Introduction

Endurance athletes often struggle to maintain proper hydration and nutrition during long workouts. Drinking too little can lead to dehydration and reduced performance, while drinking too much can cause discomfort or even hyponatremia (low blood sodium). Similarly, consuming too few or too many carbohydrates can negatively affect energy levels and overall performance.

To support athletes during training, there is a need for a system that can simulate internal hydration and carbohydrate levels and react to eating and drinking events in real time. The challenge is to use data such as heart rate, speed, temperature, and the athlete's pre-workout intake to generate personalized, adaptive recommendations for how much to drink and how many carbohydrates to consume throughout the workout. These recommendations must adjust to changes in workout intensity, environmental conditions, and the athlete's actual in-workout eating and drinking behaviour. This makes the problem non-trivial and an important research and development challenge for the Strava+1 platform.

Definition of Success

Success for this part of the project means delivering, within 3 weeks, a working prototype that provides real-time, personalized hydration and nutrition advice during an endurance workout. The system should combine live workout data, heart rate, speed, and temperature, with the athlete's pre-workout intake and track estimated hydration and carbohydrate levels over time. It should update these estimates whenever the athlete eats or drinks during the workout. The system should simulate the workout state and react to intake events provided by the user. As part of this, the system must recommend specific amounts of fluid (in millilitres) and carbohydrates (in grams) that the athlete should consume at each update.

A successful prototype will:

- Respond in real time, calculating and delivering hydration and nutrition advice within 1 second of receiving new data.
- Continuously track estimated fluid and carbohydrate levels throughout the workout, keeping estimates reasonable based on observed trends.
- The system should update at least once per minute and provide actionable advice specifying how many grams of carbohydrates and how many milliliters of fluid the athlete should consume. It should automatically adapt recommendations based on changing workout conditions and the athlete's personal data, including heart rate, speed, temperature, pre-workout intake, and real-time consumption.
- Stay aligned with the science-informed hydration and fueling limits defined for this prototype, which are derived from established sports-nutrition research (see prototype – Hydration & Fueling Limits), in order to produce safe, physiologically realistic recommendations and avoid advising potentially harmful over-hydration or over-fueling.

In short, the prototype is successful if, within 3 weeks of development, it can deliver safe, continuously updated hydration and nutrition recommendations throughout the workout, based on live data and estimated internal levels, in a way that is timely, and adaptive.

References to Resources Consulted

My goal was to explore how an endurance athlete's internal hydration and energy state can be estimated and managed during a workout. To support this, I reviewed sports-nutrition and exercise-physiology research on sweat loss, hydration, fueling, and performance limits, and used these insights to design a set of simple, realistic, and safe rules for a prototype system that generates adaptive hydration and nutrition advice.

Here are the main resources I used:

1. Armstrong et al. (2021) – Rehydration during Endurance Exercise Link

This paper explained how dehydration affects performance and how much people should drink during long workouts. It also mentioned that drinks with carbs and electrolytes can help keep energy levels up.

2. Francisco et al. (2025) – Does Hypohydration Really Impair Endurance Performance? Link

Confirmed that performance usually drops once you lose around 2% of your body weight from sweat, which gave me a good limit to use in my prototype.

3. Jeukendrup, A. E. (2014) – A step towards personalized sports nutrition: Carbohydrate intake during exercise Link

This was useful because it explains the limits of carbohydrate absorption during exercise, showing that most athletes can only oxidize around 60 g of carbohydrates per hour unless using multiple transportable carbs. This supports placing an upper cap on single carbohydrate intake events to avoid GI overload.

4. Tiller, N. B., et al. (2019) – International Society of Sports Nutrition Position Stand: Nutritional considerations for single-stage ultra-marathon training and racing Link

This was useful because it emphasizes the importance of moderate, frequent fluid intake, recommending ~450–750 mL/h, noting that large single boluses exceed gastric emptying capacity and increase GI distress risk. This supports setting a cap on maximum fluid intake per event.

5. Costa, R. J. S., et al. (2023) – The Effect of Gut-Training and Feeding-Challenge on Markers of Gastrointestinal Status in Response to Endurance Exercise Link

This was useful because it shows that frequent, repeated carbohydrate intake during exercise improves gastrointestinal tolerance, reduces discomfort, and enhances absorption capacity. The study demonstrates that

6. Sawka, M. N., et al. (2000) – Fluid and electrolyte supplementation for exercise heat stress Link

This was useful because it explains that during exercise in hot conditions, sweat output often exceeds water intake, leading to greater fluid loss and a higher risk of dehydration. The increased need for sweat-based thermoregulation in higher temperatures implies that athletes must increase fluid intake accordingly to maintain hydration and performance.

7. Holmes, N., Bates, G., Zhao, Y., Sherriff, J., & Miller, V. (2016) – The Effect of Exercise Intensity on Sweat Rate and Sweat Sodium and Potassium Losses in Trained Endurance Athletes Link

This was useful because it found a significant positive relationship between exercise intensity and sweat rate in trained endurance athletes. With increasing intensity (e.g., higher heart rate), sweat losses and electrolyte losses increased, implying greater fluid requirements. These results support the idea that higher exertion should trigger increased fluid recommendations in the prototype.

8. Berry, C. W., et al. (2021) – Hydration and carbohydrate considerations during high-intensity exercise in the heat Link

The paper shows that high-intensity exercise in hot conditions (≈35–40 °C) produces a strong sweating response, leading to significant fluid loss and increased cardiovascular strain. It also notes that dehydration of ≥2% body mass impairs performance. These findings support increasing fluid recommendations when temperatures are high and exercise intensity is elevated.

9. Jeukendrup, A. (2014) – Carbohydrate Intake During Exercise. PMC article via NIH/PMC: Link

This was useful because it highlights that carbohydrate oxidation and intestinal absorption have physiological limits. Consuming carbohydrates beyond these limits provides no additional performance benefit and increases the risk of gastrointestinal distress. The review also discusses coordinating fluid, carbohydrate, and electrolyte intake during exercise without exceeding what can be tolerated physiologically, supporting the need for upper intake limits.

10. Godek et al. (2008) – Normative data for sweating rate, sweat sodium concentration, and sweat sodium loss in athletes: An update and analysis by sport. Link

Although focused on team sports, this paper gave reference values for realistic sweat ranges.

11. Urdampilleta et al. (2020) – Effects of 120 vs. 60 and 90 g/h carbohydrate intake during a trail marathon. Link

This study shows that a high carbohydrate intake (120 g per hour) during a long-duration mountain race can reduce neuromuscular fatigue and improve recovery of high-intensity running capacity.

12. Cleveland Clinic (n.d.) – Water intoxication (hyponatremia). Link

This clinical overview explains that water intoxication can occur when fluid intake exceeds the body's ability to excrete water (typically around 0.8–1 L per hour), leading to dangerous dilution of blood sodium levels. It highlights that risk increases with rapid, excessive intake over a short period. In the context of exercise, a moderate increase in fluid intake is justifiable due to sweat loss and elevated physiological demand, but intake must still remain within safe limits to avoid hyponatremia.

Alternative Ways to Approach the Problem

There are multiple ways to design a system that estimates an athlete's internal fluid and carbohydrate levels during a workout and updates recommendations whenever the athlete eats or drinks.

A simple option is a purely rule-based system that follows general guidelines, for example recommending fixed amounts like 150–250 ml of water every 20 minutes or 30–60 g of carbohydrates per hour. This is easy to implement but does not adapt to individual athletes, changing workout intensity, or actual intake during the session.

A more adaptive approach is a personalised rule-based model that uses science-based hydration and fueling guidelines together with live sensor data such as heart rate, speed, temperature, and estimated sweat and carbohydrate use. The system updates its estimates continuously as the athlete eats, drinks, or changes effort, providing guidance that is realistic and responsive while still lightweight enough for real-time use.

Machine learning methods could also be used to predict hydration and fueling needs based on patterns in historical data. While such approaches may offer higher accuracy, they require large datasets, significant computational resources, and extensive scientific instrumentation, making them less suitable for a real-time prototype developed within a limited three-week timeframe.

Another alternative is a fully physiological simulation that mathematically models sweat loss, glycogen depletion, and nutrient absorption. While such models can be highly accurate, they rely on detailed physiological inputs that are difficult or impossible to measure during normal workouts and require substantial development and validation effort, making them impractical to implement within a three-week prototype timeframe.

Motivated Decision

For the prototype, I implemented a personalized, adaptive system that estimates the athlete's internal fluid and carbohydrate levels during a workout. The system is built around scientifically grounded baselines for hydration and fueling, then continuously updates in real time as the athlete exercises, eats, or drinks. It ensures recommendations are safe, realistic, and tailored to the athlete's actual conditions, accounting for effort, environmental factors, and intake.

This approach supports the project goal of providing personalized, real-time hydration and nutrition guidance while remaining feasible for a lightweight, real-time prototype.

Prototype

Individual Variability

Before explaining how the model works, it's important to mention a big limitation: **every athlete is different**. People don't sweat the same amount, even if they run the same speed, in the same temperature, and have the same body weight. Some athletes barely sweat, while others could fill buckets. The same thing applies to carbohydrates: some athletes burn through carbs very fast, while others rely more on fat and burn carbs slower.

Things that influence these differences include:

- fitness level
- genetics
- body size
- heat acclimation
- clothing
- hydration status before starting
- training intensity
- even stress or caffeine intake

Because of this, no simple model can give perfectly accurate numbers for every person. So the model in this prototype should be seen as a **rough estimate**, not a medical tool. It gives the user an idea of what might be happening, but real-world values may be higher or lower depending on the individual.

The goal is not to be perfectly precise for every possible athlete and condition, but to give estimates that are reasonable. The model is calibrated so that an athlete working at a typical endurance intensity produces values roughly in line with published reference studies.

Note: The coefficients used in these models (e.g., the baseline sweat rate, heart-rate multipliers, temperature factors, and the carb-burn scaling values) were not selected to represent exact physiology, but rather calibrated so that a typical endurance athlete exercising at moderate intensity produces estimates that fall within ranges commonly reported in the scientific literature.

Defining Inputs

Before building the model, it's important to define exactly what data the system receives during a workout. Each incoming sample includes real-time sensor measurements, user-specific static information, and pre-workout nutrition, which allows the system to estimate carbohydrate and hydration status more accurately.

Category	Field	Type	Unit / Format	Description
Real-time Data (measured)	`heart_rate`	integer	bpm	Athlete's instantaneous heart rate
	`speed`	float	km/h	Athlete's current movement speed
	`ambient_temp_c`	float	°C	Ambient temperature at the time of measurement
User Profile (static)	`weight_kg`	float	kg	Athlete's body weight
	`pre_carb_g`	float	g	Estimated carbohydrate intake from pre-workout meals
	`pre_fluid_ml`	float	ml	Estimated fluid intake from pre-workout meals

Hydration & Fueling Limits (Safety Constraints)

These rules define the hard safety boundaries used by the prototype to ensure hydration and fueling recommendations remain physiologically realistic and well tolerated during endurance exercise. They are not intended as performance targets, but as conservative limits derived from sports-nutrition research to prevent unrealistic, unsafe, or gastrointestinally stressful recommendations within the simulated system.

Rule Type	Scientific Guideline	Prototype Rule / System Behavior	Rationale (Why the System Does This)	Refs
Hydration threshold	Dehydration > ~2% body weight reduces performance	System aims to keep recommended fluid intake above 2%	Prevents performance decline and maintains physiological function	[1], [2], [8]
Max mealing limit	Very large single intakes reduce gut tolerance	For this prototype, never exceed 750 ml fluid or 60 g carbohydrates in a single intake	Avoids exceeding gastric emptying and carb absorption limits; reduces GI distress from overly large boluses	[3], [4]

Rule Type	Scientific Guideline	Prototype Rule / System Behavior	Rationale (Why the System Does This)	Refs
Small frequent fueling	Frequent small feedings improve gut comfort & uptake	For this prototype, the system recommends eating or drinking again once the previous intake is estimated to be absorbed	Supports better absorption, steady energy delivery, and reduced GI distress by following evidence that smaller, more frequent feedings are better tolerated during endurance exercise	[5]
Absorption window	Hourly absorption capacity limits	For this prototype, the system tracks absorbed intake over a rolling 60-minute window and prevents recommendations that would exceed 1,500 ml of fluid or 120 g of carbohydrates per hour	Hourly intake recommendations in sports nutrition are constrained by physiological absorption and tolerance limits. The prototype applies conservative upper safety ceilings to ensure realistic and safe behavior in the simulated system.	[9], [11], [12]

Hydration & Fueling Adjustments

These rules apply small, proportional adjustments to hydration and fueling recommendations based on changing workout conditions such as temperature and exercise intensity. They are intended to improve the realism of the prototype's recommendations by accounting for known trends in sweat loss and physiological strain.

Rule Type	Scientific Guideline	Prototype Rule / System Behavior	Rationale (Why the System Does This)	Refs
Temperature adjustment	Higher temperatures increase sweat loss	For this prototype, when temperature rises by +5 °C above 20 °C, the system will increase fluid recommendations by +10%	Research shows that exercising in hot conditions causes greater sweat losses and increases the risk of dehydration. To account for this, the prototype applies a simple proportional adjustment to fluid needs.	[6]
Intensity adjustment	Higher exercise intensity increases sweat rate	For this prototype, when HR exceeds 160 bpm or speed exceeds 15 km/h, the system will increase fluid recommendations by +15%	Research shows that higher exercise intensity leads to significantly greater sweat losses, meaning athletes require more fluid to maintain hydration. The prototype applies a simple increase to account for this.	[7]

Rule Type	Scientific Guideline	Prototype Rule / System Behavior	Rationale (Why the System Does This)	Refs
Heat + high effort combo	Combined environmental heat and high exertion increase physiological strain and sweat losses	For this prototype, when temperature exceeds 30 °C and heart rate exceeds 85% of max, the system will increase fluid and carbohydrate recommendations by 10–15%	Research shows that high-intensity exercise in hot conditions significantly elevates sweat rates and cardiovascular strain, supporting increased fluid needs. The prototype also applies a proportional increase in carbohydrate intake as a design choice to account for higher metabolic demands.	[8]

Implementation

All code can be found in feed.py.

Athlete State

The AthleteState class keeps track of the athlete's key internal values during a workout. It stores current fluid and carbohydrate levels, totals, what the athlete has eaten or drunk, and the system's current advice. Cooldowns prevent repeated advice too quickly, and absorption history helps simulate how the body processes fluids and carbs over time.

```python
class AthleteState:
    def __init__(self, weight_kg, pre_fluid_ml, pre_carbs_g):
        self.weight_kg = weight_kg

        # Dynamic internal estimates
        self.fluid_level_ml = pre_fluid_ml
        self.carb_level_g = pre_carbs_g

        # Totals (for charts, debugging, recommendations)
        self.total_fluid_loss = 0
        self.total_carb_use = 0

        # Advice on how much the athlete should drink or eat
        self.current_advice = {
            "drink_ml": 0,
            "eat_g": 0
        }

        # History for when the user drank or ate
        self.stomach_ml = 0
        self.absorbed_history = []
        self.hourly_absorbed_ml = 0
```

```
        self.stomach_carbs_g = 0
        self.carb_absorbed_history = []
        self.hourly_absorbed_carbs_g = 0
        self.carb_cooldown_remaining = 0

        # Cooldowns for eating/drinking
        self.hydration_cooldown_remaining = 0
```

Workout Data

The WorkoutData class represents a single snapshot of sensor inputs during a workout. It stores heart rate, speed, and temperature, and optionally what the athlete has just drunk or eaten. Each instance is used by the engine to update the athlete's state and generate advice.

```
class WorkoutData:
    """
    A single point/tick of sensor inputs.
    """
    def __init__(self, heart_rate, speed, temperature, drink_ml=None,
eat_g=None):
        self.heart_rate = heart_rate
        self.speed = speed
        self.temperature = temperature
        self.drink_ml = drink_ml
        self.eat_g = eat_g
```

Sweat-Loss Estimation Model

I use a simple sweat-loss model that reacts to effort and temperature instead of trying to simulate full human physiology. Research shows that sweat rates vary widely between athletes, with average values around 1.28 ± 0.57 L/h [10], but real rates can range from about 0.5 L/h to over 2 L/h. Because sweat loss cannot be predicted accurately using only heart rate and temperature, the model uses a lightweight "best-guess" approach based on measurable signals: a baseline sweat rate, increased loss with higher heart rate, additional loss in hotter conditions, and slightly higher rates for heavier athletes. This reflects common sports-science patterns and produces realistic minute-to-minute behavior without requiring laboratory measurements.

```
# Sweat loss model (ml/min)
def estimate_sweat_loss(self, hr, temp):
    base_sweat = 6  # ml/min low-end baseline (0.36 L/h)

    hr_factor = max(0, hr - 120) * 0.5
    temp_factor = max(0, temp - 15) * 1.2
    weight_factor = (self.state.weight_kg - 70) * 0.2

    return base_sweat + hr_factor + temp_factor + weight_factor
```

Carbohydrate-Burn Estimation Model

I created a simple carb-burn model that reacts to heart rate, speed, and body weight. Actual carbohydrate use varies widely between athletes depending on fitness, VO_2 max, and fuel mix, so this model is not intended to be physiologically exact, but rather a rough estimate that behaves realistically during a workout.

Research shows that carbohydrate oxidation increases with exercise intensity, with reported peak oxidation rates around 1.26 g/min [9]. Although carbohydrate oxidation and total carbohydrate burn are not the same physiological process, this model treats them as equivalent for simplicity, using reported oxidation rates as a practical reference to keep estimated carb burn within realistic endurance-exercise ranges.

In practice, higher heart rate and faster speed increase the estimated carb burn, while heavier body weight adds a small additional effect, allowing the system to respond believably to changes in effort without attempting to model full metabolic physiology.

```
# Simple carb burn model (g/min)
def estimate_carb_burn(self, hr, speed):
    carb_from_hr = max(0, hr - 120) * 0.03
    speed_factor = speed / 10
    weight_factor = self.state.weight_kg / 70.0

    return carb_from_hr * speed_factor * weight_factor
```

Calculate recommended fluid intake

The hydration-advice function gives a simple, safe drinking recommendation based on the athlete's current fluid level, sweat loss, and workout conditions. It first checks safety rules: never go above the 1,500 ml/hour absorption limit, and don't recommend drinking if the athlete already drank. Then it looks at how low the "tank" is and how much total fluid has been lost, increasing the advice if levels are dropping. It also applies a small baseline amount to prevent slow dehydration. Heat and high intensity raise the recommendation, while a cooldown lowers it. Finally, it caps the amount so it stays realistic and safe (max 750ml). Overall, it gives a quick minute-by-minute suggestion that reacts to effort, temperature, and hydration status without breaking any safety limits.

```
def calculate_hydration_advice(self, sweat_loss, hr, speed, temp):
    if self.state.hourly_absorbed_ml >= 1500 or self.state.stomach_ml > 0:
        return 0

    if self.state.hydration_cooldown_remaining > 0:
        return 0

    current = self.state.fluid_level_ml
    total   = self.state.total_fluid_loss
    weight  = self.state.weight_kg

    optimal_level = 700
    ok_level      = 400
    low_level     = 200
```

```
    if current >= optimal_level:
        tank_zone = 0.0
    elif current <= low_level:
        tank_zone = 1.0
    else:
        tank_zone = (optimal_level - current) / (optimal_level - low_level)

    max_safe_loss = weight * 20
    loss_zone = min(1.0, total / max_safe_loss)

    base = sweat_loss
    extra = 150 * tank_zone + 300 * loss_zone
    recommendation = base + extra

    hourly_baseline = 0.02 * weight * 1000 # 2% hydration
    per_min_baseline = hourly_baseline / 60
    recommendation = max(recommendation, per_min_baseline)

    if temp > 20:
        temp_steps = (temp - 20) // 5
        recommendation *= 1 + (0.10 * temp_steps)

    if hr > 160 or speed > 15:
        recommendation *= 1.15

    est_max_hr = 200
    if temp > 30 and hr > 0.85 * est_max_hr:
        recommendation *= 1.15

    recommendation = min(750, recommendation)
    remaining_hourly_capacity = 1500 - self.state.hourly_absorbed_ml
    recommendation = min(recommendation, remaining_hourly_capacity)

    return max(0, recommendation)
```

Calculate recommended carbohydrate intake

The carbohydrate-advice function gives a simple, safe recommendation for how many grams of carbs the athlete should take each minute. It first checks the basic limits: don’t recommend anything if the athlete is in a cooldown period and their carb tank isn’t too low, and never go past the 120 g/hour absorption cap. It then looks at how “empty” the carb tank is and how much total energy has been burned so far, adding more carbs if levels are dropping or the workout has been going on for a long time. The advice also reacts to extreme heat and very high heart rate by slightly increasing the recommendation. In the end, the value is capped so it stays realistic (max 60g) and safe. Overall, it’s a lightweight rule-based system that updates every minute and responds to fatigue, duration, and intensity.

```
def calculate_carb_advice(self, carb_loss, temperature, hr):
    # Do not advise carbs if cooling down AND last snack has not yet been
absorbed
```

```
    if self.state.carb_cooldown_remaining > 0 and
self.state.stomach_carbs_g > 0:
        return 0

    # Hourly absorption cap
    if self.state.hourly_absorbed_carbs_g >= 120:
        return 0

    current = self.state.carb_level_g
    total   = self.state.total_carb_use
    weight  = self.state.weight_kg

    optimal = 60
    ok      = 30
    low     = 15

    # tank emptiness: 0 full → 1 empty
    if current >= optimal:
        tank_zone = 0.0
    elif current <= low:
        tank_zone = 1.0
    else:
        tank_zone = (optimal - current) / (optimal - low)

    # duration / total burn factor
    max_hourly = weight * 2
    burn_zone = min(1.0, total / max_hourly)

    extra = 20 * tank_zone + 40 * burn_zone

    recommendation = carb_loss + extra

    est_max_hr = 200
    if temperature > 30 and hr > 0.85 * est_max_hr:
        recommendation *= 1.15

    return min(60, max(0, recommendation))
```

Absorption Update

The update_absorption function simulates how fluids and carbohydrates are absorbed from the stomach into the athlete’s internal state. It moves a fixed amount from stomach_ml and stomach_carbs_g into fluid_level_ml and carb_level_g each minute, tracks recent absorption for hourly estimates, and ensures the totals stay within realistic physiological limits.

```
def update_absorption(self):
    absorption_rate = 40  # ml/min

    absorbed = min(absorption_rate, self.state.stomach_ml)
    self.state.stomach_ml -= absorbed
```

```
    # Add to internal fluid level
    self.state.fluid_level_ml = min(1500, self.state.fluid_level_ml +
absorbed)

    # Track hourly absorption window
    self.state.absorbed_history.append((self.current_tick, absorbed))

    cutoff = self.current_tick - 60
    self.state.absorbed_history = [
        (t, ml) for (t, ml) in self.state.absorbed_history if t > cutoff
    ]

    self.state.hourly_absorbed_ml = sum(ml for (_, ml) in
self.state.absorbed_history)

    carb_absorption_rate = 1.5  # g/min typical for gels/chews

    absorbed_carbs = min(carb_absorption_rate, self.state.stomach_carbs_g)
    self.state.stomach_carbs_g -= absorbed_carbs

    # Add to internal carb level
    self.state.carb_level_g = min(200, self.state.carb_level_g +
absorbed_carbs)

    # Track 60-minute absorption window (carbs)
    self.state.carb_absorbed_history.append((self.current_tick,
absorbed_carbs))

    self.state.carb_absorbed_history = [
        (t, g) for (t, g) in self.state.carb_absorbed_history if t > cutoff
    ]

    self.state.hourly_absorbed_carbs_g = sum(g for (_, g) in
self.state.carb_absorbed_history)
```

Main Update

The update function simulates one tick/minute of the workout. It estimates sweat and carbohydrate losses based on heart rate, speed, and temperature, updates the athlete's internal fluid and carb levels, calculates hydration and carb advice (how much to drink and eat), processes any intake from the athlete by adding it to the stomach and setting absorption cooldowns, updates cumulative totals, advances the simulation tick, and calls update_absorption() to move nutrients from the stomach into internal stores. This ensures the athlete's state is continuously realistic and the advice remains current and actionable throughout the workout.

```
# One tick update
def update(self, workout_data):

    # 1. Compute losses
    sweat_loss = self.estimate_sweat_loss(
        workout_data.heart_rate,
```

```
            workout_data.temperature
        )
        carb_loss = self.estimate_carb_burn(
            workout_data.heart_rate,
            workout_data.speed
        )

        # 2. Update internal state
        self.state.fluid_level_ml = max(0, self.state.fluid_level_ml -
sweat_loss)
        self.state.carb_level_g = max(0, self.state.carb_level_g - carb_loss)

        # 3. Calculate advice
        self.state.current_advice = {
            "drink_ml": self.calculate_hydration_advice(sweat_loss,
workout_data.heart_rate, workout_data.speed, workout_data.temperature),
            "eat_g": self.calculate_carb_advice(carb_loss,
workout_data.temperature, workout_data.heart_rate)
        }

        # 4. Update if the user ate or drank
        if workout_data.drink_ml:
            intake = workout_data.drink_ml
            self.state.stomach_ml += intake

            # Add scaled cooldown
            absorption_rate = 40  # ml/min
            self.state.hydration_cooldown_remaining += intake / absorption_rate
        if workout_data.eat_g:
            intake = workout_data.eat_g
            self.state.stomach_carbs_g += intake

            # Cooldown based on intake
            absorption_rate = 1.5
            self.state.carb_cooldown_remaining += intake / absorption_rate

        # Update cumulative loss over entire workout
        self.state.total_fluid_loss += sweat_loss
        self.state.total_carb_use += carb_loss

        # Advance simulation time and update cooldowns/absorption
        self.current_tick += 1
        self.state.hydration_cooldown_remaining = max(
            0,
            self.state.hydration_cooldown_remaining - 1
        )
        self.state.carb_cooldown_remaining = max(
            0,
            self.state.carb_cooldown_remaining - 1
        )
        self.update_absorption()
```

Testing

In case of the Real-Time, Continuous tracking and Science limits tests, the prototype is tested using a normal baseline athlete state:

```
AthleteState(weight_kg=70, pre_fluid_ml=1000, pre_carbs_g=60)
```

This represents an average athlete who starts the workout well-hydrated and properly fueled.

All workout data used in the tests is manually generated rather than taken from real-world sessions. This makes it easier to test the system in a controlled and repeatable way, because specific conditions, such as steadily increasing heart rate, sudden intensity spikes, or unusually high temperatures, can be created on purpose. By manually crafting the input values, the prototype can be tested under both normal and extreme scenarios without depending on unpredictable real-world recordings. This allows the behaviour of the system to be inspected more clearly.

Real-Time Hydration & Nutrition Advice

Goal

Verify that the system can process a single new workout data point, including updating the athlete's state, calculating fluid and carbohydrate losses, updating intake and absorption, and generating advice within 1 second.

Testing strategy

To evaluate real-time performance, the system is tested with a sequence of 120 workout data points. Each point represents one minute of exercise, and includes heart rate, speed, temperature, and mid-workout intake events (300 ml fluid and 15 g carbohydrates). These values, except intake events, increase gradually and loop back into realistic physiological ranges, creating a long, varied workout with fluctuating intensity and repeated eating/drinking events.

This setup ensures that the engine processes a wide range of conditions: rising effort, environmental changes, and repeated intake that triggers absorption, cooldown logic, and safety checks. The key metric is the total time required to handle each individual data point, including computing sweat and carbohydrate losses, updating internal state, processing intake, adjusting absorption, and generating advice.

The test is considered successful if every single update is completed within 1 second, matching the real-time requirement defined earlier.

Setup

Test here

```
import time

# Simulated workout data
```

```
workout_data_samples = []

hr = 132
speed = 13.0
temp = 20.0

for i in range(120):
    # Add data point
    workout_data_samples.append(
        WorkoutData(
            heart_rate=hr,
            speed=speed,
            temperature=temp,
            drink_ml=300,
            eat_g=15
        )
    )

    # Increase values gradually in cycles
    hr += 2
    speed += 0.1
    temp += 0.05

    # Loop heart rate back to a realistic range
    if hr > 185:
        hr = 140

    # Loop speed realistically
    if speed > 18:
        speed = 13.5

    # Loop temperature realistically
    if temp > 30:
        temp = 21

# Track response times for generating hydration and carbohydrate advice
response_times = []

for data_point in workout_data_samples:
    start_time = time.time()

    # Process a single workout data point (update state, calculate losses,
advice, absorption)
    engine.update(data_point)

    end_time = time.time()
    elapsed = end_time - start_time
    response_times.append(elapsed)

# Convert seconds to milliseconds for readability
response_times_ms = [t * 1000 for t in response_times]

# Print metrics
print("Advice delivery times (ms):", ["{:.2f}".format(t) for t in
```

```
response_times_ms])
print("Max response time: {:.2f} ms".format(max(response_times_ms)))
print("Average response time: {:.2f}
ms".format(sum(response_times_ms)/len(response_times_ms)))
```

Results

```
Advice delivery times (ms): ['0.03', '0.01', '0.01', '0.01', '0.00',
'0.00', '0.00', '0.00', '0.00', '0.01', '0.00', '0.00', '0.00', '0.00',
'0.00', '0.00', '0.01', '0.00', '0.00', '0.00', '0.01', '0.00', '0.00',
'0.00', '0.01', '0.00', '0.01', '0.01', '0.01', '0.00', '0.00', '0.01',
'0.01', '0.01', '0.01', '0.01', '0.01', '0.01', '0.01', '0.01', '0.01',
'0.01', '0.02', '0.01', '0.01', '0.01', '0.01', '0.01', '0.01', '0.02',
'0.01', '0.01', '0.02', '0.01', '0.02', '0.01', '0.01', '0.01', '0.02',
'0.01', '0.02', '0.01', '0.01', '0.02', '0.01', '0.01', '0.02', '0.01',
'0.01', '0.03', '0.01', '0.01', '0.01', '0.01', '0.01', '0.01', '0.01',
'0.01', '0.01', '0.01', '0.01', '0.01', '0.01', '0.01', '0.01', '0.01',
'0.01', '0.01', '0.01', '0.01', '0.01', '0.01', '0.01', '0.01', '0.01',
'0.01', '0.01', '0.01', '0.01', '0.01', '0.01', '0.01', '0.01', '0.01',
'0.01', '0.01', '0.01', '0.01', '0.01', '0.01', '0.01', '0.01', '0.01',
'0.01', '0.01', '0.01', '0.01', '0.01', '0.01', '0.01']
Max response time: 0.03 ms
Average response time: 0.01 ms
```

The system processes each new workout data point extremely quickly, with all updates, including calculating fluid and carbohydrate losses, updating internal state, handling intake, and generating advice, completed in well under 1 millisecond. The maximum processing time was 0.03 ms and the average was 0.01 ms. There are no spikes or delays, showing stable and consistent performance for real-time updates throughout a typical workout. All processing times were far below the 1-second requirement, meaning this test was fully successful.

Continuous Tracking of Fluid & Carbohydrate Levels

Goal

Verify that the system continuously updates fluid and carbohydrate estimates in a smooth, realistic way throughout the workout.

Testing Strategy

The system processes a sequence of workout data where heart rate, speed, and temperature gradually increase over time.

Two setups are used:

- Setup 1: A simple increasing-intensity workout where the athlete does not consume anything. Fluid and carbohydrate levels should steadily decrease over the session.

- Setup 2: A similar workout, but less intense and the athlete drinks and eats halfway through. Fluid and carbohydrate levels should increase at that moment and then decline again as the consumed nutrients are gradually absorbed and used.

For both setups, the system generates graphs that show the estimated fluid and carbohydrate levels after each new workout data point. The test is considered successful if:

- Levels decrease smoothly as the workout progresses.
- Slopes steepen appropriately under higher effort or heat.
- There are no unrealistic jumps, spikes, or discontinuities.
- In Setup 2, the temporary rise from consuming fluid/carbs appears clearly and returns to a realistic declining trend once absorbed.

Setup 1

Test here

```
# Simulated workout data
workout_data_samples = [
    WorkoutData(heart_rate=132, speed=13.0, temperature=20.0),
    WorkoutData(heart_rate=134, speed=13.1, temperature=20.0),
    ...
    WorkoutData(heart_rate=180, speed=17.3, temperature=29.5),
    WorkoutData(heart_rate=180, speed=18.0, temperature=30.0),
]

# Simulate workout
for data_point in workout_data_samples:
    # Process a single workout data point (update state, calculate losses, advice, absorption)
    engine.update(data_point)

    # Store the calculated values for the graph
    ...

# This creates the nice plots with all the data displayed in it
create_very_nice_plot(...)
```

Setup 2

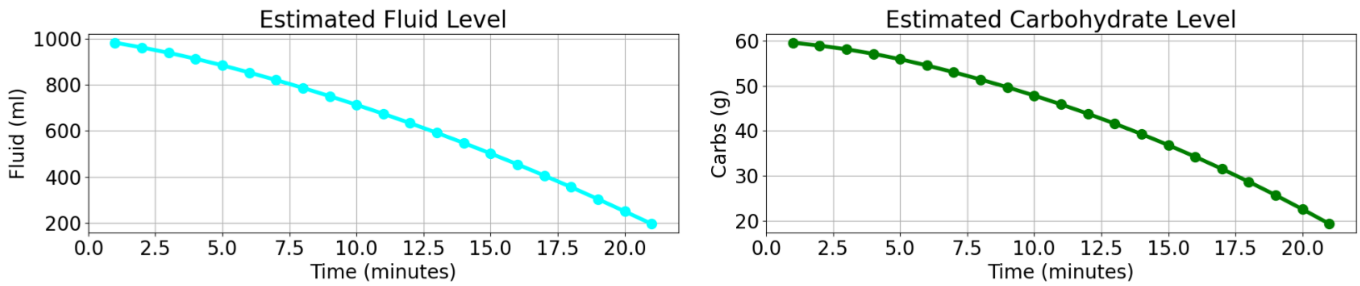
Test here

```
# Simulated workout data
workout_data_samples = [
    WorkoutData(heart_rate=132, speed=10.0, temperature=20.0),
    WorkoutData(heart_rate=133, speed=10.1, temperature=20.1),
    ...
    # Athlete rehydrating and having a snack
    WorkoutData(heart_rate=144, speed=11.4, temperature=21.2, drink_ml=300,
```

```
eat_g=15),
    ...
    WorkoutData(heart_rate=145, speed=12.0, temperature=22.0),
    WorkoutData(heart_rate=145, speed=12.0, temperature=22.0),
]

# Simulate workout
for data_point in workout_data_samples:
    # Process a single workout data point (update state, calculate losses,
advice, absorption)
    engine.update(data_point)

    # Store the calculated values for the graph
    ...

# This creates the nice plots with all the data displayed in it
create_very_nice_plot(...)
```

Results

Setup 1



The results look realistic and match what is expected from basic sports-science principles. At the start of the workout, the estimated sweat rate is reasonable for moderate-intensity endurance exercise. As the workout becomes harder and the temperature load increases, the model shows higher sweat loss, which is a normal and well-known physiological response to increased effort and heat.

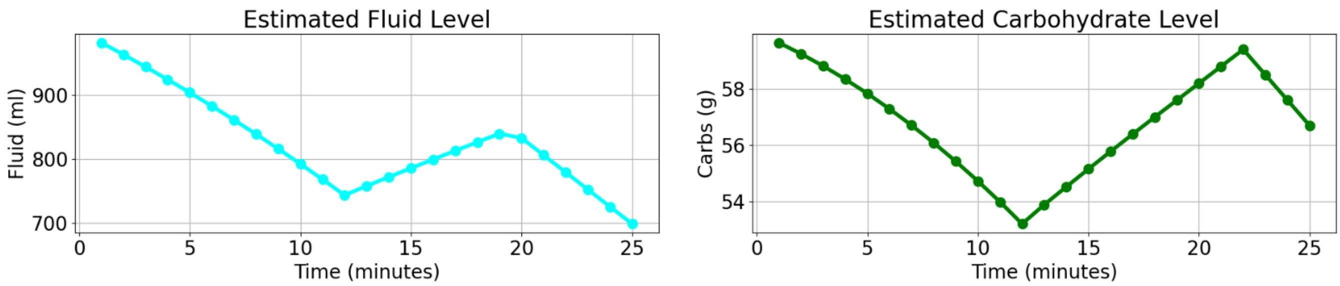
Both the fluid and carbohydrate levels decrease smoothly over time, without any sudden jumps or unrealistic changes. This reflects how sweat loss and energy use build up gradually during continuous exercise.

The actual values also make sense. Early in the workout, the estimated sweat loss corresponds to typical endurance-exercise sweat rates (around 1.28 ± 0.57 L/h). Later in the session, the sweat rate becomes much higher, which is expected given the intentionally high intensity and heat used in this setup. These higher values represent an extreme but still plausible scenario.

Carbohydrate depletion follows a similar logic. The estimated burn rate stays within commonly reported ranges for moderate-to-high intensity endurance exercise (roughly 0.5–1.3 g/min), and increases as the workout becomes more demanding.

Overall, the curves behave the way you would expect physiologically: as effort and heat increase, both sweat loss and carbohydrate use increase as well. While the model is simplified and does not try to simulate the full human body, it produces smooth, sensible values that align with published research. This makes the results suitable for the model's goal of providing reasonable real-time estimates rather than exact physiological measurements.

Setup 2



In the second setup, the system correctly handles mid-workout intake. When the athlete consumes 300 ml of fluid and 15 g of carbohydrates halfway through the workout, both graphs show a clear but smooth rise in levels. After this increase, the model gradually absorbs these nutrients and returns to a declining trend as the workout continues. The absorption is neither instantaneous nor abrupt, matching real physiological behavior. Fluid and carb levels remain stable with no spikes or distortions, confirming that the system handles intake events realistically while maintaining continuous tracking. Setup 2 also meets all success criteria, showing correct intake, absorption, and continued smooth decline afterward.

Adaptive Recommendations (Minute-by-minute advice)

Goal

Verify that the system produces actionable hydration and carbohydrate advice at least once per minute, expressed as hydration (milliliters) and carbohydrates (grams) quantities, and that this advice adapts correctly to individual workout variables.

Testing Strategy

Adaptive behavior is validated using **multiple short, controlled workouts** instead of a single long session with many changing variables. Each workout lasts **20 minutes** and starts from the **same baseline athlete state and baseline workout profile**. Only **one variable is modified per workout**, while all other inputs remain constant. This makes it possible to directly attribute any change in hydration or carbohydrate recommendations to the modified variable alone.

To verify athlete personalization, **only the baseline workout** is executed multiple times with different athlete states (body weight, pre-workout hydration, and pre-workout carbohydrate levels). All workout inputs remain identical across these runs, ensuring that any differences in recommendations are caused solely by athlete-specific parameters.

The following controlled workouts are used:

- **Baseline workout (reference condition)**
    - Duration: 20 minutes
    - Moderate, constant heart rate, speed, and temperature
    - No intake

    - Establishes stable baseline hydration and carbohydrate recommendations and serves as the reference for all adaptive tests

- **Heat adaptation workout**
    - Duration: 20 minutes
    - Temperature is gradually increased
    - Heart rate and speed remain identical to the baseline workout
    - Verifies that fluid recommendations increase in response to heat alone

- **Heart rate adaptation workout**
    - Duration: 20 minutes
    - Heart rate is gradually increased
    - Speed and temperature remain identical to the baseline workout
    - Verifies adaptation to increased physiological effort

- **Speed adaptation workout**
    - Duration: 20 minutes
    - Speed is gradually increased
    - Heart rate and temperature remain identical to the baseline workout
    - Verifies adaptation to increased mechanical workload

- **Intake during workout**
    - Duration: 20 minutes
    - Identical to the baseline workout
    - A single fluid and carbohydrate intake occurs halfway through the workout
    - Verifies that intake correctly influences subsequent recommendations

The test is considered successful if:

- A new hydration (ml) and carbohydrate (g) recommendation is produced at every one-minute update
- Recommendation changes are directly attributable to the single variable modified in each workout
- Intake events influence subsequent advice
- Identical baseline workouts produce different recommendation patterns for different athlete states

Setup

Test here

```
# Athlete state (switch manually)
state = AthleteState(weight_kg=70, pre_fluid_ml=1000, pre_carbs_g=60) # Average athlete, properly hydrated/fueled
# state = AthleteState(weight_kg=70, pre_fluid_ml=100, pre_carbs_g=5) # Average athlete, badly hydrated/fueled
# state = AthleteState(weight_kg=195, pre_fluid_ml=1000, pre_carbs_g=60) # Eddie Hall, "properly" hydrated/fueled

engine = HydrationFuelEngine(state)
```

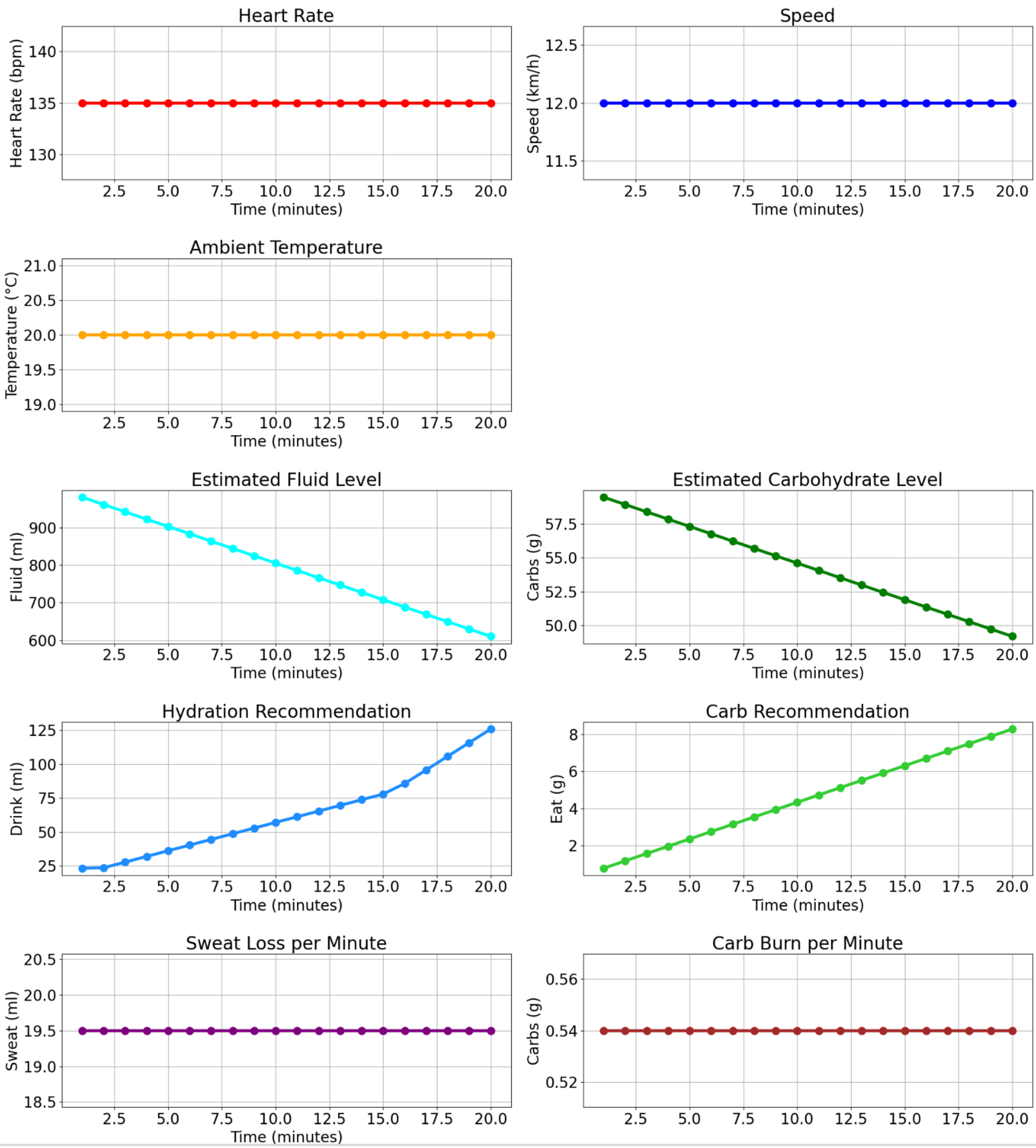
```
# Generate workout data for all phases (switch manually)
workout_data_samples = []

# ==================================================
# BASELINE WORKOUT (20 min)
# ==================================================

for i in range(20):
    workout_data_samples.append(
        WorkoutData(
            heart_rate=135,
            speed=12.0,
            temperature=20.0
        )
    )


# ==================================================
# HEAT ADAPTATION WORKOUT (20 min)
# ==================================================

# temp = 20.0
# for i in range(20):
#     temp += 0.5
#     workout_data_samples.append(
#         WorkoutData(
#             heart_rate=135,
#             speed=12.0,
#             temperature=temp
#         )
#     )


# ==================================================
# HEART RATE ADAPTATION WORKOUT (20 min)
# ==================================================

# hr = 135
# for i in range(20):
#     hr += 2
#     workout_data_samples.append(
#         WorkoutData(
#             heart_rate=hr,
#             speed=12.0,
#             temperature=20.0
#         )
#     )


# ==================================================
# SPEED ADAPTATION WORKOUT (20 min)
# ==================================================

```

```
# speed = 12.0
# for i in range(20):
#     speed += 0.3
#     workout_data_samples.append(
#         WorkoutData(
#             heart_rate=135,
#             speed=speed,
#             temperature=20.0
#         )
#     )


# ==================================================
# INTAKE DURING WORKOUT (20 min)
# ==================================================

# for i in range(20):
#     workout_data_samples.append(
#         WorkoutData(
#             heart_rate=135,
#             speed=12.0,
#             temperature=20.0,
#             drink_ml=300 if i == 10 else 0,
#             eat_g=15 if i == 10 else 0
#         )
#     )

# ==================================================
# MUCH LOWER INTAKE DURING WORKOUT (20 min)
# ==================================================

# for i in range(20):
#     workout_data_samples.append(
#         WorkoutData(
#             heart_rate=135,
#             speed=12.0,
#             temperature=20.0,
#             drink_ml=100 if i == 10 else 0,
#             eat_g=5 if i == 10 else 0
#         )
#     )


# Simulate workout
for data_point in workout_data_samples:
    # Process a single workout data point (update state, calculate losses, advice, absorption)
    engine.update(data_point)

    # Store the calculated values for the graph
    ...
```

```
# This creates the nice plots with all the data displayed in it
create_very_nice_plot(...)
```

Results

Baseline



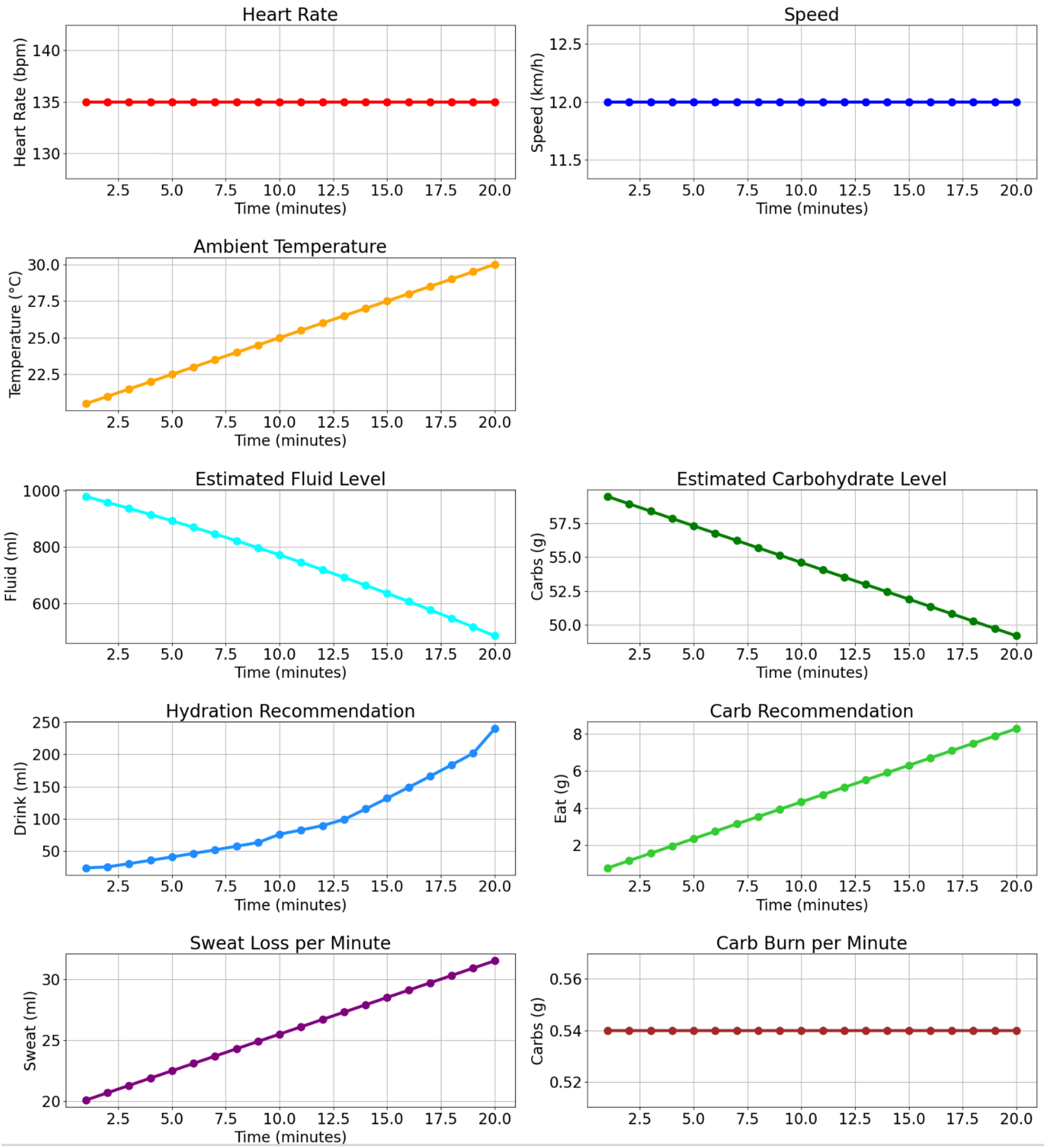
In this test, the system behaves correctly under constant workout conditions. Hydration and carbohydrate recommendations are generated at every one-minute update throughout the 20-minute session.

Hydration advice increases steadily over time with no sudden jumps or drops. This shows that the system remains stable when heart rate, speed, and temperature do not change.

Carbohydrate advice follows the same pattern, increasing smoothly at each minute. No irregular values or gaps are observed.

Overall, the baseline test confirms that the system produces consistent, predictable recommendations under steady conditions and provides a reliable reference for comparison with all other tests.

Heat Adaptation



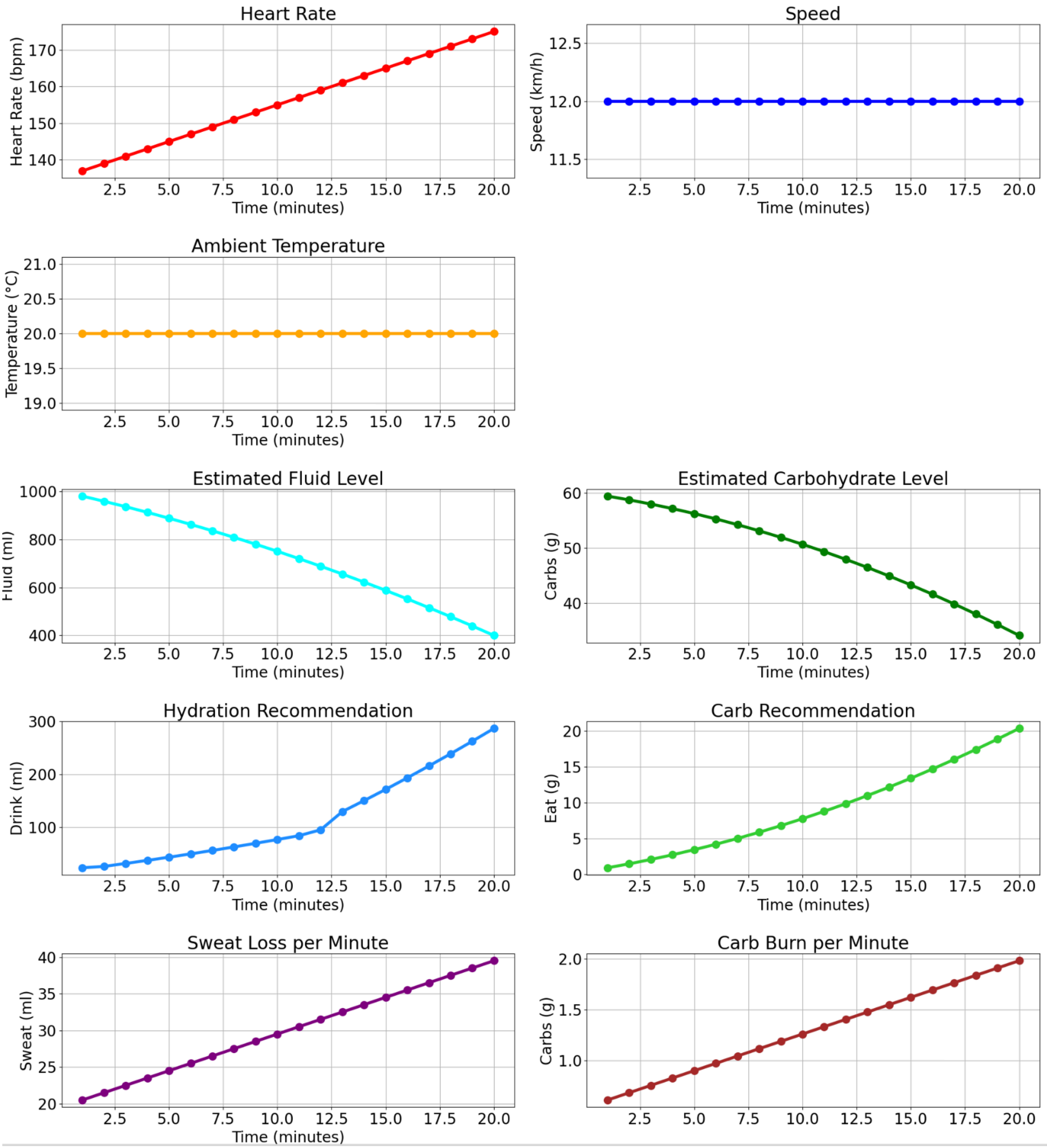
Compared to the baseline workout, the heat adaptation test shows a clear and direct increase in hydration recommendations while carbohydrate advice remains largely unchanged.

As temperature rises over the 20-minute session, hydration advice increases more steeply than in the baseline case. This indicates that the system correctly responds to heat stress by recommending additional fluid, even though heart rate and speed stay constant. The hydration curve remains smooth, with no sudden spikes or instability.

This behavior aligns with the underlying estimates: as temperature increases, the estimated sweat loss per minute also rises steadily, clearly visible in the sweat-loss graph. In contrast, carbohydrate recommendations closely match the baseline pattern and continue to increase at a similar rate, confirming that carbohydrate advice is not influenced by temperature alone.

Overall, this test confirms that the system isolates temperature as an adaptive trigger: hydration recommendations increase in response to higher sweat loss from heat, while carbohydrate recommendations remain stable.

Heart Rate Adaptation



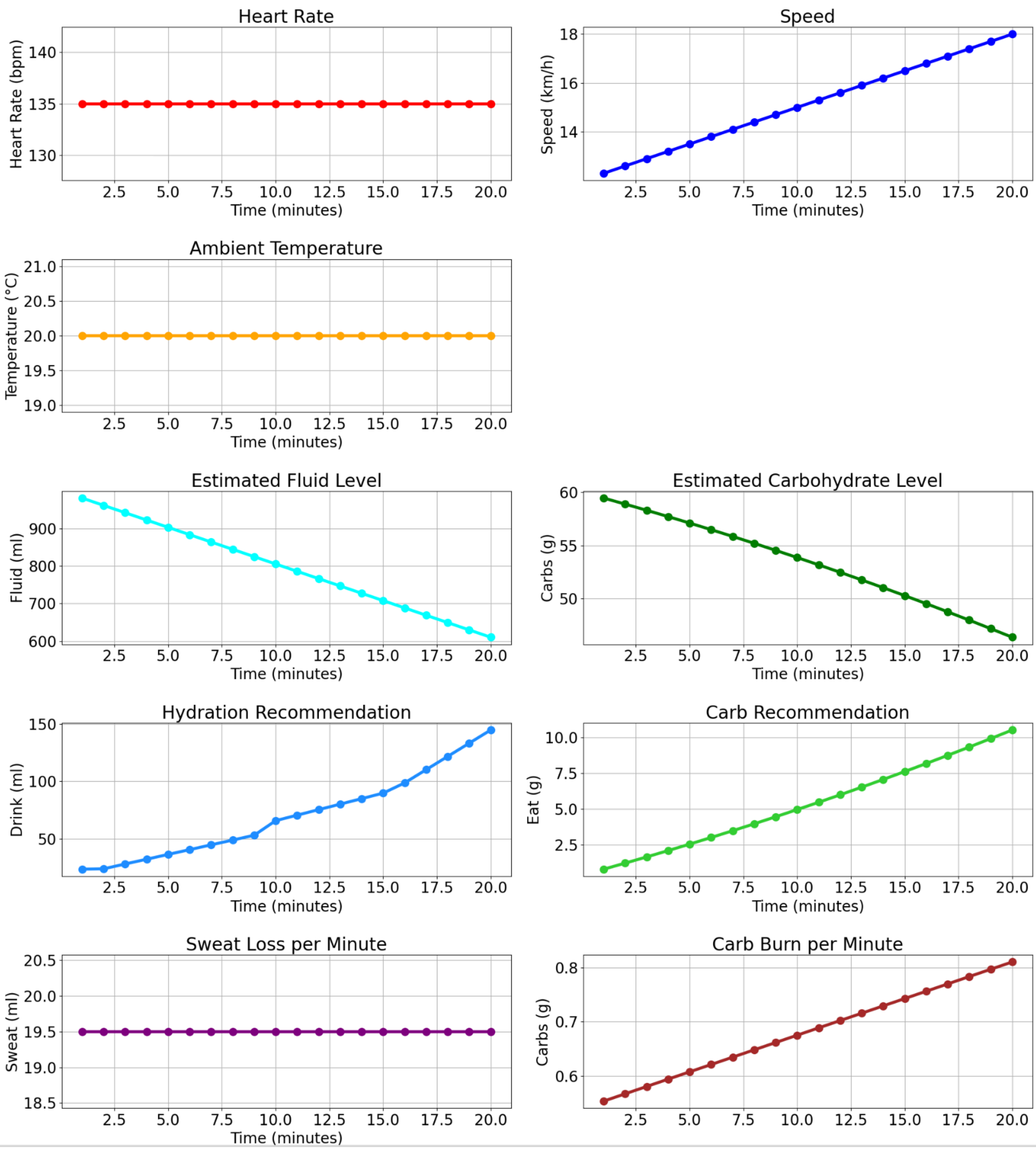
Compared to the baseline workout, increasing heart rate leads to higher hydration and carbohydrate recommendations over the same 20-minute period.

As heart rate rises while speed and temperature remain constant, hydration advice increases more rapidly than in the baseline case. This aligns with the underlying estimates: sweat loss per minute increases steadily as heart rate rises, which is clearly reflected in the hydration recommendations. The hydration curve remains smooth and stable throughout.

Carbohydrate recommendations also diverge from the baseline pattern as the workout progresses. As heart rate increases, the estimated carbohydrate burn per minute rises, leading the system to gradually recommend larger carbohydrate amounts. This confirms that carbohydrate advice responds to physiological effort rather than time alone.

Overall, this test demonstrates that the system adapts both hydration and carbohydrate advice in response to increased heart rate, with recommendation changes clearly driven by rising sweat loss and carbohydrate burn while maintaining consistent minute-by-minute output.

Speed Adaptation



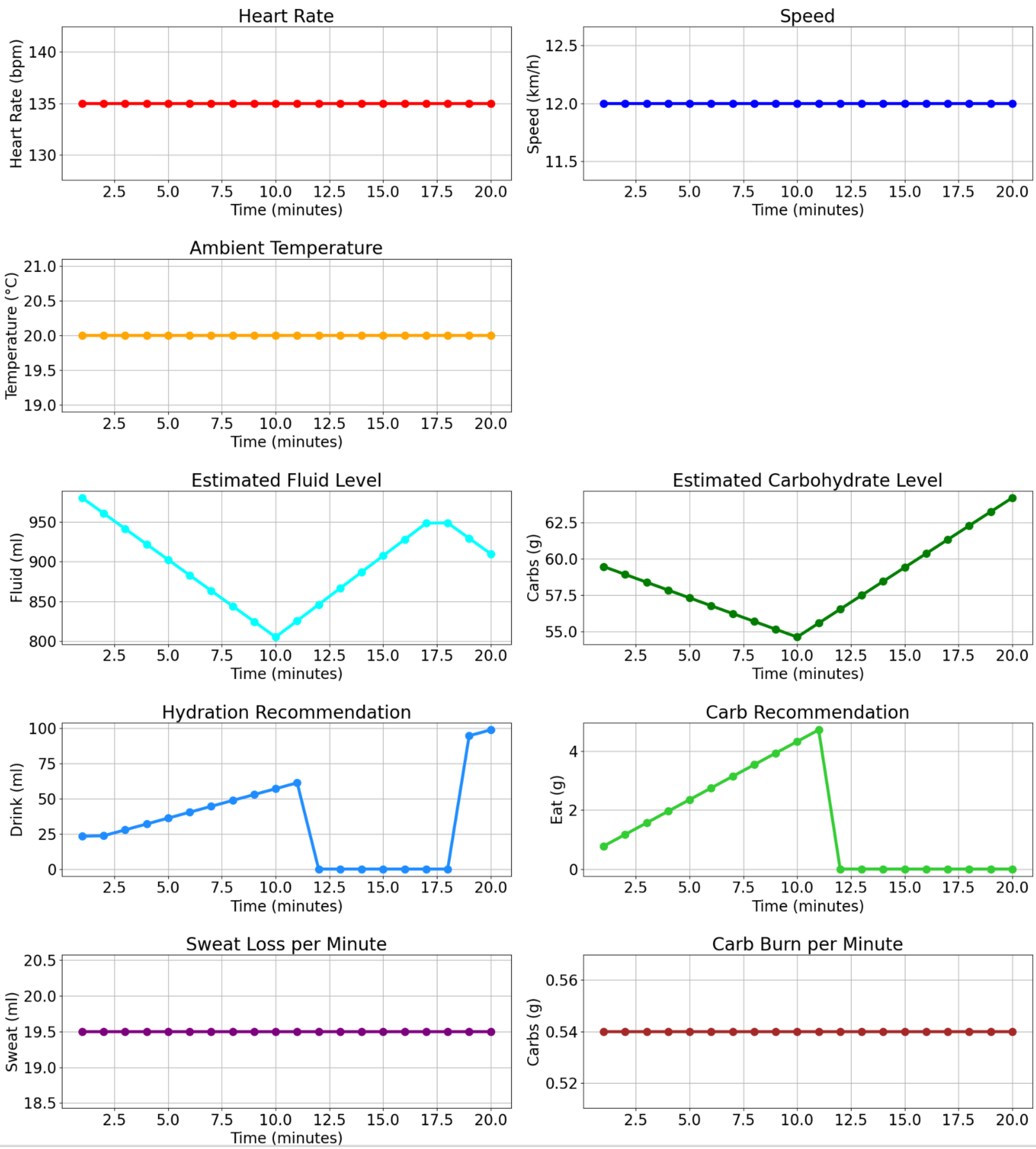
Compared to the baseline workout, increasing speed results in higher hydration and carbohydrate recommendations over the same 20-minute period.

As speed increases while heart rate and temperature remain constant, hydration advice rises only slightly compared to the baseline case. This indicates that increased mechanical workload has a limited direct effect on fluid needs when heart rate and heat remain unchanged. The hydration curve remains smooth and stable throughout.

In contrast, carbohydrate recommendations diverge more clearly from the baseline pattern. As running speed increases, the estimated carbohydrate burn per minute rises steadily, which is clearly visible in the carb-burn graph. In response, the system gradually recommends larger carbohydrate amounts, reflecting the higher energy demand associated with greater mechanical effort.

Overall, this test confirms that the system responds to increased speed primarily through higher carbohydrate recommendations, with only a modest increase in hydration advice, while maintaining consistent minute-by-minute output.

Intake during workout



Compared to the baseline workout, the intake test shows a clear interruption in both hydration and carbohydrate recommendations immediately after the athlete consumes fluid and carbohydrates halfway through the session.

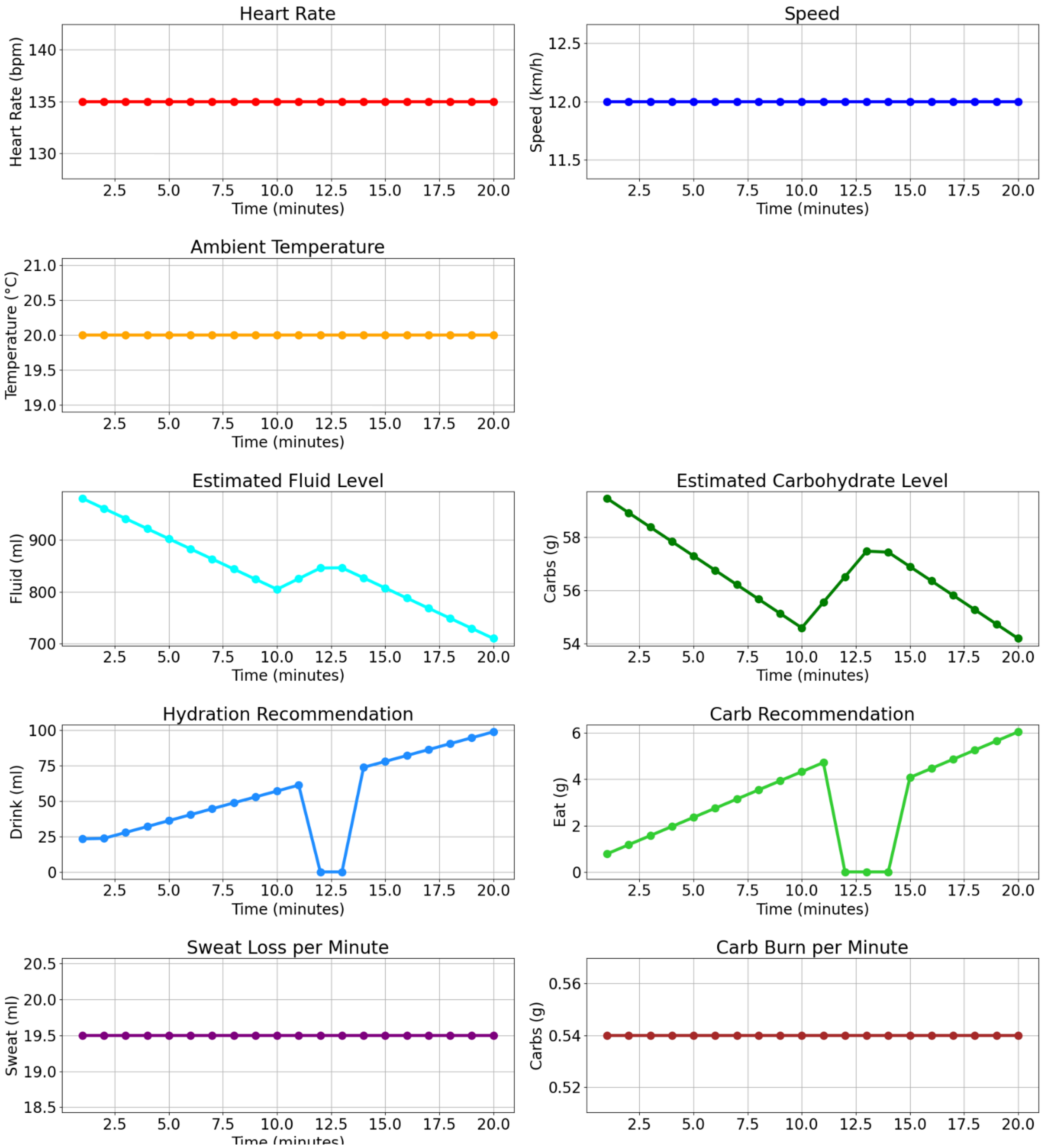
Before the intake event, hydration and carbohydrate advice follow the same steady, increasing pattern as in the baseline case. At the moment of intake, both recommendations drop sharply to 0, indicating that the system correctly accounts for the consumed fluid and carbohydrates and temporarily stops recommending additional intake.

After the intake event, hydration advice resumes later in the workout and increases again, while carbohydrate recommendations remain at 0 for the remainder of the 20-minute session. This occurs because carbohydrate absorption is slower, meaning the previously consumed carbohydrates continue to cover the athlete’s needs throughout the rest of the workout. This behavior differs clearly from the baseline case, where both recommendations continue to rise steadily over time.

This behavior is also visible in the internal state estimates: the estimated fluid and carbohydrate levels increase immediately after intake, confirming that the consumed nutrients are correctly added to the system state before subsequent recommendations are generated.

Overall, this test confirms that, relative to baseline, the system correctly incorporates in-workout intake into its recommendation logic and adjusts subsequent advice accordingly, while still producing consistent minute-by-minute output.

Lower Intake during workout



Compared to the normal intake scenario, this test uses a smaller mid-workout fluid and carbohydrate intake under otherwise identical conditions.

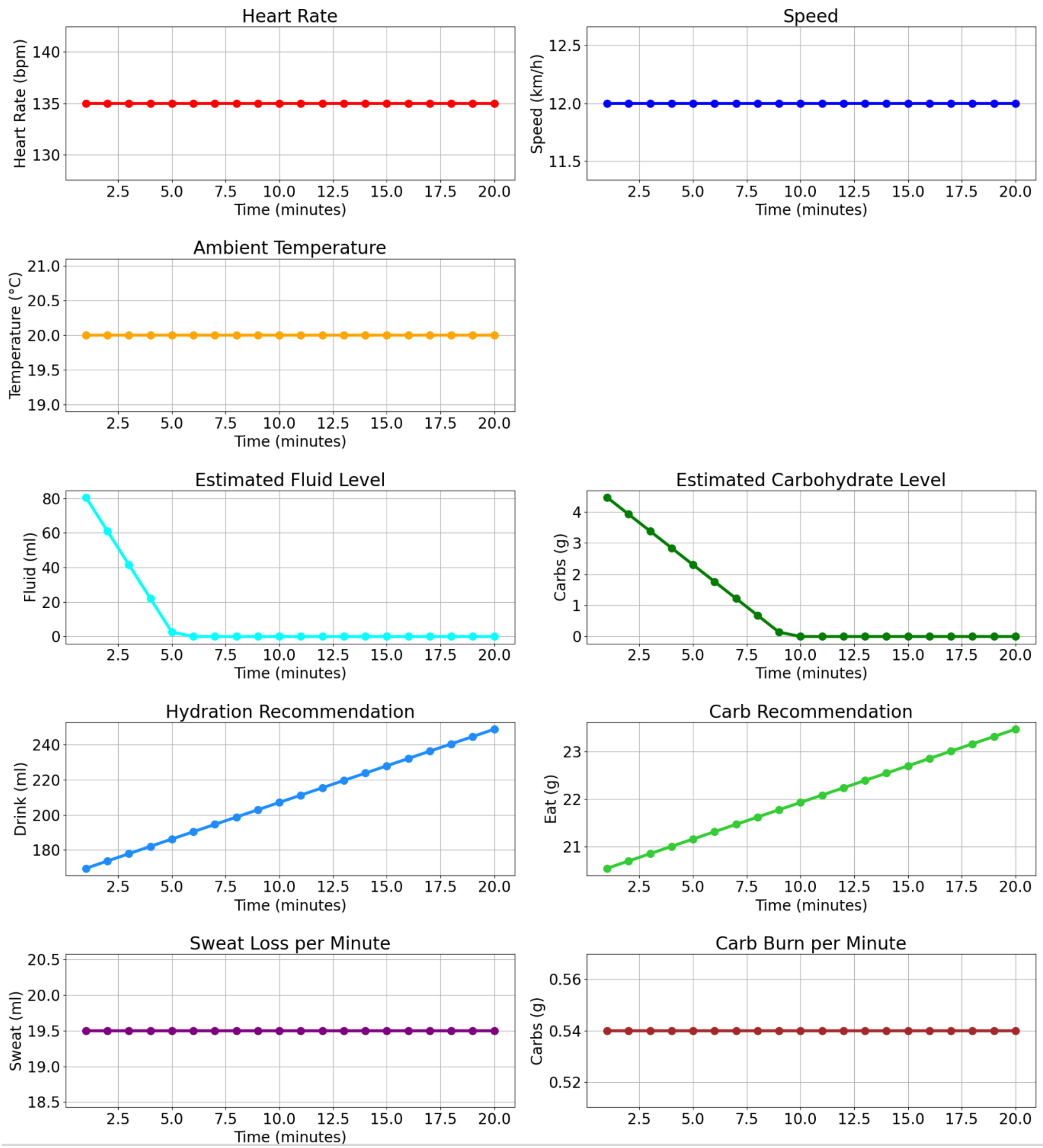
As a result, the interruption in recommendations is noticeably shorter. Hydration advice drops to 0 after intake but resumes sooner than in the normal intake case, since the smaller fluid volume is absorbed more quickly. The hydration curve therefore shows a brief dip rather than a prolonged zero-advice plateau.

Carbohydrate recommendations show the same pattern. After intake, carb advice temporarily falls to 0, but because fewer carbohydrates were consumed, the absorption window clears earlier and recommendations resume within the same 20-minute session. This contrasts with the normal intake test, where carb recommendations remain suppressed for much longer.

The internal state estimates support this behavior: estimated fluid and carbohydrate levels increase after intake but decline again more rapidly than in the normal intake case, allowing recommendations to restart sooner.

Overall, relative to a normal intake, this test confirms that the system scales its suppression period with intake size, correctly resuming hydration and carbohydrate recommendations earlier when smaller amounts are consumed.

Baseline Badly Hydrated



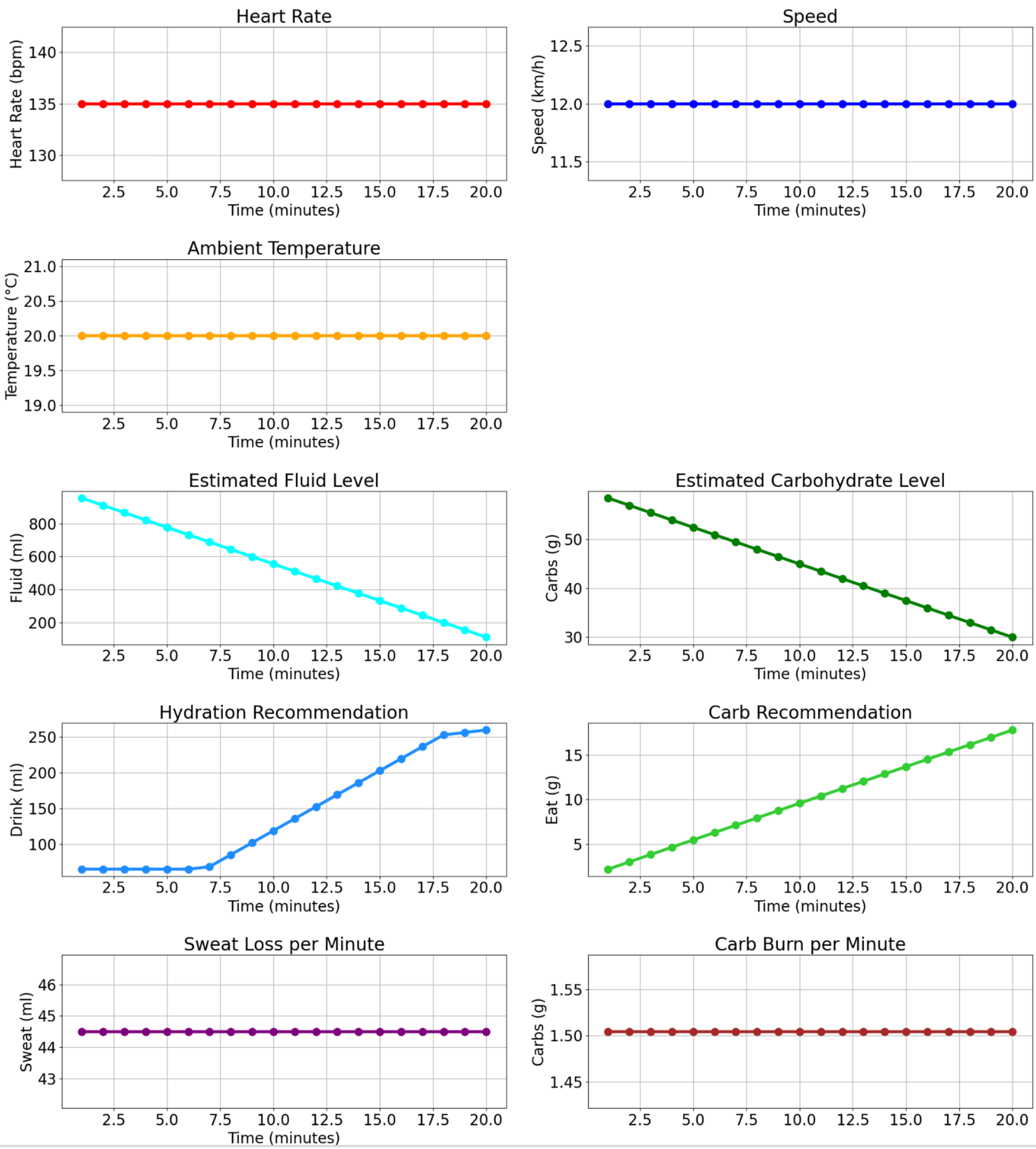
Compared to the normal baseline, this test starts from extremely low pre-workout fluid and carbohydrate levels, which is clearly visible in the estimated internal level graphs reaching near zero early in the session.

As expected, both hydration and carbohydrate recommendations are higher across the entire 20-minute workout, with both curves shifted upward relative to baseline. Hydration advice increases smoothly over time, indicating that the system accounts for the initial hydration deficit under otherwise unchanged conditions.

Carbohydrate recommendations show a similar upward shift, reflecting the very low starting carbohydrate level. The progression remains stable with no irregular behavior.

Given how low the initial internal fluid and carbohydrate levels are, the recommendation magnitudes could reasonably be expected to be higher, especially early in the workout. Overall, the test confirms correct personalization based on pre-workout state while highlighting conservative behavior under severe deficits.

Baseline Heavy Athlete



Compared to the baseline workout with an average-weight athlete, this test uses a much heavier athlete while keeping pre-workout hydration and carbohydrate levels in the same normal range. Under identical workout conditions, both hydration and carbohydrate recommendations start substantially higher than in the baseline case.

At the beginning of the workout, both hydration and carbohydrate recommendations are roughly four times higher than in the baseline scenario. This immediate difference reflects direct scaling with athlete body weight rather than gradual accumulation over time.

This behavior is supported by the underlying estimates: the sweat loss per minute is significantly higher for the heavier athlete, and the carbohydrate burn per minute is also markedly elevated compared to baseline. These higher absolute losses explain the stronger hydration and fueling recommendations despite identical heart rate, speed, and temperature.

As the workout progresses, hydration advice continues to increase more steeply than in the baseline scenario while remaining smooth and stable. Carbohydrate recommendations follow a similarly shifted pattern, maintaining consistent minute-by-minute increases.

Overall, this test confirms that the system correctly accounts for substantially higher sweat loss and carbohydrate burn associated with greater body mass, producing stronger initial and ongoing recommendations while preserving stable and predictable behavior.

Stay aligned with science-informed hydration and fueling limits

Goal

Verify that all hydration and carbohydrate advice generated by the system stays within the science-informed limits defined for this prototype to ensure safe and physiologically appropriate recommendations.

Testing Strategy

To verify alignment with these science-informed prototype limits, a single targeted test scenario is used. This scenario combines repeated fluid and carbohydrate intake during a long, high-intensity workout, allowing all hydration and fueling safety constraints to be evaluated under the same conditions. The goal is to stress-test every limit while keeping the setup simple and consistent.

Guideline Category	What It Tests
Hydration limits	- Hydration advice per update never exceeds **750 ml** - The system never recommends drinking once hourly absorbed fluid exceeds **1,500 ml** - The system does **not** recommend new fluid until the previous drink has been fully absorbed
Carbohydrate limits	- Carb advice per update never exceeds **60 g** - Hourly absorbed carbohydrates never exceed **120 g** - The system does **not** recommend new carbohydrate intake until previously consumed carbs have been fully absorbed

The test is considered successful if all of these constraints are respected throughout the scenario, with no recommendation or absorbed total violating the prototype's defined safety limits.

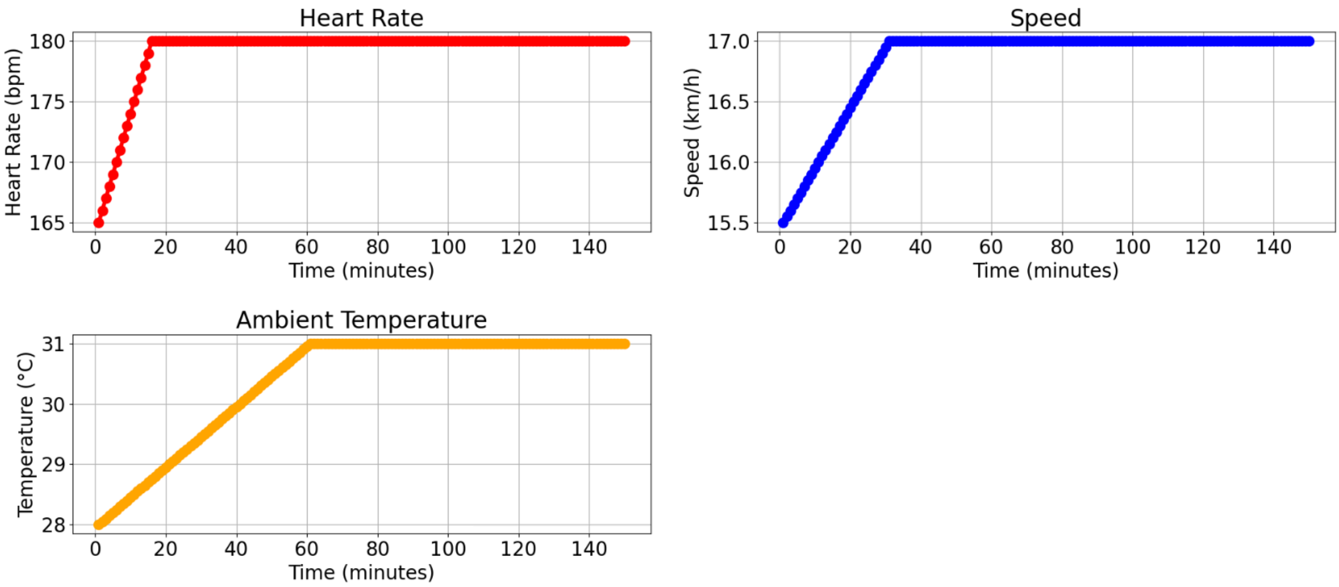
Setup

Test here

```python
# Simulated workout data
workout_data_samples = []

hrate = 165
speed = 15.5
temp = 28.0

for i in range(60):  # 60 minutes
    workout_data_samples.append(
        WorkoutData(
            heart_rate=hrate,
            speed=speed,
            temperature=temp,
            drink_ml=0,
            eat_g=None
        )
    )

    # Keep intensity and heat high
    hrate = min(hrate + 1, 180)
    speed = min(speed + 0.05, 17.0)
    temp = min(temp + 0.05, 32.0)

for i in range(90):  # 90 minutes
    workout_data_samples.append(
        WorkoutData(
            heart_rate=hrate,
            speed=speed,
            temperature=temp,
            drink_ml=750 if i == 0 or i == 30 else 0,   # Drink 1500ml
(half at minute 60, half at minute 90)
            eat_g=60 if i == 0 or i == 30 else 0 # Eat 120g (half at minute
60, half at minute 90)
        )
    )

# Simulate workout
for data_point in workout_data_samples:
    # Process a single workout data point (update state, calculate losses,
advice, absorption)
    engine.update(data_point)

    # Store the calculated values for the graph
    ...

# This creates the nice plots with all the data displayed in it
create_very_nice_plot(...)
```

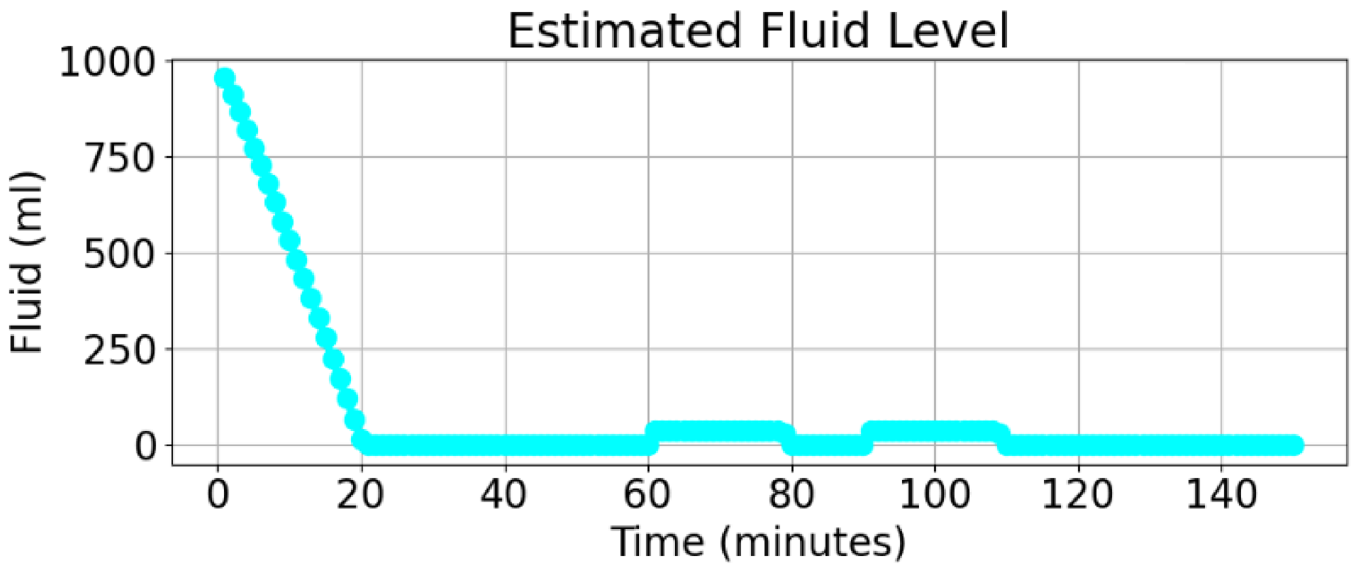
Results

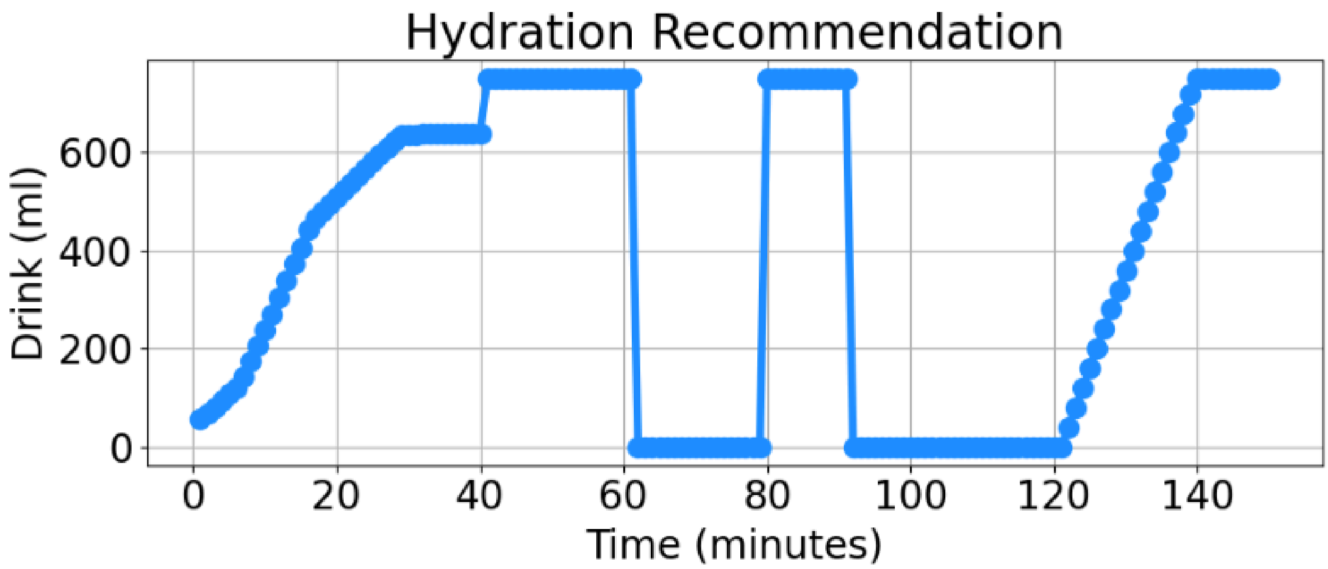
Workout conditions



This test simulates an intentionally extreme endurance scenario. Heart rate rises quickly to a very high level and then remains near maximal for most of the session, while running speed also increases early and stabilizes at a sustained high pace. At the same time, ambient temperature steadily rises into a hot range and remains elevated for the duration of the workout. Together, these conditions create a prolonged combination of high cardiovascular strain, high mechanical workload, and significant heat stress, resulting in exceptionally high sweat loss and energy expenditure rates. This setup is designed to stress-test the system’s safety limits rather than represent a typical or easily sustainable workout.

Hydration limits





In this case, the system follows all hydration safety rules exactly as intended. As workout intensity and temperature rise, the engine gradually increases its drinking recommendations up to the 750 ml per-drink cap but never exceeds it. Once the athlete consumes a drink, the recommendation immediately drops to 0 ml, and the system does not advise drinking again until the previously consumed fluid has been fully absorbed. Because the hydration model absorbs water at a fixed rate of 40 ml per minute, this creates the long zero-advice plateau between roughly minute 60 and minute 80, where absorption constraints correctly override sweat loss and intensity effects.

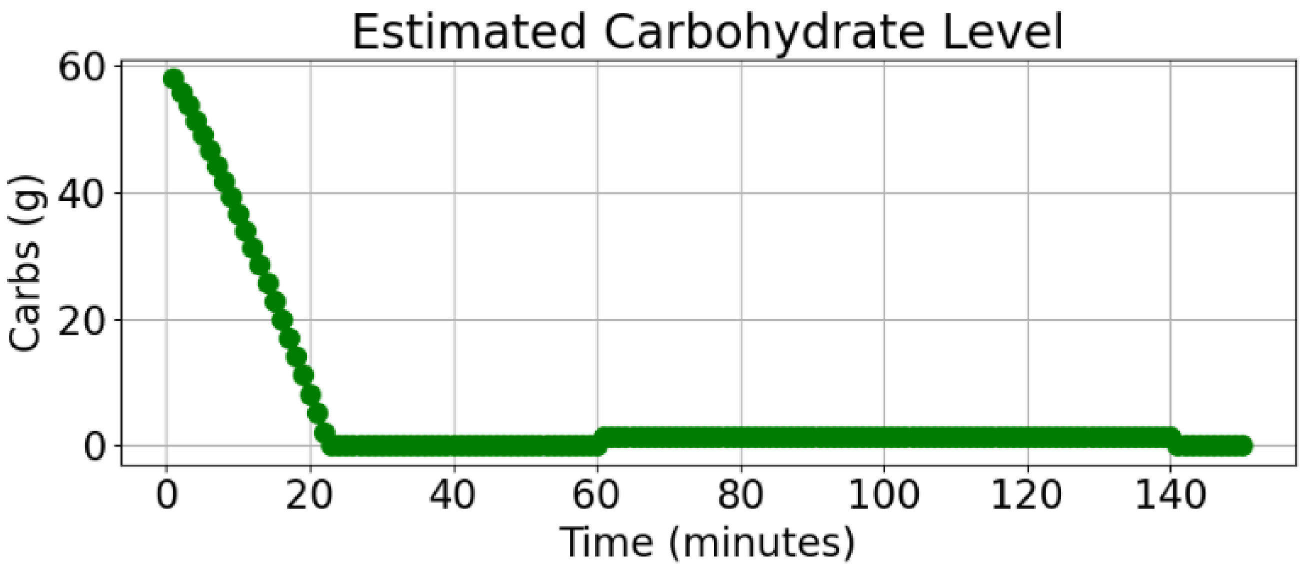
After the first 750 ml intake has been absorbed, the system resumes increasing its advice and again approaches the 750 ml upper limit without crossing it. A second intake occurs later in the session, but the recommendation remains at 0 ml for an extended period because the hourly absorbed fluid total exceeds the 1,500 ml safety threshold. Only once this rolling total drops below the limit does hydration advice resume.

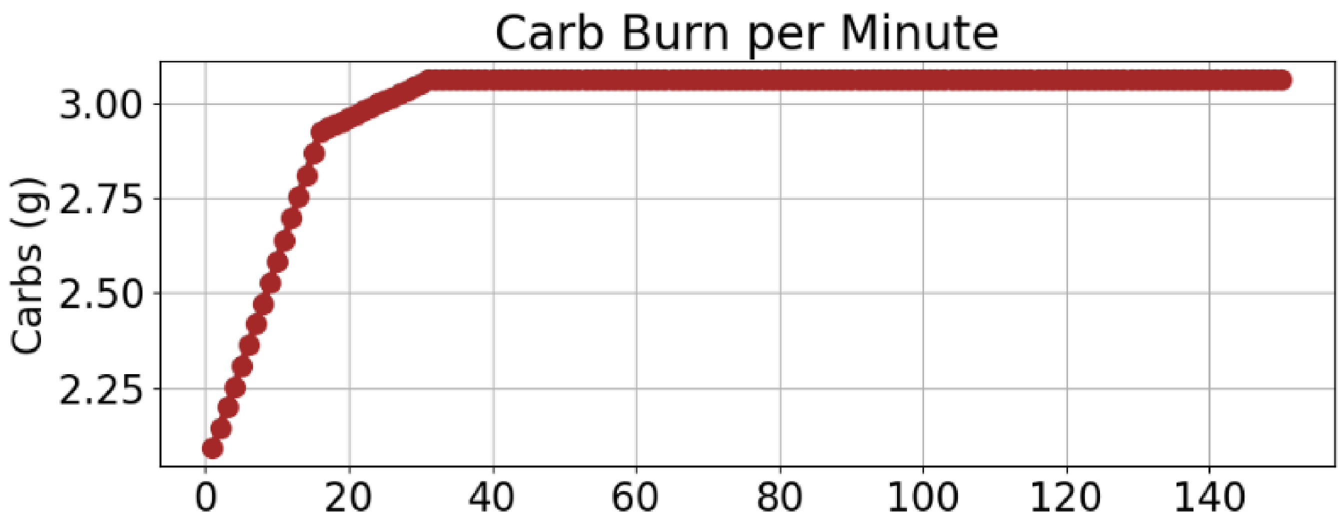
Under the extreme conditions simulated in this test, sweat loss per minute is consistently higher than the rate at which fluid can be absorbed. As a result, the estimated internal fluid level is unable to recover meaningfully and remains near zero for much of the workout despite repeated intake events. This behavior is clearly visible in the fluid-level graph and reflects a physiological bottleneck rather than a failure of the safety logic.

It is important to note that only a very small subset of athletes could realistically sustain such extreme combinations of intensity, heat, and sweat loss for this duration. In these edge cases, the model may produce less accurate absolute fluid-level estimates, even though the safety constraints and decision logic remain correct.

Overall, this test highlights two key points: first, that the hydration safety rules behave exactly as designed under extreme stress; and second, that the model is not universal. These results strongly suggest that absorption rates and loss parameters should be tuned per individual athlete to improve accuracy under extreme or atypical conditions, rather than relying on a single fixed physiological model for all users.

Carbohydrate limits





In this case, the carb system behaves exactly the way the rules expect. At the start of the workout, the recommendations slowly increase as the athlete uses more carbs, and they eventually reach the 60 g per-intake limit, but never go over it. This shows that the per-update maximum is working correctly.

When the athlete eats 60 g at minute 60, the recommendation instantly drops to 0 g. The system then stays at 0 because it's not allowed to recommend more carbs until the previous snack has been fully absorbed. Since carbohydrate absorption is slow in this model (1.5 g per minute), the first 60 g is still not absorbed by minute 90. When another 60 g is consumed at that point, the system continues recommending 0 g, confirming that the "no recommendation until absorbed" rule is applied correctly.

As with hydration under extreme conditions, the results clearly show that carbohydrate burn can exceed what the model is able to absorb. This causes estimated carb levels to remain low and keeps recommendations suppressed for a long period, even after intake. Only a small number of athletes could realistically sustain such conditions, and under these extremes the model may produce physiologically unrealistic outcomes. This highlights that, like hydration, the carbohydrate model is not universal and would need individual tuning for extreme workloads.

Overall, the test shows that the carb logic behaves correctly: it stays under the per-snack maximum, waits for absorption before recommending more, and naturally remains below the hourly absorption limit.

Critical Analysis of the Solution's Fitness

The solution was evaluated on two main fronts: computational efficiency and overall capability to meet the real-time performance requirement. From a performance perspective, the system demonstrates extremely low processing overhead. Each workout data point is processed in 0.00–0.03 ms, with an average of 0.01 ms, which is effectively negligible and far below any real-time constraint. This comfortably meets the success criterion that each update must complete within 1 second. The update step consists of constant-time arithmetic operations and manages only fixed-size 60-entry histories, which represent the absorption window for the last 60 minutes (one data point per minute). Because these histories never grow beyond 60 items, both time and space complexity remain O(1) per update, ensuring scalability regardless of workout duration.

Theoretically, the system could be configured to process data more frequently, for example, once per second rather than once per minute. This would increase the number of absorption entries from 60 per hour to 3,600 per hour, and in turn slightly increase processing time. However, such rapid intake events (eating or drinking every second) are not realistic in real-world workouts. The prototype is intentionally designed around one-minute ticks, which match typical endurance-training data resolution and make the fixed 60-entry window appropriate and efficient. Under these assumptions, the solution performs well within all required constraints and remains robust for its intended use case.

Overall, the solution is computationally efficient, stable, and suited for real-time hydration and fueling estimation. While the physiological model could be expanded for higher accuracy, the current implementation demonstrates strong fitness for the intended purpose of delivering lightweight, minute-by-minute recommendations.

Conclusion

This project successfully delivered a working prototype within the three-week timeframe that provides real-time, personalized hydration and carbohydrate recommendations during endurance workouts. The system processes live workout data efficiently, continuously tracks estimated internal fluid and carbohydrate levels, reacts correctly to eating and drinking events, and generates minute-by-minute advice expressed in clear, actionable quantities. All real-time performance requirements were met comfortably, with processing times far below the defined limits.

The testing results show that the model behaves in a scientifically plausible and internally consistent way. Fluid and carbohydrate estimates change smoothly over time, respond logically to changes in heart rate, speed, temperature, body weight, and intake events, and remain within the science-informed safety limits defined for the prototype. Under normal and moderately demanding conditions, the model produces values that align well with ranges reported in the sports-science literature, making it suitable as a practical estimation tool rather than a precise physiological simulator.

At the same time, the tests clearly demonstrate that the model is not universally perfect for all athletes and all conditions. Under extreme scenarios, such as very high body mass, severe pre-workout deficits, or prolonged combinations of high intensity and heat, the model can produce values that may be too conservative in some cases or overly aggressive in others. These outcomes highlight the inherent limitations of using simplified, fixed coefficients to represent complex human physiology. They also show that individual differences in sweat rate, carbohydrate metabolism, and absorption capacity cannot be fully captured by a single generic model.

Despite these limitations, the most important outcome is that for a large group of typical endurance athletes, particularly average-weight individuals training at common endurance intensities, the model provides a reasonable and useful representation of what is happening internally during a workout. It offers timely guidance that adapts to changing conditions while respecting safety constraints, which is precisely the intended role of a real-time training support tool.

In conclusion, the prototype meets its defined goals: it is fast, adaptive, safe, and scientifically grounded. While future work could improve accuracy by adding individual calibration, learning from historical data, or integrating additional physiological signals, this implementation demonstrates that even a lightweight model can deliver meaningful and actionable hydration and fueling guidance within strict development constraints.

Future Research

This prototype focuses on providing reasonable, real-time estimates rather than precise physiological accuracy. The current approach uses simplified rule-based and mathematically lightweight models that behave realistically but are not personalized to each athlete's unique biology. For future research, more advanced methods could be explored to increase accuracy.

Improving the physiological realism of such a system would require approaches beyond the scope of this 3-week prototype. More sophisticated techniques, such as machine learning models or detailed physiological simulations could offer far more accurate and individualized predictions. However, they require large amounts of high-quality data, repeated athlete-specific testing, and scientific equipment such as sweat-rate sensors, metabolic carts, or lab-grade glycogen measurements. These methods are powerful but resource-intensive, making them unsuitable for a lightweight proof-of-concept.

Another potential direction is the development of an algorithm that predicts the optimal timing for rehydration or carbohydrate intake. Rather than relying solely on reactive thresholds, the system could forecast future hydration and carbohydrate levels and issue recommendations before the athlete reaches a critical point. This would require integrating effort forecasting, environmental factors, and absorption timing into a predictive decision-making system, an interesting but non-trivial extension for future work.

Both of these directions were outside the scope of this short development period, especially since a functioning simulation environment first had to be built before any higher-level modeling could even be explored. Given this constraint, the focus remained on creating a reliable real-time system rather than developing athlete-specific physiological models or predictive intake algorithms. The current design therefore offers rough but practical estimates suitable for live workout feedback, while leaving substantial room for more advanced, personalized, and predictive modeling in future iterations.

Help received

I did not receive help from anyone during this part, except for guidance from teachers who helped me shape the testing approach and provided advice on how to write the report. All design choices were developed independently, using information derived from the cited research papers and academic sources.