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MODELING REALITY: REVISITING CALVERT'S FITNESS SIMULATION

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ABSTRACT

Wearable sensors have gained mainstream acceptance for health and fitness monitoring despite the absence of clinically validated analytic models for clinical decision support. Individual sensors measuring, say, EKG signal and heart rate can provide insight on cardiovascular response, but a more complete picture of health and fitness requires a more complete portfolio of sensors and data. This paper outlines the research underway to revisit and reconfigure the 1976 Calvert systems model of the effect of training on physical performance. Specifically, we use wearable sensor data from clinical trials to supplement a hybrid model created by nesting Perl's Performance-Potential model within Calvert's transfer function approach to system simulation. Contemporary simulation tools combined with wearables clinical trial data is the foundation for a more agile platform for simulation of fitness and exploration of causality between training and physical performance. This platform offers the opportunity to strategically integrate data from various wearable sensors in a fashion enabling improved support for post-injury and return to sport decision-making.

Keywords: Wearables, fitness monitoring, Calvert model, return to sport, post injury physical therapy.

NOMENCLATURE

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HR	Heart rate in beats per min (BPM)
RTP	Return-to-Play
SmO2	Muscle oxygen level (percentage)

1. INTRODUCTION

Calvert's model [1] (shown in Figure 1) was introduced in 1976 as a system model to help predict competitive performance, based on cardiovascular health, strength, skill, and psychological aspects. Due to the difficulty of combining these components, his model calculations were simplified into one that strictly looked at the fitness and fatigue emanating from training. Although this model is a good basis for predicting the outcome times of an athlete, Calvert indicated there are many factors that were not discussed since they were out of reach, and that further research needed to be done. Returning to the original four-component model remains attractive as a more accurate model. With the advent of commercially available, relatively low-cost wearable systems for biometric measurements, there arises the opportunity to create more objective and detailed measures of individual "fitness" whether it be for athlete performance or post-surgical patient rehabilitation [2-4]. For instance the ability to capture muscle oxygen saturation is now easily obtained with wearables in a way that was simply not possible at the time of Calvert's original research. In the present work we create a hybrid Calvert model by nesting Perl's Performance-Potential model to replace the cardiovascular and strength arms of Calvert's model with the fitness and fatigue equations of Perl [5], thus creating a novel four-component model that is more tractable for the type of wearable fitness data available today.

While we believe the hybrid Calvert model will simplify the use of objective fitness data available for simulation, establishing important qualitative data (e.g., skill) remains a barrier. This type of data is generally considered indeterminate unless broad assumptions or Likert-type scales are used to annotate workout or training data. Given this ambiguity, subsequent forms of the Calvert model attempted to make calculations more tractable by reducing the four-component model to, say, a two-component model. While this produces a computational framework that more readily enables transfer function development and calculations to proceed, some of the richness of the qualitative elements of Calvert's model are lost. Our strategy is to utilize machine learning classification methods to find discrete values of the subjective components (again, "skill" levels). For this, it is necessary train the hybrid Calvert model with annotated data sets for specific athletic training regimens. In particular, the reinforcement techniques described by Sutton [6] have been used to train unconstrained 6DOF kinematic models and if we view the hybrid Calvert model as unconstrained, then the same reinforcement techniques may find relevant fitness patterns within the data sets.

Today's contemporary assessments are dominated by subjective, self-reported measures and this is believed to compromise the quality of, say, training load assessments and the development of training programs that benefit a person's progress. We propose that data produced from wearables arising from clinical trials is the essential "primary data" underpinning advanced modeling work to eventually inform clinical decisions about training programs involved in returning to normal health and fitness. Further, the phenomena of "sports specialization" has exacerbated the trend for flawed training decisions relying heavily on training protocols using patients'/athletes' subjective data to understand their limits. The tendency for information to be nested in proprietary form has impeded the ability to create platforms other researchers can contribute to or expand. We believe that such a platform is an unmet need in the market that we wish to address.

Since the time of Calvert's original work, it is now possible to improve the fidelity of his system model in four ways:

1. Acquisition of primary data from common wearable sensors used in sports and fitness, under a protocol with specific exercise regimes in different sports.
2. Normalization and harmonization of data from different sources, each linked to the determinants of performance: endurance, strength, skill, and psychological factors.
3. Collection of performance data annotated with qualitative factors impacting performance such as sleep, diet, mood and injury that can be part of reinforcement learning
4. Implementing the model in a contemporary simulation program such as MATLAB to foster dissemination and broader use of Calvert's model.

Preliminary work has revealed that these aims are not as trivial as one would easily suspect, and we believe the "lessons learned" in our research will assist others in their simulation efforts.

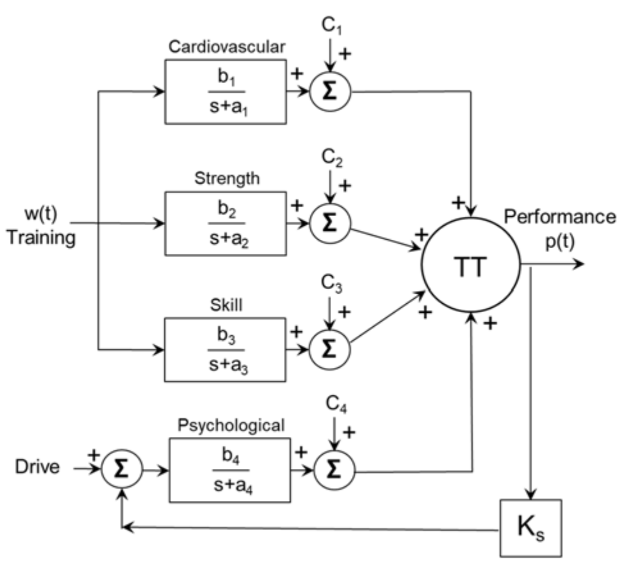

FIGURE 1: MULTICOMPONENT MODEL OF CALVERT TO EXPLAIN EFFECTS OF DIFFERENT FORMS OF TRAINING ON PERFORMANCE (ADAPTED FROM [1]).

Parameters	Cardio	Strength	Skill	Psychological
Heart Rate	✓			
Muscle Oxygen Saturation	✓			
Maximum Force		✓		
Motivation Level				✓
Daily Mood Survey				✓
Rate Perceived Exertion				✓
Motor Learning			✓	
Functional Movement Screen			✓	
Sports-specific skills assessment			✓	
Coach assessment			✓	

TABLE 1: INITIAL CLINICAL TRIAL PRIMARY DATA SUPPORTING THE FOUR COMPONENTS OF THE CALVERT MODEL.

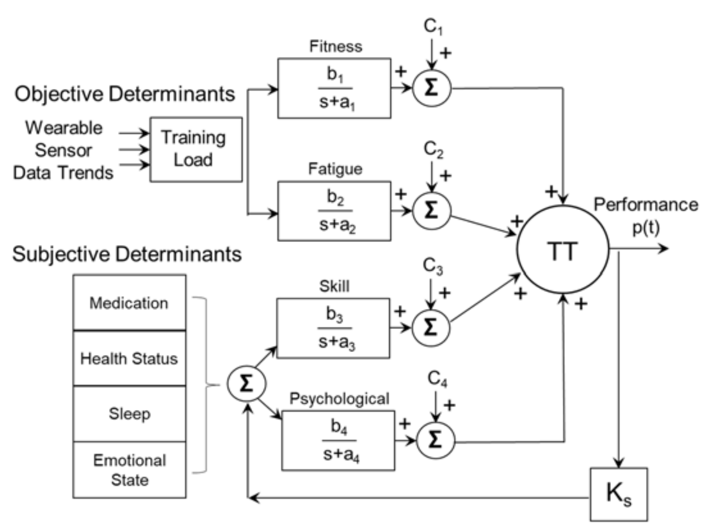

FIGURE 2: HYBRID MODEL OF CALVERT WITH THE PERL MODEL NESTED FOR FITNESS AND FATIGUE AND WEARBLE SENSOR DATA USED TO COMPUTE TRAINING LOAD (Adapted from [1],[5]).

2. MATERIALS AND METHODS

The current research program involves four activities:

1. Primary data acquisition. Acquisition of primary data from common wearable sensors used in sports and fitness, under a protocol with specific exercise regimes in different sports. Collection of subject data was performed under the auspices of an approved clinical Study Protocol CWRU-2018-0957 for wearable sensors. For the initial phase of study, we collected heart rate (Polar-10 sensors), muscle oxygenation (MOXY sensors), and physical stress data (VivaLnk sensors). These parameters are shown in Table 1.
2. Wearables data integration. Our initial pass at collecting primary data was to better understand any issues associated with data collection and integration of wearable devices *from different manufacturers*. This was believed to be prudent in the event issues arose; we did not want to undertake the full study protocol without a preliminary look at the data. This might seem trivial, but integration involves a unique set of challenges due to a lack of standards – sensor data originates from different manufacturers with completely different signal time scales, frequency, and output formats. The "R" programming language was chosen as our initial integration platform to explore the data integration issues since it is readily available and open source. Eventually the integration algorithms would need to migrate to the MATLAB platform. The exercise protocol for our pilot data is shown in Table 2.
3. Qualitative data collection. The collection of qualitative factors impacting performance such as sleep, diet, mood injury, genetics, is a part of the Study Protocol and will commence as part of the full-scale study. In the next phase preliminary work we anticipate testing a Likert-type scale for the "Skill" and "Psychological" parameters shown in Table 1. Specific data will be collected when allowed post-COVID19.
4. Model Calibration. Figure 2 illustrates the hybrid Calvert model modified for the present research program; test objective data has been implemented in MATLAB/Simulink. Several unknows exist in the model and the on-going research effort is to use the data collected under the Study Protocol to (a) resolve the coefficients in the transfer functions for specific performance measures, and (b) and (b) enable the assessment of the C1-C4 coefficients that integrate/calibrate specific performance parameters corresponding with athlete performance.

Our goal in this work is best expressed in the words of Calvert: "Although this general model has obvious deficiencies and many variations could be proposed, it accounts for the major determinants of performance. Each component transfer function should probably be nonlinear and should definitely contain a saturation type limiter, since there are physiological limits to how much training can be tolerated (which themselves change as training progresses). In spite of this, the framework should be useful in the design of crucial experiments in the future." We concur and have collected pilot data as an exploratory effort.

3. RESULTS AND DISCUSSION

The workout schedule (Table 2) for collegiate women soccer players is the basis of data for the present work. When we are permitted to resume access to full team workouts post-COVID19, then a similar workout schedule will be conducted with 5 groups of 5 athletes, creating a more statistically sound basis for data analysis. Currently, workouts are individual-based, with athletes working "at-home" (again, during the pandemic). Despite this limitation we believe that the data collected is adequate – yet still realistic – to explore.

Day 1:	Stage 1	Warmup (10 minutes)
	Stage 2	Dribbling
	Stage 3	Cool down (10 minutes)
Day 2:	Stage 1	Warmup (10 minutes)
	Stage 2	Beep Test
		then 1 minute break
	Stage 3	Cool down (10 minutes)
Day 3:	Stage 1	Warmup (10 minutes)
	Stage 2	3 sets of box to box sprints x10
		then 1 minute break
	Stage 3	Cool down (10 minutes)
Day 4:	Stage 1	Warmup (10 minutes)
	Stage 2	Ladder Drill with sprints
	Stage 3	Cool down (10 minutes)
Day 5:	Stage 1	Warmup (10 minutes)
	Stage 2	3x5 of 30 second jog,
		20 second run,
		10 second sprint,
		2 minute break
	Stage 3	Cool down (10 minutes)
Day 6:	Stage 1	Warmup (10 minutes)
	Stage 2	Beep Test
	Stage 3	Cool down (10 minutes)
Day 7:	Stage 1	Warmup (10 minutes)
	Stage 2	Technical work with ball
		Shooting drills
	Stage 3	Cool down (10 minutes)

TABLE 2: PILOT EXECISE SEQUENCE FOR WEARABLE PRIMARY DATA COLLECTION.

A sample of wearable data for heart rate and muscle oxygenation is shown in Figure 3, plotted on the same axis for convenience in comparison. Data trends are not all that surprising, and we have the expected changes during warm-up and cool down, as well as the expected trends of heart rate dropping as muscle oxygenation rises. The plots themselves are intuitive results and fairly unremarkable, but what is challenging is the process of extracting data from the commercial sensors and then harmonizing all the data into a single data file. Our inability to control and harmonize the so-called time-stamp – shown as the baseline in Table 3 – creates a data management issue. In Table 3 we see an abundance of "NA" values where times could not be synchronized. Here, we allowed the "R" program to blend the data allowing the routines to default to "NA" but this classic problem of data voids may become more significant later. For instance, the calculation of heart rate variability (HRV) will need to "overlook" the "NA" values; more to the point, is HRV potentially impacted in a way that we would first compute HRV, assign to a default baseline time, then blend HR, HRV, and SmO2 after the calculations? We are seeking primary data that can be shared and believe that any type of filtering and averaging could introduce bias that may limit the use of our primary data by others.

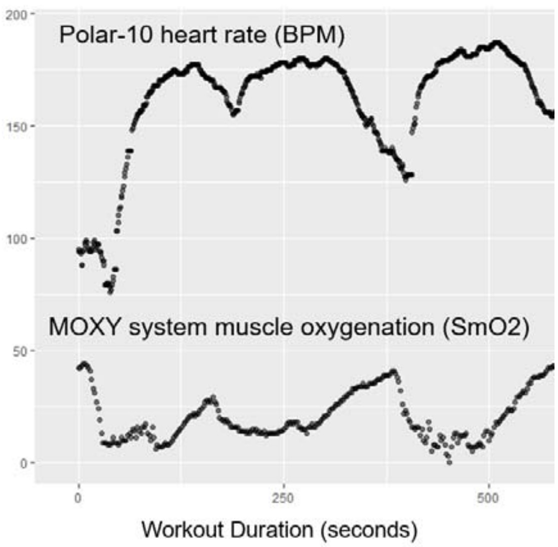

FIGURE 3: SAMPLE PLOT OF HEART RATE (HR, BPM) AND MUSCLE OXYGENATION FOR SENSOR LOCTED ON THE VASTUS LATERALIS MUSCLE (PERCENT O2)

Equally challenging is extracting data from the sensors. Some systems allow you to capture data, but you must assume that the wearable system software has not introduced bias, but since most manufacturers will not let you "see their homework" you are left to assume you have as good a set of "raw data" as is possible. Further, there tends to be the need to use proprietary algorithms for import/export, and these not only change with model, but also the export formats can be somewhat difficult to use. Some systems export data in JSON format, others enable TXT or CSV formats. Generally the manufacturers assume the user is an athlete looking for aggregate fitness indicators, and not seeking raw data for clinical trials. Creating interface routines is required, and thus data I/O is a much bigger challenge with off-the-shelf devices versus a custom design system.

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	Baseline	HR	SmO2.Live
1	0.00	95	42
2	0.95	94	NA
3	1.89	94	NA
4	2.00	NA	42
5	2.84	93	NA
6	3.79	88	NA
7	4.00	NA	43
8	4.74	88	NA
9	5.68	94	NA
10	6.00	NA	44
11	6.63	95	NA
12	7.58	97	NA
13	8.00	NA	44
14	8.52	98	NA
15	9.47	99	NA
16	10.00	NA	43
17	10.42	98	NA
18	11.37	96	NA
19	12.00	NA	42
20	12.31	95	NA
21	13.26	94	NA
22	14.00	NA	41
23	14.21	94	NA
.... 24	15.15	94	NA

TABLE 3: SAMPLE DATA ILLUSTRATING PRESENCE OF 'NA' IN DATASETS USING 'R'

Our preliminary modeling and pilot data collection efforts have encourages continuing the development of an updated version of Calvert's model. As we develop strategies for computing the unknown coefficients (Figure 2) our efforts will reveal and produce open-source algorithms that can benefit other researchers.

Our preliminary modeling and pilot data collection efforts have encouraged continuing the development of an updated version of Calvert's model. As we develop strategies for computing the unknown coefficients (Figure 2) our efforts will reveal and produce open-source algorithms that can benefit other researchers. However, three main questions remain:

- Can our strategy for developing a new version of the Calvert model, in fact, create a predictive training model that incorporates knowledge about physiological adaptations which would allow hypothesis-driven research?
- Can this model be demonstrated applicable for other sports that don't have measurements like time (say, volleyball) to determine outcome?
- Is it realistic to expect the transfer functions shown in Figure 2 be established independently of the integration coefficients C1-C4?

4. CONCLUSION

Advances in accuracy and cost of wearables has created an opportunity to revisit the Calvert model and explore components of analysis not feasible when the work was published in 1976. We believe there is room to improve the model and make it more accurate. Expanding upon this model with aspects such as diet, amount of sleep, injury, mood, and energy level, creates a more complete and open platform that can facilitate other research team activity.

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