image: Human islet of Langerhans created by Stable Diffusion). Hence, administration of insulin is required to maintain glucose levels, which is crucial as both low and high glucose are detrimental to health. This is usually done through an insulin pump attached to the body. A continuous glucose sensor is also attached to measure the glucose levels so that a control algorithm can estimate appropriate insulin dose. In this project we design Reinforcement Learning (RL) based Artificial Pancreas Systems (APS) for the glucose control problem. The figure below shows the main components of an APS.



Maintaining glucose levels is a life-long optimisation problem, complicated due to the disturbances associated with daily events (meals, exercise, stress, etc), delays present in glucose sensing and insulin action, observability, and safety constraints among others. A simulation of glucose regulation, using a RL-based APS is shown below, where the optimal glucose range is shaded in green severe hypoglycemia / hyperglycemia highlighted by the red dotted line. The blood glucose measurements are presented in the top, while the administered insulin by the RL agent is presented in the bottom. The disturbances related to meal and carbohydrate content of the meals are presented in the bottom.

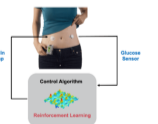


**RL4H**  
Reinforcement Learning for Health



**RL4T1D: Reinforcement Learning for Automating Treatment in Type 1 Diabetes.**

**Background:** Type 1 Diabetes (T1D) is caused by the autoimmune destruction of the islet beta-cells and results in absolute insulin deficiency (cover image: Human islet of Langerhans created by Stable Diffusion). Hence, external administration of insulin is required to maintain glucose levels, which is crucial as both low and high glucose levels are detrimental to health. This is usually done through an insulin pump attached to the body. A continuous glucose sensor is also attached to measure the glucose levels so that a control algorithm can estimate the appropriate insulin dose. In this project we design Reinforcement Learning (RL) based Artificial Pancreas Systems (APS) for the glucose control problem. The figure below shows the main components of an APS.



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# Conclusion

- **Meaningful contributions** emerge through **multi-disciplinary collaborations/research**.
- CAPSML is easily accessible and encourages clinical and lived experience experts to explore AI systems and run custom simulations for learning (**diabetes & AI education**).
- CAPSML improves research through clinicians & health experience **expert feedback**.
- A first step towards improving **trust/explainability of AI systems** in glucose control.
- CAPSML can be extended to allow researchers to test/compare their systems addressing current limitations in **reproducibility and benchmarking**.
- **The final solution takes time**. Stay patient, be respectful and keep going. . .

# Thank You

## Acknowledgement

- This research was funded by the Australian National University (ANU), School of Computing; Our Health in Our Hands (OHIOH) strategic initiative; National Computation Infrastructure (NCI Australia) under the ANU Merit Allocation / ANU Startup Schemes.

## Team

- **Collaborators:** OHIOH Team; Dr David O'Neal, Dr Barbora Paldus, & Dr Dale Morrison from the Diabetes Technology Research Group, St Vincent's Hospital, Melbourne; Dr Charith Chitraranjan, University of Moratuwa (UoM).
- **Research Students:** David Timms (Master's Research Project, ANU), Jordan Triming (Honours Project, ANU), Samuel Price (Honours Project, ANU), Dilshan Rakshitha; Prasanjith Lorensuhewa, Damika Anupama (Honours Project, UoM).
- **Supervisors:** Sam Cantrill, Dr Chirath Hettiarachchi, Dr Nicolo Malagutti, Prof. Christopher Nolan, Dr Elena Daskalaki, Prof. Hanna Suominen.