Modeling Biological Rhythms to Predict Mental and Physical Readiness

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Abstract **—The human body is composed of various biological clocks that impact physical and mental health functioning. Modeling biological rhythms provides the means to understand the effect of internal and external factors on human mental and physical performance. So far, biological rhythms have mostly been studied in controlled laboratory settings thus limiting the long term study and modeling of these rhythms. This paper presents the results of our exploratory study of modeling human rhythms with longitudinal physiological data collected from consumer devices in the wild. We used data from four people continuously wearing Empatica (E4) wristbands and Oura smart rings for approximately four months to build models of human rhythms. We then used those model parameters in a machine learning approach to predict mental and physical readiness. Our results showed that most models built with a combination of sensors and rhythmic features obtained a prediction accuracy above the baseline measure of 66% (Max accuracy = 82.7%). These results provide insights into the feasibility of using consumer devices to model biological rhythms and use them to assess human and performance and health.**

I. Introduction

Our internal biological clocks influence performance levels over time; these levels naturally rise and fall throughout the day according to our routines and schedules [1]. When people complete tasks at times that do not align with their optimal energy levels, they may not be as productive as intended. Disruption and misalignment in biological rhythms, e.g. wrong sleep and awake time result in negative health and performance both on physical and mental levels [1]. Saeed Abdullah noted that “around 80% of the population live against their innate rhythms, mostly by adhering to work schedules that demand waking up earlier than our internal clock dictates” [2]. The question that researchers have been exploring is how can we boost human health and performance in a way that reduces stress and acts in accordance with our biological rhythms?

There have been attempts to associate inactivity with low productivity and work performance. Researchers have been implementing measures to boost performance by including reminders for users to take stretch breaks and move their bodies every hour, the motivation being that in the workforce a healthy employee is a more productive employee. IBM gave out 40,000 Fitbits over the course of two years and found that those who participated in the wellness challenge reached an average of 8,800 steps per day, more than double the average of people who did not participate [3]. While not directly indicative of an increase in productivity, healthy employees will be less likely to call in sick [4]. For technology to shape user wellbeing and improved productivity, it will need to collect information to “learn” more about the wearer. What seems to be lacking is a direct biometric measure of both productivity and alertness.

Our research aims to explore the feasibility of discovering and modeling biological rhythms using physiological data collected from consumer-level devices in the wild. This paper chronicles a four-month study to track biometric indicators such as body temperature, galvanic skin response, resting heart rate, heart rate variability and sleep patterns and to model physiological and behavioral rhythms from the E4 wristband devices. The parameters obtained from the rhythm models were then used to predict the readiness score measured by the Oura ring using classification.

This study is the first to explore the predictability of human readiness using machine learning via features obtained from rhythm models. To our knowledge, this is also the first continuous and long-term collection of many physiological signals via wearable devices in the wild. We anticipate this data set to be useful to other researchers in the field. In the following sections, we discuss the related work in this domain followed by a description of data collection, processing, and analysis methods for building rhythm models and thereby predicting the overall readiness scores.

II. Related work

Biological rhythms including the circadian rhythm or rest-activity cycle, feeding cycles, breathing, heartbeat, hormone secretion, and female menstrual cycle have been extensively studied in controlled studies [5, 6, 7]. Advancements in sensing technology have made it possible to track physiological and behavioral signals to understand the physical and mental aspects of human biology and their relationship with health and performance. For example, to understand human cognitive performance via physiological responses, a study by the U.S. Air Force Research Laboratory [8] monitored the functional state of 7 participants in real-time using six channels of brain electrical activity (from an EEG) as well as eye, heart, and respiration measures. The study showed the EEG features were best at tracking and predicting cognitive performance. Another study by Abdullah et al. [9] gathered patterns of phone usage from 20 participants over the course of 40 days to predict optimal alertness levels for different tasks. The findings demonstrate that patterns of rhythmicity vary among individuals and the usage of mobile devices correlates with alertness.

Wearable devices such as the Fitbit, Empatica, and Oura ring are now able to track biometrics including heart rate, skin conductance, and sleep duration and quality with high accuracy [10, 11, 12]. Lier et al. evaluated the Empatica E4 under what they call "a comprehensive validity assessment protocol" [13]. They compared the Empatica E4 to ECG for measuring heart rate and to a measure of skin conductance on the fingers for measuring EDA. For this comparison, they evaluated 60 participants engaging in a stress-inducing activity, singing in public. They found that E4 assessments valid "at the parameter and detection [of stressors] level" when compared to the reference devices [13]. The authors highlight the Empatica E4 as being especially useful in gathering data on EDA and ultimately assert that their study supports prior validity studies of the Empatica E4. In our study, we use both E4 and the Oura ring to collect physiological and behavioral signals.

We will use the collected data to model biological rhythms to first determine their characteristics and features and then use those features in a machine learning pipeline to predict the readiness score. Our approach is inspired by the work in Doryab et al.'s study that modeled biobehavioral rhythms to predict readmission risk following pancreatic surgery [14]. Data collected from 49 patients via Fitbit devices (heart rate, sleep, and activity) was analyzed to detect rhythmicity and disruption in patients' biological rhythms during treatment. The machine learning models built from rhythmic features were shown to be predictive of the readmission risk [14]. In our study, we use a wide range of physiological signals including heart rate, heart rate variability, skin temperature, and skin conductance (collected from E4) as well as sleep, readiness, and activity (collected from the OURA ring). To our knowledge, such a longitudinal data set (for approx. four months) of physiological and behavioral data does not exist and we believe this data can be useful for other research studies in human behavior and health. Furthermore, our study reveals the impact of different physiological signals in the prediction of readiness that has not been studied before.

III. Methodology

The objective of this research was to understand patterns in the rhythmic features derived and draw connections between bio-physiological indicators and overall readiness. The following sections describe the approaches taken to collect, process, model, and evaluate participants' biological rhythms.

A. Data Collection

Data was collected from Oura rings and Empatica E4 devices to track biometric data including body temperature, galvanic skin response, resting heart rate, heart rate variability and sleep patterns for four months. Four participants who were part of the research team wore both devices continuously to collect data. Each participant had a unique ID for anonymity and collected data individually. Participant 1 collected 112 days' worth of data, participant 2, 92 days, participant 3, 101 days, and participant 4, 76 days. Participants synced their devices to the cloud each day to provide cumulative, up-to-date raw data for analysis.

The Oura ring is a consumer wearable that tracks users' sleep, activity, and readiness [15]. The Oura ring develops an overall sleep score by tracking total sleep duration, sleep efficiency, restfulness, REM sleep, light sleep and deep sleep patterns, latency (the time it takes to fall asleep), and bedtime start and end [16]. The activity tracking feature measures total time inactive per day, hourly activity, whether the user has met the personalized daily activity goal, workout frequency, and volume, and time spent in recovery from physical activity [15].

Fig 1. Oura Ring with three sensors

The Oura ring also measures readiness, which is a measure of physical and mental capacity throughout the day [17]. This measure incorporates resting heart rate, heart rate variability, recovery index, body temperature, previous night's sleep, and previous day's activity into its calculation for determining the quantitative score. Readiness scores range from 1-100. 85+ indicates "excellent" readiness, 70-84 indicates "good" readiness, 60-69 indicates "pay attention" to your readiness, and below 60 indicates "take action to rest and recharge" [17]. The readiness score helps users distinguish days that are well suited for challenging oneself from days when rest is necessary to recover. We used the readiness score as a dependent variable/predictand to determine whether the biometric data from the E4 could predict readiness.

The Empatica E4 is a consumer wrist wearable that tracks and measures real-time physiological data [18]. E4 sensors include the PPG sensor which measures blood volume pulse (BVP), EDA sensor which measures the fluctuating changes in the electrical properties of the skin, an accelerometer (ACC), an infrared thermophile which reads skin temperature (TEMP), a heart rate (HR) sensor, an event mark button and an internal real-time clock [18]. The E4 can record up to 60 hours of data at a time before needing to be uploaded to the cloud platform. On the platform, users can view and manage data through various visualizations. The Bluetooth streaming mode allows the user to view sensor data of the connected device in real-time [18]. Fig. 1 depicts the Oura ring as well as the Empatica E4 wristband and highlights the features and sensors embedded in the device [18]. The sensors, found in the center of the band, are activated when pressed against the skin during wear.

B. Data Processing

The raw data from all sensors in E4 were used to model biological rhythms and to identify their characteristics and features. Those features together with readiness assessments from the Oura ring were then used in a machine learning pipeline to predict the overall readiness. The Empatica data was pulled from the E4 manager through Python and ran through various data preprocessing scripts. First, the data was assigned a timestamp for each unique value and then grouped into hourly averages. These hourly averages formed the dataset that was used for modeling rhythms. Then, the hourly data was compiled into an aggregate file per sensor and each file was grouped into seven-day intervals to generate a weekly model of rhythms. The readiness score from the Oura ring was also aggregated to a weekly number. The features from weekly rhythms and the weekly readiness scores formed the dataset that was used in the machine learning approach.

To explore the cyclical patterns of one's physio-biological data, we used a comprehensive rhythms analysis toolkit called Chronomics Analysis Toolkit (CATkit) to model rhythmic patterns from data collected from the Empatica E4 device [19]. The resulting files were the basis for the research team's models and acted as the input to the CATkit.

B. Modeling of Biological Rhythms

The five attributes that characterize a biological rhythm include mesor, period, amplitude, phase, and waveform. The *mesor* is the midpoint around which the cycle oscillates. The *period* is the time between two consecutive peaks or the full length of a cycle. *Amplitude* is half the range of oscillation and *phase* is the displacement between a specific point in the cycle and a reference point (typically uses the peak). For biological rhythms, the reference time is usually chosen concerning the sleep-wake cycle of the subject. Fig 2. visually depicts the characteristics of a wave.

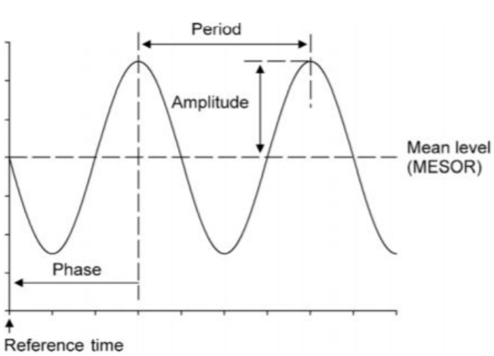

Fig 2. Characteristics of a Wave

1) *Periodogram:* CATkit's periodogram output was used to retrieve an estimate of a rhythm's period and amplitude as a signal can be reproduced by a series of sinusoidal waves. The periodogram depicts the relative importance of various frequency values where the peaks in the sinusoidal wave can be seen. The recurrence of these peaks explains the oscillation pattern of the observed data which provides a time period by which to evaluate the data [19]. The periods are determined by evaluating the recurrence and frequency of the peaks in the graph. Fig. 3 shows an example of the output generated by the

periodogram with detected significant periods of 24, 720, 240, and 960 hours. These periods were used to model rhythms via Cosinor as described in the next section.

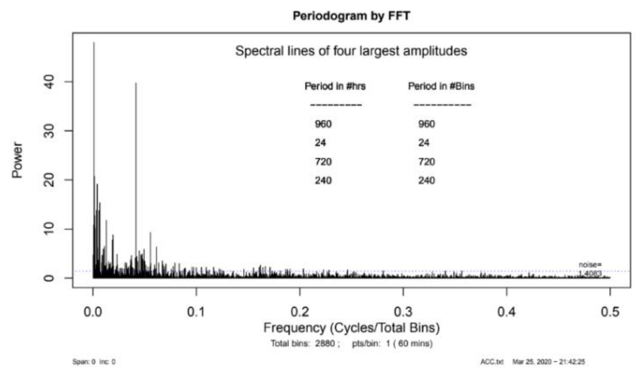

Fig 3. Periodogram Output

2) Cosinor: Cosinor is a regression technique that obtains an estimate of the rhythm-adjusted mean (MESOR), the amplitude, and the measure of phase (acrophase) for the chosen period [19]. The function fits one or more cosine curves to the data and minimizes the sum of squares of the differences between the predicted and actual values of the model for the specified period [19]. Statistical significance is determined for the period with respect to the null hypothesis (no rhythm) to decipher if the model accurately represents the individual's biological rhythm.

The single cosinor calculates the best fit of the cosine model at specified periods. We identified the strongest period from the periodogram to be used in the single cosinor function. When the single cosinor is used at the Fourier frequencies of the model, the results yielded mirror the periodogram precisely up to six decimal points [19].

Fig. 4 is a sample output from the single-component Cosinor function where the period, mesor, standard error (s.e.), amplitude (Amp), percentage rhythm (PR) and acrophase (Phi) can be seen. Acrophase is a measured phase, specifically the lag from a defined reference time point to the crest time in the fitted curve, whereas percentage rhythm is a reported proportion of variance accounted for by the model [19].

Start time: 201903071548 ;   End time: 202003061650

Function: temp   ACC.txt ; TimeCol= 1 Ycol= 2 RefDateTime= NA
noTaper   −25Mar20−21.46.50 Units= Hour Interval= 8762.03 Increment= 8762.03 header= TRUE Set= c(960, 720, 240, 24) Start/End= 8762.03 / 4

Each Period from single−component COSINOR: value

Interval	Period	P	PR	Mesor	s.e.	Amp	s.e.	Phi	s.e.
0.000 − 8761.033	960.00	0.583	0.099501	−1.0769678	0.0309028	0.0440812	0.0430732	−78.7261	40.8179
0.000 − 8761.033	720.00	0.435	0.15334	−1.0679001	0.0234716	0.0434572	0.0336896	−132.842	39.5839
0.000 − 8761.033	240.00	0.049	0.5543	−1.0535081	0.0214982	0.0767153	0.0312081	−217.01	22.142
0.000 − 8761.033	24.00	1.49e−14	5.6994	−1.0427969	0.0210155	0.240213	0.0296675	−216.025	7.06753

Fig. 4 Cosinor Output

IV. Analysis

In our analysis, we explored 1) the correlations between the weekly average readiness score and the rhythm features for that week, and 2) the predictability of the readiness score from the rhythmic features. The following describes the methods in more detail.

A. Pearson Correlation

Correlation analysis is a statistical tool used to evaluate the strength of the relationship between two quantitative variables [14]. A correlation value of 1 indicates a perfect positive correlation whereas a correlation of -1 indicates a perfect negative correlation. Correlation analysis led us to understand which variables contributed most to forecasting Oura's readiness score.

B. Classification

To evaluate the feasibility of rhythms in predicting readiness, we chose a 24-hour period to build cosinor models and to obtain the rhythmic features described above. We built a cosinor model for each week of data that characterized the rhythmic cycle of that week. We then created a dataset with the obtained features from those weekly models and used it in a classification approach for predicting the weekly average readiness score.

Binary classification was used to categorize the predicted readiness score and actual readiness score from that time period. Readiness scores were classified as 1 ("high") for scores above 70, and 0 ("low") for scores below 70. The readiness categories were then used as the ground truth in the machine learning method. The logistic regression models were built from the rhythmic features (mesor, Phi, PR, and amplitude) generated by the cosinor for each biological phenomenon tracked by the Empatica E4. In total, ten models were created, based on heart rate, skin temperature, EDA, BVP, and accelerometer data. We generated two types of models namely feature-based and sensor-based. The feature-based models made for mesor, Phi, PR, and amplitude where data from all sensors were included (i.e. the mesor model includes acc_mesor, hr_mesor, eda_mesor). Sensor-based models were built for each sensor using all four features for that particular sensor (i.e. the heart rate model includes hr_mesor, hr_phi, and hr_amp). Lastly, we built a model that included a combination of all features and all sensors.

To evaluate the machine learning performance, the full data set of rhythm features were divided into test sets and training sets. We used leave-one-person-out cross validation where at each round, the data of three participants were used for training and tested on data from the 4th person. These models were compared using average accuracy prediction from all four tests of the models.

V. Results

A. Rhythm Modeling

Using periodogram outputs, we were able to detect and observe different periods in each time series data between sensors and between participants. Fig. 5 and Fig. 6 show examples of periodograms built from temperature data of two participants. As demonstrated, other than the 24-hour cycle, the detected periods are different for the two participants. This highlights differences in individual rhythms even though they are built from the same type of signal.

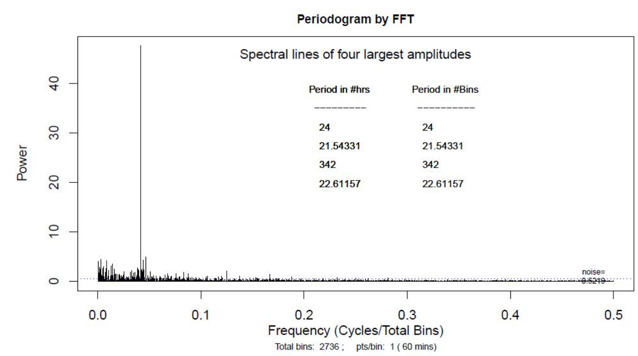

Fig. 5 Periodogram of Temperature for Participant 1

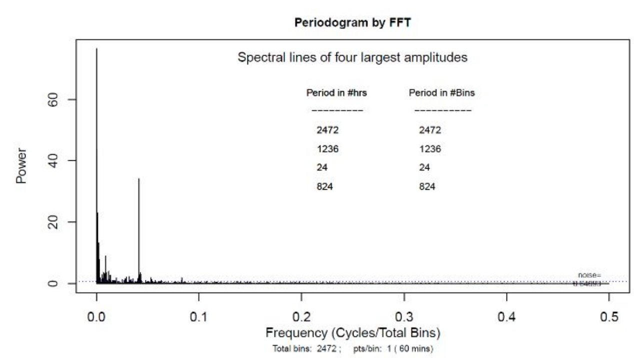

Fig. 6 Periodogram of Temperature for Participant 2

These findings were further demonstrated by the corresponding cosinor analysis of the periods. As illustrated in fig. 7 and fig. 8 the differences are vast between the two participants in terms of the periods greater than 24 hours but are also clear for the 24-hour period.

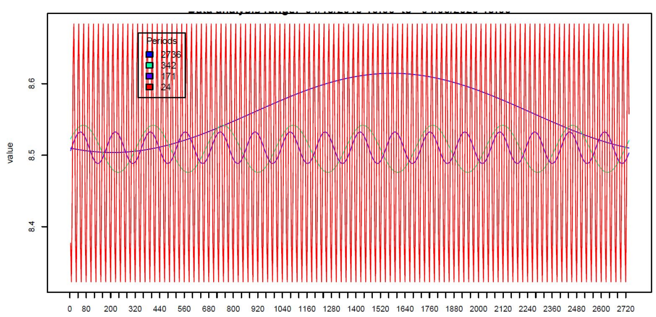

Fig 7. Cosinor Plot of Temperature for Participant 1

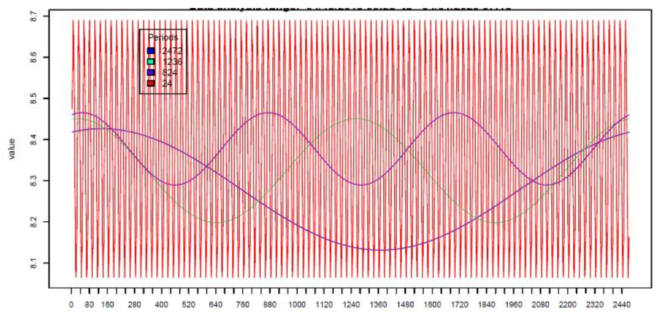

Fig 8. Cosinor Plot of Temperature for Participant 3

B. Correlation Analysis

A correlation analysis was performed to determine how the rhythmic features of each E4 sensor correlate with Oura's weekly average readiness scores. The researchers focused on finding the strongest correlations per feature, per person, and then overall. Overall correlations were analyzed with all of the participant data aggregated for a holistic view of which features had the most significant correlation.

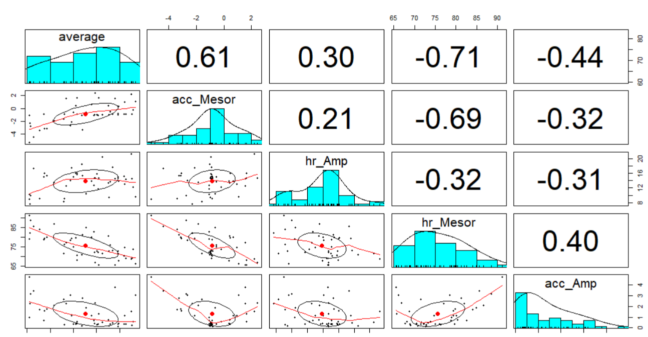

Fig 9. Correlation coefficients and their associated scatterplots

The analysis showed the acceleration mesor feature and average readiness moved in the same direction approximately 54% of the time. The heart rate mesor feature and average readiness moved in opposite directions approximately 70% of the time. Fig. 9 shows the results of the four most correlated features with average readiness. In total, we had 45 weeks of data from all participants indicated per row. The p-value between heart rate mesor and readiness was $6.24*10^{-8}$ (p <0.0001) indicating a significant correlation.

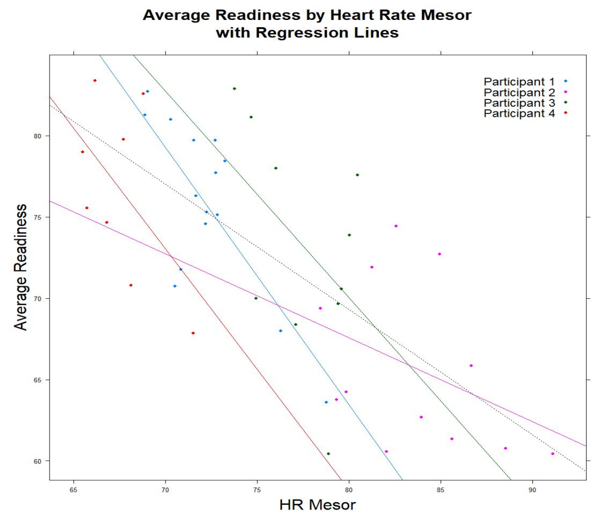

Fig. 10 Correlation Between Heart Rate Mesor and Readiness

A Deeper correlation analysis was performed to determine the correlations per participant in the study based on the varying features (See fig. 10). We found differing results per participant of which feature had the strongest linear relationships with average readiness. Table 1 shows the results of the strongest positive and negative relationships.

TABLE I. RELATIONSHIPS WITH AVERAGE READINESS

	Participant ID			
Value	***1***	***2***	***3***	***4***
Max	EDA Phi	EDA PR	ACC Mesor	EDA Amp
Positive Correlation	0.37	0.41	0.66	0.58
Min	HR Mesor	HR Mesor	EDA Mesor	ACC Phi
Negative Correlation	-0.76	-0.46	-0.77	-0.59

An important insight that can be gained from the correlation analysis is the understanding that individuals have personalized biological clocks. Because of this, rhythms and average readiness correlations vary per person. For example, for participant 1, EDA Phi showed the strongest positive correlation (0.37), but for participant 4, it showed a moderately weak correlation (-0.13). While overall correlation conclusions were found on the aggregated dataset, individualizing the results provided more actionable insights on a per person basis.

C. Readiness Prediction

Using binary classification, we determined whether the predicted readiness scores matched the actual readiness scores from the data. The models were compared using prediction accuracy percentage and are listed in order of highest to lowest accuracy in table 2.

TABLE II. MODEL ACCURACY

Feature Model	Accuracy (%)	Sensor Model	Accuracy (%)
Phi	82.70%	Temperature	72.90%
Amplitude	66.70%	HR	68.80%
PR	66.70%	EDA	64.20%
MESOR	60%	BVP	67.10%
Model with all sensors/features	43%	Acceleration	61.50%

The model based entirely on the Acrophase (Phi) feature from all five sensors performs the best across all test sets with a nearly 10% higher accuracy rate over the next best model. This model's performance indicates that the timing of the peak of one's biological rhythms may have predictive power in mental and physical readiness. The temperature model performs second-best with an average accuracy rate of 72.9%, which indicates that wrist temperature may also be a useful predictor of readiness. Analyzing the true readiness scores of the four test sets, the baseline of high readiness scores was found to be 66%. Six of the listed models predict at or above the baseline, suggesting they can be used as predictive models. Notably, the model with all sensors and all features performs poorly with an average accuracy percentage of 43%. This is likely due to model complexity, as some feature and sensor variables correlate strongly with one another.

VI. Conclusion

We studied the relationship between rhythmic bio-physiological features and overall readiness to determine which features best predict readiness. The rhythmic features derived from the E4 sensor data were used to create models to predict overall readiness. Most models predicted readiness at accuracy rates above the majority class baseline (high readiness) proving to be a feasible method of analysis. Additionally, our correlation analysis showed that the Mesor rhythmic features for acceleration and heart rate were most highly correlated with overall readiness. Although data was collected from a small group of people, we believe our study results still demonstrate the viability of using physiological data from wearable devices to characterize biological rhythms to gain insight into human mental and physical outcomes. In the future, we plan to replicate this study with a larger participant pool over at least one year to observe and discover differences in individual biological rhythms. We will then build a rhythm-aware system to recommend best actions that are aligned with the biological rhythms of the person to optimize their health and performance.

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