An Infrastructure for AI Coverage in Personal Fitness Training

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Abstract: The combined technological state of computer-vision, computation speed, and artificial intelligence (AI) have provided an opportunity to improve the state of public health. We can achieve this by filtering exercise data through a standard method to produce cross-compatible data sets. This method is only possible by modeling human movement using standard physical methods such as an open thermodynamic system. The challenge in modeling a biological system with mechanical method is lack of certainty and predictability in biological systems of which the laws of physics rely heavily on. That gap is bridged by observing human movement and deriving the key equations at runtime. The technology was developed to augment personal trainers; however, we have introduced a language that can only be interpreted using advanced statistical analysis; skills most personal trainers lack.   Therefore, we trained leading Large Language Models (LLMs) to act as the coaching communication layer by providing the base data and training data for it to design language for delivery. By combining the eyes to generate the data and then the brain to interpret it, the LLMs help us communicate it in a digestible and incremental way. Backed by highly developed computer vision, physics, and training stacks, AI can now cover personal training and support further scientific development.

Introduction

The knowledge base surrounding exercise science relies heavily on peer-reviewed journal articles as the primary source of credibility within the scientific community. This system is highly effective for advancing foundational knowledge; however, when professionals publicly disagree within the scope of peer-reviewed literature, it can unintentionally weaken public confidence in the field. While the scientific process itself does not depend on public trust, the impact of scientific knowledge on public health does. Without broad acceptance of scientific guidance, even well-supported efforts to promote health through research and education struggle to achieve meaningful outcomes.

Fitness professionals rely heavily on body composition metrics, such as dual-energy X-ray absorptiometry (DEXA) scans, to evaluate client progress. These measurements are widely used because they are accessible and often reimbursable through insurance systems. However, body composition represents a secondary signal of health when compared to level of physical performance. Research suggests that physical performance may be a more direct and actionable indicator of health than traditional body composition metrics when it comes to reducing all-cause mortality risk [1][2][3][4].

Approaches to rapid weight loss are frequently associated with reductions in fat-free mass, including muscle and bone [5][6]. These losses are clinically significant, as decreased muscle mass and bone density are independently linked to increased mortality risk and cognitive decline [7][8].

Together, this highlights a key distinction: interventions focused solely on weight or fat loss may undermine long-term health, whereas those that prioritize physical performance more closely align with improved health outcomes. With these recent scientific developments, the current practices derived from tracking visceral fat using DEXA no longer meet the fiduciary responsibility of health and medical care providers.

What is needed is a standardized framework that can signal progress when evaluating the exercise results. Such a framework shifts the focus to physical performance as the primary indicator of health, rather than secondary signals like body composition. By quantifying physical activity, it becomes possible to align training, feedback, and decision-making around outcomes that directly reflect functional capability. In this paper, we propose a technological system designed to quantify human physical activity and performance in a standardized way. By establishing a shared framework for measurement and analysis, this system enables clearer signals of progress, more consistent application across individuals, and a more effective path toward improving both individual performance and population-level health outcomes.

Open Thermodynamic System

The first step in quantifying human physical performance is to model it using fundamental physical methods. Human physical activity is best modeled as an open thermodynamic system because both mass and energy cross the body's boundaries (human being the body).
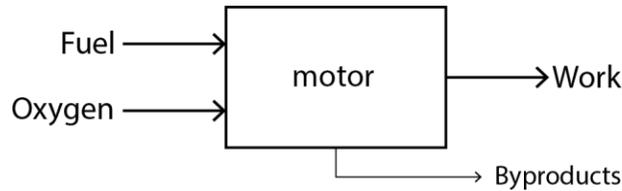

Figure 1: Generic Open Thermodynamic System

Mechanical Work (W) is Force (F) multiplied by Vertical Displacement (D) of the center of mass (COM) of the object being moved. Mechanical Work is an energy metric and is commonly represented as foot-pounds, joules, or calories.

$$W = F * D$$

Pumps and motors have predictable mechanical output per repetition making the application of an open thermodynamic system to a motor easy to comprehend. Where most people get lost when modeling a human being in an open thermodynamic system is that there is no guarantee of equal performance on an event-to-event basis; in-fact two reps are most likely never to generate the exact same data set. Therefore, we can only utilize the open thermodynamic model for humans if we are able to observe the activity during runtime.

In the case of a resistance exercise (barbell, dumbbell, kettlebell, etc.), both the center of mass of the human (internal work) and an external resistance such as barbell (external work) are being displaced. In this case, the expanded work equation can be represented like this.

$$TW = IW + EW$$

The equation is expanded to two bodies (internal and external) being displaced. This equation can be expanded to accommodate many forms of external force such as military, fire and police gear.

In any case, the true range of motion must be observed and quantified based on what is already known about the subject and what we can infer from the video.   Below is a conceptual flow for processing event data into a viable work metric.
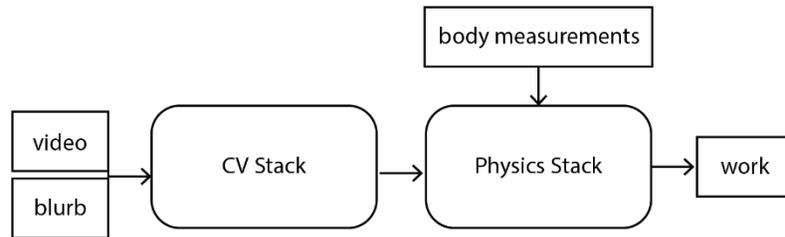

Figure 2: Event Work Derivation

Now that we can accurately derive the work equation for an event at runtime, we can add more variables to the system such as time.

Deriving Body Center of Mass

As a pre-requisite to event processing the subject must perform a calibration which consists of entering height, weight and taking a body scan with their phone. A mass distribution profile is applied to the subject so that when we simulate positions the system can calculate the vertical center of mass of the body in that position.
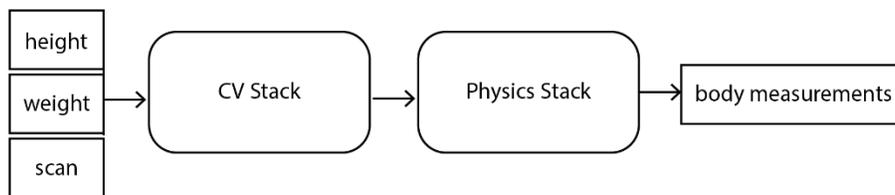

Figure 3: User Calibration Process

At runtime, the CV stack provides raw data which is then processed by the physics stack to produce range of motion once it has observed a full movement cycle. This development allowed us to move from resistance exercises to a broad full range of human movement patterns. We have custom trained object trackers and pose-based positioning systems that allow us to track body orientation and just about any type of resistance object including full military, fire and police gear.

Human Movement Drivers

The key difference between modeling a human vs an engine as an open thermodynamic system is that the engine is predictable based on specifications, and the human must be observed during runtime to derive the correct equation. Another key difference is that humans have many ways it can perform work. An engine has one.

This system has defined 18 key movement drivers that define human performance. For the Squat movement driver, we have a muscle activation map which shows which muscles have been activated for that movement driver with high, medium and low coloring (darkest = highest activation).
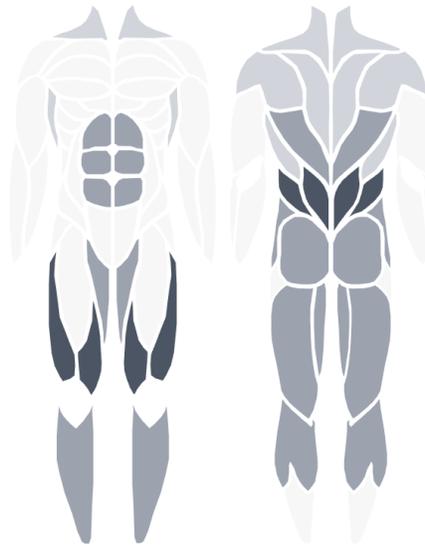

Figure 4: Squat Driver Muscle Activation Map

Another key computation is the mass fraction (MF-driver) for the driver which is the ratio of the subject's muscle mass (MM-body) activated by this driver (AM-driver). This is variable between subjects.

$$MF_{driver} = \frac{AM_{driver}}{MM_{body}}$$

Autoregulation

Our system is trained to find the sweet spot between adaptation and risk by combining the cv stack with observable (work equation inputs) and non-observable metrics (autoregulation). Science tends to get soft when dealing with biological systems. Autoregulation is how we harden soft science because the autoregulation interpretations are backed by statistical precedence.

The subject can include a form of autoregulation in their blurb at submission with formal or informal statements. "Really hard" or "super easy" generally tell us what we need to know, and we then do our best to interpret those accurately. We also use velocity to help us infer what the subject meant based on what we have seen historically from the subject.

Formal autoregulation feedback defines the stimulus as either rate of perceived exertion (RPE) or reps in reserve (RIR). RPE can be any value from 5-10; a scale of 1-10 but we do not concern ourselves with anything under 5 because it does not register as quantifiably fatiguing. RIR can be any integer from 0-5. Mathematically, RPE and RIR are inverses equations. From there we can accurately predict a one-rep max from a 3, 5, or even a 10-rep set. Similarly for an endurance event, if the subject states that they were running at 90% pace we know how to estimate maximum pace over that distance given the subject's history.
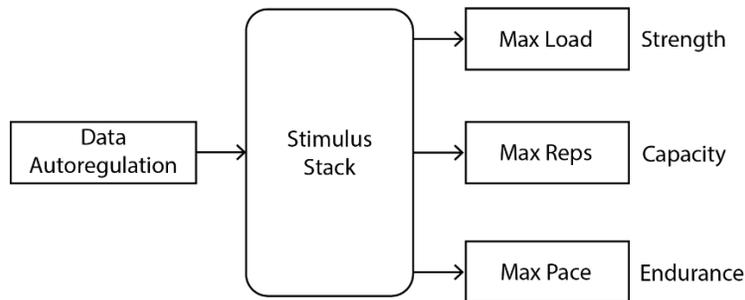

Figure 5: Autoregulation Result by Type

We sought out expert coaches for both endurance and strength athletes. We were given some tables that the industry has put together, we took those tables and ran regression analysis to provide our system with equations that are more flexible than the original tables.

The following diagram shows how current state of fitness + activity stimulus + autoregulation work together to predict the improved or new state of fitness and then perpetuate the continuous improvement cycle.

Figure 6: Stimulus + Autoregulation Loop

The system can work if the user only submits the week-four test autoregulation feedback. Providing feedback on non-peak weeks can help the system correct the intended stimulus before the end of the block, which should expedite progress and reduce the risk of injury or over-training.

Performance Metrics

We have documented our method for deriving the work equation for an event at runtime. Another metric we can extract from the exercise video is time (T) which allows us to compute Power (P).

$$P = \frac{W}{T}$$

Time is useful for classifying exercise into performance categories such as a strength, work capacity, and endurance; time scopes had to be defined to ensure proper interpretation and mapping of results. Strength ends at 7 seconds due to the phosphagen energy system (ATP-phosphocreatine) effect of which muscles can rapidly replenish energy for about 7-10 seconds of intense exercise [9][10]. Phosphocreatine (PCr) can be replenished during rest and takes from 2-4 minutes because it requires the blood to supply oxygen first. Oxygen takes about 2 minutes to reach from lung to muscle and then it can take up one to two minutes for the muscle to absorb the new oxygen supply [11][12]. Therefore, work capacity ends at 180 seconds because that is about how long it takes for the blood stream to replenish muscles with oxygen and effectively provide more PCr.

We define an event's key performance indicators (KPI's) as movement classification, power output, duration, and body weight. While the performance metric, FITNDEX Rating, organizes many performance indicators and is derived from plotting power output over a custom time scale for a given movement driver.
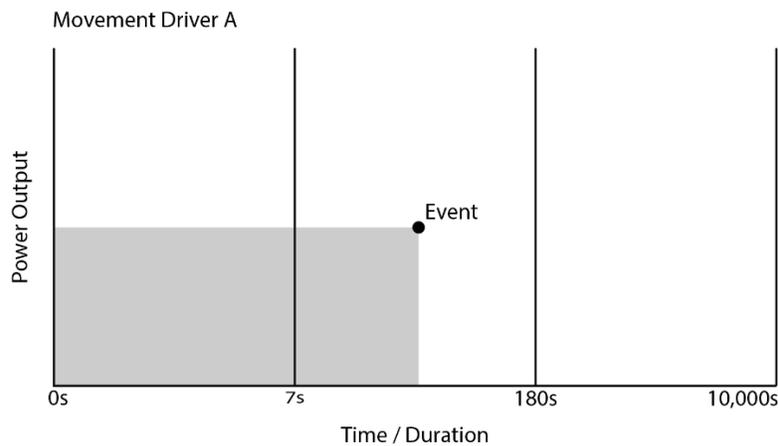

Figure 7: Single Event Fitndex Rating for Movement Driver A

Generating the value for the area under the curve requires defining the power metric and the x-axis in more detail. The details of how we define the time scale and time increments (I) will remain proprietary for now.

$$FITNDEX_{event,driver} = \left(\frac{P_{event}}{MF_{driver}}\right) * \left(\frac{I_{event}}{I_{total}}\right)$$

The power output is effectively upgraded by the fraction of active muscle for that driver and then the upgraded value is downgraded based on the ratio of active time increments vs the total number of time increments. We decided to move away from a traditional times scale to give exercises of any duration the opportunity to contribute to the performance metrics evenly.

The following diagram displays the personal record curve (PRC) which displays how data can plot out with some example events.
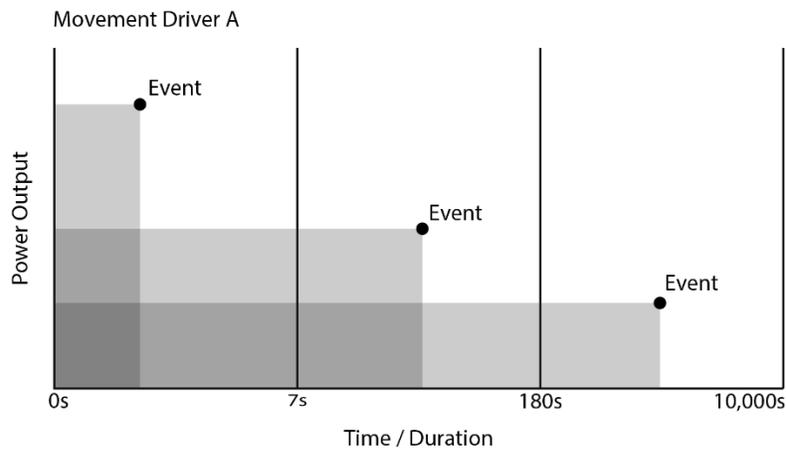

Figure 8: Muli-Event Fitndex Rating for Movement Driver A

The area under this curve is the athlete's fitness rating i.e. FITNDEX for a given exercise. The key here is that there is no overlap in the area, therefore, if the subject hammers the same patterns repeatedly with slight improvement, their composition is purely based on performance profile, not volume of qualifying events.
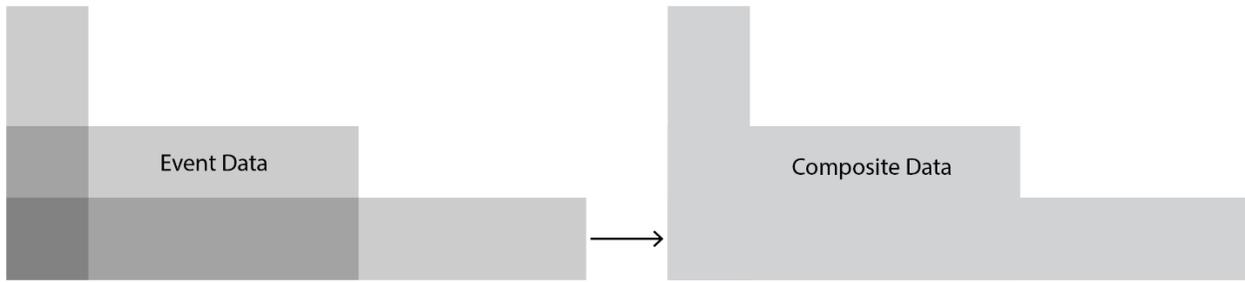
Figure 9: Personal Record Curve – Area Under Curve

When we calculate the composite FITNDEX for a series of exercises we effectively remove the overlap by using a time increment differential approach where the number of time increments of the current events is reduced by the time increments of the previous event.

$$FITNDEX_{composite,driver} = \sum_{i=0}^{n=events} \left(\frac{P_i}{MF_{driver}} \right) * \left(\frac{I_i - I_{i-1}}{TI} \right)$$

This method can take in any combination of exercises to generate a FITNDEX rating for that driver. Now all athletes have a normalized metric to speak to when discussing a certain movement driver. However, we must generate a single metric which includes the FITNDEX rating for all movement drivers.

Metacycle

We are introducing the term metacycle as an alternative to a macrocycle. A macrocycle is typically a season or year. While our system is a continuous adaptive cycle governing the evolution of training cycles over time, which implies a higher order of logic than macro. This system still has the flexibility to prioritize training for a peak event and then schedule a deconditioning recovery period for recovery when requested by the user.

Objective Function

The objective of the metacycle is to maximize the surface area of the performance diagram over an absolute scope and a recent scope. This combined metric helps ensure that recent activity is well-rounded and synergistic to health outcomes.

Below is an example of how the fitndex rating can plot out for all 18 of the movement drivers. Every exercise is most likely to have portions of its mechanics performed by more than one of the movement drivers. Therefore, a single event can result in moving the rating to more than one of the legs. The area of this diagram is the user's FITNDEX Rating.
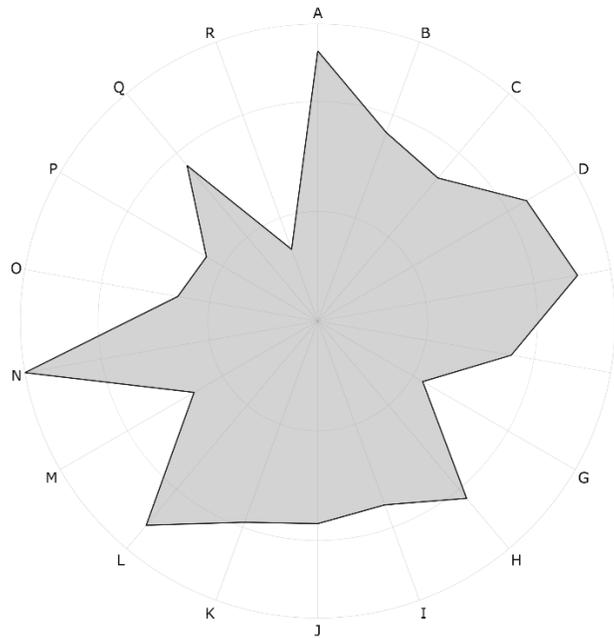

Figure 10: Performance Diagram

Stimulus Matrix

The stimulus matrix is where we rely most heavily on our intelligence stack, which is a combination of our systems in-house processes along with integration of third-party Large Language Models (LLMs) using the paid application programmable interface (API) services. Below is a diagram showing the flow of data that perpetuates our intelligence layer.
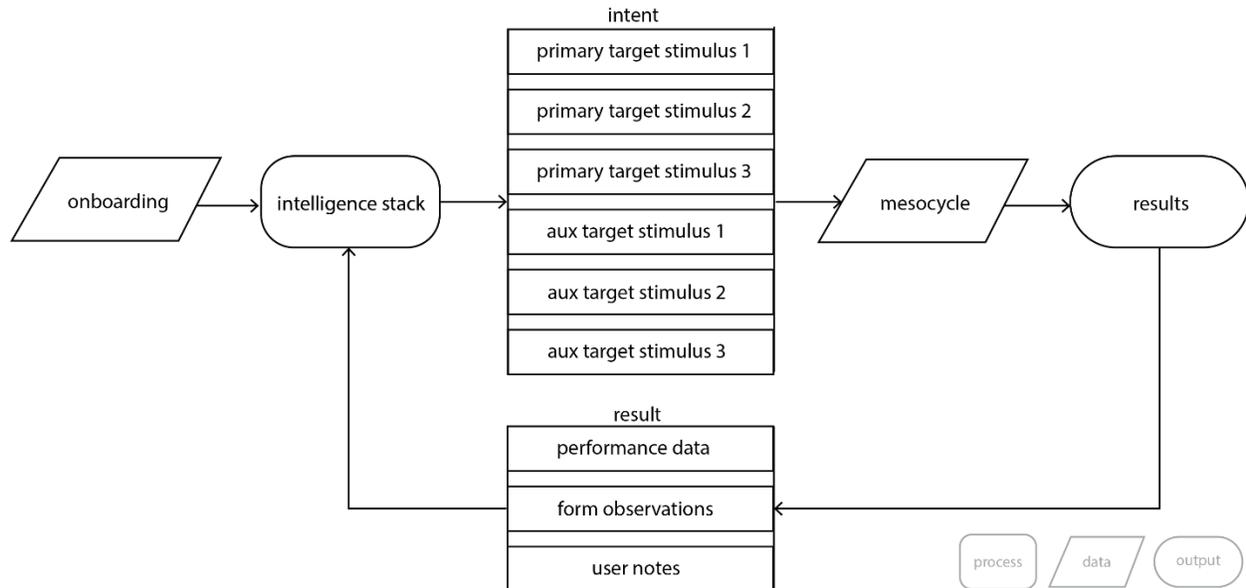

Figure 11: Mesocycle Intelligence Loop

The system needs a kickstart that is currently provided by an onboarding process. The system will most likely not have a full performance profile. Therefore, the system enters a priming phase before progressing into an optimization phase.

Path to Optimization

It is unrealistic to expect the system to converge on an optimized model out of the box. Therefore, the system has three distinct phases that lead to optimization.

- Priming Phase – All activity until the system has a baseline for all 18 movement drivers
- Learning Phase – Small training experiments designed to assess the subject's response to certain stimulus patterns for an individual driver and for the human system as a whole
- Optimization Phase – Posed with endless options, the **system minimizes the amount of mechanical work** the user must perform to meet their mesocycle stimulus matrix.

Optimization Environment

Optimization programs are computational systems designed to identify the best possible outcome within a defined set of constraints. They operate by representing a system using state variables, which describe the current condition of the system being modeled, such as physical performance metrics, workload, recovery status, or environmental factors. These variables evolve over time as the system responds to inputs and interventions.

An optimization model evaluates possible decisions or actions against an objective function, which represents the desired outcome, such as maximizing performance. Constraints define the limits within which the system must operate, which could be limitations on exercise selection based on subject's movement-driver state or volume limitations due to lifestyle.

This framework allows complex biological processes, such as human physical training, to be modeled as dynamic systems where data-driven decisions can guide adaptation, improvement, and long-term health outcomes.
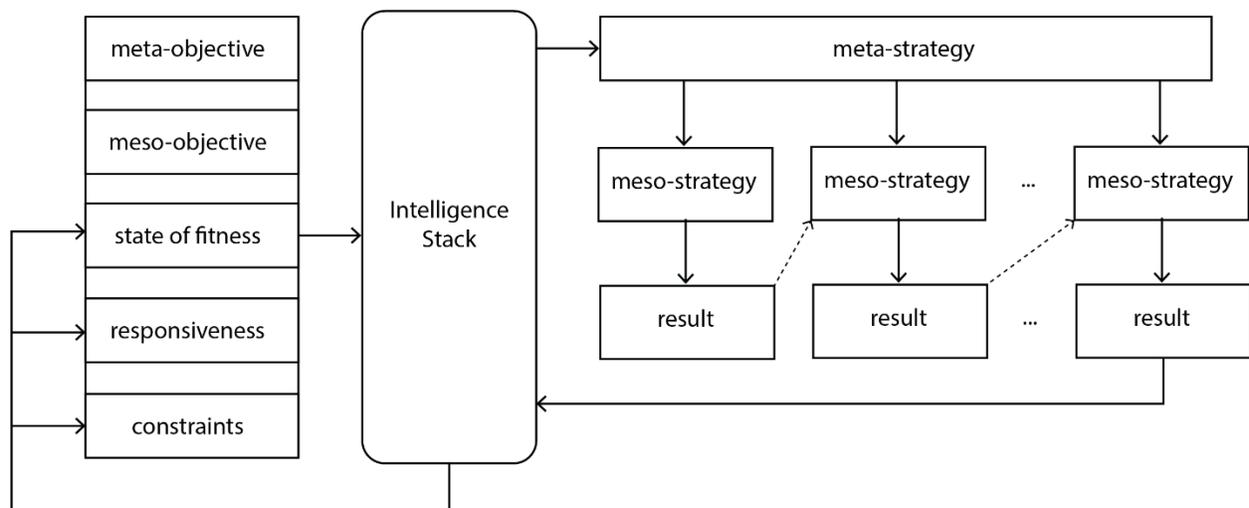

Figure 12: Strategic Optimization Flow

Anthropomorphism

In the interest of gaining public trust in the system, personification of the software makes sense. This capitalizes on a key psychological cognitive process where observers interpret human-like traits from systems designed to follow a systematic process. We leaned into this.

Meet KAELIS – Kinetic Analysis Engine for Load, Intensity and Strategy. KAELIS is the personification of the personal trainer. And just like any good trainer, KAELIS can observe physical activity, process it into meaningful data, design corrective strategies, communicate it and then observe the results as feedback to the next iteration.

KAELIS combines all technical processes into one roof designed to direct communication and strategy through the guise of a chatbot.
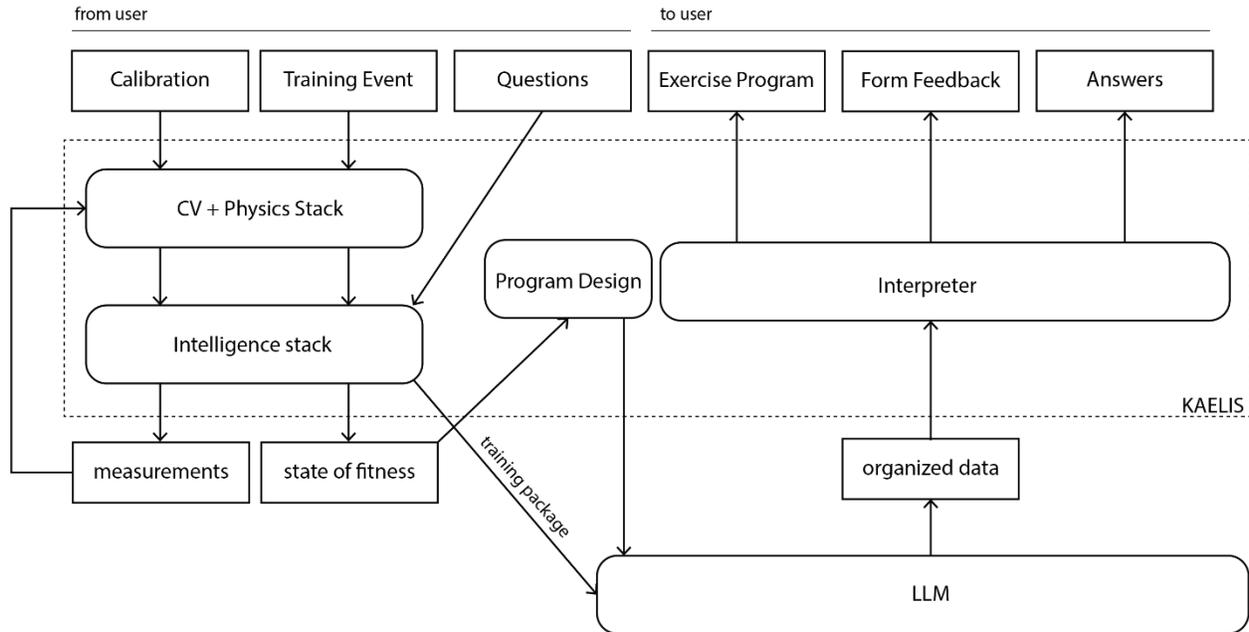

Figure 13: KAELIS Information Flow

Conclusions

We have developed a system that enables AI-driven coverage in personal training. This application is made possible by modeling the human body as an open thermodynamic system and quantifying physical performance through the unifying language of mathematics. By grounding the model in measurable variables and consistent physical principles, the system produces outputs that are transparent and verifiable, strengthening its reliability and trustworthiness.

This approach establishes the foundation for what can be described as human physical fitness engineering. Standardization allows findings to accumulate into stable conclusions rather than fragmented interpretations, creating a clearer pathway toward broader scientific and public acceptance. We have focused on interfacing with the public with the development of an AI trainer because it is the clearest path to restoring public health. This is just the beginning with this technology. From here, new theories will be conceptualized and will have a home for experimentation. This is just the beginning.

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