

# Understand your cycle. Anticipate what comes next.

We're building a personal cycle model that updates with hormone measurements. Wearable signals and daily experiences complete the long-term picture. The aim is to make the biology behind each cycle easier to understand and use in everyday life.

Where am I in my cycle?  
What happens next?  
Which patterns repeat for me?

## The approach

Published models of hormonal feedback provide the biological starting point. Personal measurements update the estimated cycle state. Forecasts should show a range of possible outcomes and change as new information arrives.

Hormone measurements are essential. Wearables provide indirect signals between samples; self-reports capture the person's experience. We will test whether additional personal parameters and wearable signals improve predictions beyond the hormone history alone.

## The first study

We plan to predict future urine LH, E3G and PdG measurements, then compare a mechanistically grounded model with strong statistical forecasts using exactly the same available information.

The proposed main scenario uses three fixed measurement days per week to forecast two study days ahead. These are research choices, not established optimal frequencies. Evaluation starts after one observed personal cycle interval, and the available history grows with new measurements. Test participants remain separate from those used to train the global model.

The statistical comparison is selected within training data from a multichannel Gaussian process and a small state-space model. Persistence and a population cycle template provide simpler reference points. We assess each hormone, forecast uncertainty and numerical reliability. The main comparison is a complete study, including if the result is negative or inconclusive. Additional personal parameters and wearables are exploratory extensions.

## The product question

Our thesis is that personal history could make forecasts more useful while keeping the measurement burden manageable. We still need to learn which forecasts people would use regularly, how often they would measure, and what they would pay for.

# From a model to everyday use.

## Data and evidence

Existing mechanistic models give us candidates for one reproducible biological core. mcPHASES is a candidate dataset combining hormones, wearable signals and self-reports. Access is governed by a research data-use agreement; access and raw-data suitability have not yet been established for this project. Other analyses of the same collection do not provide independent external validation.

The prediction targets are native urine measurements. Their relationship to serum hormones requires a separate observation model. A successful forecast would not validate unmeasured serum concentrations or uniquely identify a person's biological parameters. The comparison evaluates the whole prediction pipeline, including that observation model.

## Where we are

The first study is specified in research proposal version 3. We have not yet analyzed individual raw data or measured forecasting performance. Data access and an independent validation cohort remain open. Customer demand and willingness to pay are hypotheses to test. The business model and open-source strategy are undecided; eigen is a working name.

## What could follow

A personal history across cycles could support recurring-pattern analysis and help choose informative measurement times. Later studies could investigate why hormonal changes affect people differently, including their effects on mood and brain function. Clinical applications and forecasts of responses to interventions need separate validation.

## Founding team

### Annemarie Schimkat

Co-Founder & CEO

Management & Technology @ Technical  
University of Munich

### Arian Gohari

Co-Founder & CTO

Computational Biology @ Technical University of  
Munich

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