Really Can't Hold On Anymore? Physiological Indicators Versus Self-Reported Motivation Drop During Jogging

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Abstract: Motivational dynamics in jogging constitute a pivotal factor influencing a runner's performance, persistence, and overall engagement in the running activity. The manifestation of diminished motivation is concomitant with a cascade of physiological responses, capable of being represented through biological signals, for which biosignal monitoring, a common practice in evaluating athletic performance, emerges as a valuable tool. Should biosignals, as dynamic indicators during exercise, exhibit discernible shifts correlating with changes in motivation, the prospect of actively modulating motivation levels and intervening in athletes' performance during exercise becomes feasible. This study consists of collecting comprehensive biological data, including electrocardiogram (ECG), surface electromyogram (sEMG), and respiration signals (RSP), from runners who participated in a 20-minute running session. Participants were asked to self-report a decrease in motivation during jogging. Using heart rate variability analysis, self-similarity matrix and deep learning methodologies, this work seeks to explore whether the discomforts reported and triggered by decreased motivation had discernible effects on monitored physiological signals, thus advancing our understanding of the nuanced relationship between physiological responses and motivational states in running.

1 INTRODUCTION

Etymologically, the word *motivation* is derived from the Latin word *movere*, which denotes the driving force behind an individual's actions (Ryan et al., 2010).

Given the pivotal role of motivation as a behavioral driver, researchers have aimed to comprehend how motivational processes manifest in people's participation and performance in sports, consequently seeking avenues for intervention in sports performance. Motivation has been proposed and confirmed to contribute significantly to student achievement in physical education (PE) and participation in sports (Melliti et al., 2016). As dropout from sport is often attributed to a lack of motivation and self-regulation skills, it is essential to understand the underlying motivational processes (Weiss and Williams, 2004).

As examples, incorporating kinetic music in the gym and providing continuous verbal encouragement from the coach to the endurance athlete during exercise are effective strategies for influencing individuals to engage in and sustain physical activity. These methods enhance motivation levels, particularly in the context of endurance sports, where they are frequently employed. Endurance sports are characterized by repeated isotonic contractions of large skeletal muscle groups. Classical examples include running, swimming, and cycling among summer sports, and cross-country skiing or speed skating among winter sports (Morici et al., 2016). Motivation, as a driving force, is highly manipulative of the athlete, performance, and outcome of the competition during endurance sports. Athletes must repeatedly override this inherent motivational response, which refers to the instinctive or natural inclination to avoid discomfort, fatigue, or the negative effects associated with resisting temptation, to persevere and succeed in endurance sports(Taylor et al., 2018).

Optimizing endurance performance involves addressing motivational interventions and their sustained maintenance. Individuals experiencing a decline in motivation during exercise often express

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physiological discomfort, prompting the need to discern whether it stems from an actual physiological change or acts as a trigger for perceived discomfort leading to thoughts of quitting. Understanding this is crucial, as persisting in exercise despite genuine physiological discomfort may exacerbate issues, while effective management of motivation becomes essential for maintaining or enhancing the exercise state.

This study delves into the impact of altered physiological states, specifically discomfort reported and triggered by decreased motivation, on monitored physiological signals. A hypothesis was formulated, suggesting that the discomfort individuals express when their exercise motivation drops is reflected by abnormalities in physiological signals. The inquiry seeks to determine whether the physiological discomfort resulting from decreased motivation influences exercisers' health status, thus enhancing the precision of motivational interventions. The findings aim to shed light on the intricate relationship between motivation-induced discomfort and physiological signals, contributing to a deeper understanding of the dynamics at play during exercise. Electrical biological signals (ECG, sEMG, RSP) are utilized in this study obtained from wearable devices, ensuring minimal disruption to exercisers and paving the way for innovative integration of motivation-related functions into smart exercise devices.

2 RELATED WORK

Considerable progress has been made in investigating how motivation affects sports performance, athlete behavior, and competitiveness in competitions. Individual sports are motivated to sport because of internal factors (such as enjoyment or skill development and mastery) and external factors (such as rewards, health, and appearance) (Moradi et al., 2020). Those factors are full of uncertainty and variability. As a personalized drive, motivation is highly individualized and the interaction with external environmental factors is complex. Most researchers agree on the existence of individual differences in motivational preferences or traits (Kanfer and Ackerman, 2000).

Despite individual differences, the importance of maintaining or boosting motivation during exercise is crucial. The incorporation of physiological signal tracking in wearable devices has become a foundational aspect of exercise, enhancing the relevance of apps or products aimed at improving motivation for users. The researcher tries to realize the function of boosting motivation by using music when the mood is low by making mood judgment based on physiological signal EDA in wearable devices (Baldassarri et al., 2023). (Bauer and Kratschmar, 2015) presents the application requirements needed to increase runners' motivation and control training, based on heart rate monitoring and using the music for regulating the runners pace. While mental state identification has progressed personalized motivation enhancement, the significance of physiological states during low motivation levels is underexplored. Physiological discomfort, emphasized when individuals halt exercise due to decreased motivation, underscores the need to integrate the exerciser's physiological state in personalized motivational enhancement systems. The abnormality of reported physiological discomfort during low motivation levels in terms of physiological signaling remains uncertain, warranting analysis and tracking of physiological signals for insights into the state during motivation drops.

The selection of representative biosignals allows individually monitoring of physiological changes produced in organ systems during endurance exercise. The cardiovascular and musculoskeletal systems are the two main organ systems affected during aerobic exercise. Electrocardiography (ECG) is a tool that can be used to study electrical abnormalities in patients with cardiac disease (Krittayaphong et al., 2019).

The surface Electromyographic (sEMG) signal is a biomedical signal that measures the electric currents generated in muscles during their contraction that represent neuromuscular activities. EMG signals are one of the most commonly used data for studying human activities and behaviors (Liu and Schultz, 2022; Hartmann et al., 2022; Cai et al., 2023; Liu et al., 2023; Hartmann et al., 2023; Cai et al., 2024). The nervous system always controls muscle activity (contraction / relaxation) (Reaz et al., 2006).

Furthermore, the researchers also proposed that changes in motivation may also be reflected in changes in reported respiration rate (Martin et al., 2018). Currently, physiological signals are widely used in the field of sports psychology. Multimodal information and multichannel physiological signals to measure emotional responses offer more information for emotion recognition. Possible physiological signals include ECG, electromyogram (EMG), electrooculogram (EOG), electroencephalogram (EEG), skin conductance response (SCR), galvanic skin response (GSR), pulseoximetry, skin temperature, anterial blood pressure (ABP), blood volume pulse (BVP), and electrodermal activity (EDA), among others (Wu et al., 2015; Shi et al., 2023).

The relationship between various types of physiological signals (e.g.,ECG, sEMG, and RSP) and motivation levels has not been explored, which becomes this study's research topic, focusing on whether physiological signals are associated with decreased self-reported motivation.

3 DATA

Acknowledging the gap in dedicated databases for investigating motivational dimensions in jogging, a methodologically rigorous experiment has been designed. The primary objective is to induce a noticeable reduction in motivation during physical exertion, simultaneously capturing biometric signals from participating individuals. This systematic paradigm is crafted to build a comprehensive database, enabling an in-depth exploration of the interrelationship between motivational states and physiological signals within the jogging context.

3.1 Experiment Design

3.1.1 Selections of Biosignals

Aerobic training requires the perfect matching of the respiratory and cardiovascular systems, in order to provide the muscles with the necessary supply of energy to be transformed into mechanical work (Beh, 1990). The state of the respiratory, cardiovascular, and skeletal muscle systems during jogging is closely related to the current performance of the athlete. Changes in these three physiological systems are significant when exercisers are exercising, attempting to quit, or after quitting exercise. Based on my own exercise experience, observation and communication with jogging athletes, shortness of breath, elevated heart rate, and muscle fatigue are commonly cited physiological discomforts during exercise. It's also proved by this study's post-questionnaire, which is presented in section 5. The selection of biological signals representative of all three physiological systems is undertaken to characterize the present state of the system. These signals include ECG, RSP, and sEMG.

3.1.2 Self-Reported Motivation Drops

The waning of motivation, serving as a behavioral driver, significantly influences an individual's determination to persist in exercise. Consequently, we define a drop in motivation as the inclination not to continue with the exercise, which may arise from factors such as shortness of breathing, rapid heartbeat, anxiety, fatigue, among others. In the experiment, the exercisers' diminished motivation implied their reluctance to continue exercising.

To capture instances of motivation drop without disrupting the jogging process, each participant held a small rubber duck smaller than the palm of their hand. When an exerciser experienced a defined drop in motivation, they were required to squeeze the rubber duck, thereby completing a self-report of the diminished motivation. Throughout the designated exercise period (20 minutes), participants were permitted to squeeze the little yellow duck an unlimited number of times, yet were obligated to persist until the completion of the predefined exercise duration. The purpose of this design is that it is desired to collect as much physiological data about motivation drops as possible from participants.

3.1.3 Experiment Procedure

The study conducted a jogging experiment, capturing ECG, RSP, and sEMG signals, selected for their relevance to an exerciser's ongoing performance. Participants jogged on a treadmill under specified conditions, completing pre- and post-questionnaires covering personal details, motivation levels, emotional responses, and physiological sensations.

The running duration of 20 minutes was determined to allow runners of diverse backgrounds to experience at least one power drop at an appropriate speed. The treadmill settings included 11 evenly divided subsections, with each mode further divided into 3 phases: 2 warm-up segments at 6 km/h for approximately 3.6 minutes and 8 constant-speed running segments lasting around 15 minutes. Two modes, moderate (7 km/h) and high (8 km/h), along with a relaxation mode (5 km/h for about 1.5 minutes), were designated. These settings applied to male participants, and adjustments were made for female participants by reducing speed by 0.5 km/h in each phase. Additional details are provided in Table 1.

Running speed varied according to individual runner backgrounds, and the trials were conducted indoors on a treadmill to control environmental variables. Recognizing motivation's sensitivity to environmental factors, the experiment implemented measures to minimize external stimuli, such as covering the treadmill screen to create a silent environment. Subjects refrained from wearing headphones to eliminate temporal cues during exercise, and communication between subjects and experimenters was limited, intentionally cultivating a "boring and monotonous" experimental setting.

The goal was to induce as many motivation drops as possible, ensuring a balanced database. Two treadmill modes were configured: the "high" mode, designed to induce motivation drops even for habitual exercisers (comprising over 60% of subjects exercising 3 hours or more per week), and the "moderate" mode, more suitable for non-habitual exercisers.

Before the experiment, participants were briefed on the definition of "motivation drops," and instances of these feelings were self-reported by squeezing a rubber duck. The entire session was audio-recorded, and debriefing timings were manually documented.

The rubber duck, chosen for its ergonomic size, ensured minimal additional exertion and avoided generating abnormal physiological signals during reporting. All participants provided informed consent, signed a data protection agreement, and agreed to audio recording during the experimental sessions. To ensure safety, participants were required to provide information about their health status in the pre-questionnaire, including their medical history, and were informed they could voluntarily halt the experiment if they experienced any abnormalities intolerable to their body.

Table 1: Two mode of running.

Setting	Mode 1		Mode 2	
	Pace (km/h)	Incline (°)	Pace (km/h)	Incline (°)
Warm-Up	6	6	5.5	5
Moderate	7	7	6.5	6
High	8	8	7.5	7
Cooldown	5	5	4.5	5

3.2 Data Acquisition

In this study, 11 subjects, free from known cardiac diseases, participated in data collection activities, comprising six females and five males aged 22 to 37, with weights ranging from 51 kg to 100 kg. Eight subjects engaged in regular endurance exercise, while two did not have a fixed exercise routine. The participation time for each subject was approximately 35 minutes, covering various activities. All subjects provided written informed consent for data storage and subsequent studies, with the dataset shared in anonymized form.

The study employed ECG and sEMG sensors from PLUX's Cardio BAN and Muscle BAN, along with a wired RSP sensor connected to PLUX's Hub, using OpenSignals software for data collection. These sensors facilitated signal acquisition during exercise, and the collected data were pseudonymized to ensure participant anonymity.

3.3 Dataset

The dataset, adhering to the h5-format, was systematically recorded for 11 subjects, encompassing a total duration of 211 minutes and 36 seconds (equivalent to 3 hours, 31 minutes, 36 seconds) of data.

One subject's data did not include a self-reported motivation drop; however, for the efficient allocation of academic resources, it was retained in the dataset.

In the following Table 2, 11 subjects reported a total of 68 motivation drops. Male subjects reported 41 motivation drops, while female subjects reported 24 motivation drops. On average, each male subject reported 8.2 times motivation drops, while the average number of motivation drops reported by female subjects was only half of that reported by male subjects.

Table 2: Dataset statistical results.

	Male	Female
Numbers	5	6
Amounts of MDs	41	24
Averaged number of MDs	8.2±4.83	4±4.43

Notably, one participant exhibited a sustained motivational state throughout the entirety of the experiment. Among instances wherein motivation drops occurred, the temporal spectrum for reaching the first episode varied, with the swiftest occurrence transpiring at 86 seconds and the most protracted interval extending to 1061 seconds (17 minutes and 41 seconds) 1. The manifestation of diminished motivation appears to be subject to individual variability.

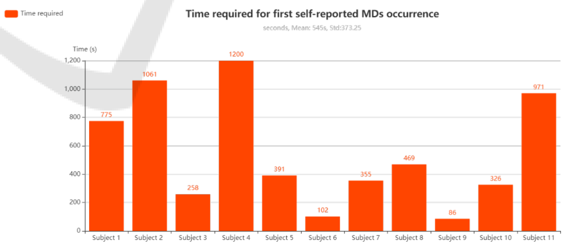

Figure 1: The time it takes for the first motivational drop to occur among different subjects.

4 METHODOLOGY

In this section, the methodologies employed for the analysis and detection of occurrences of diminished motivation are delineated, encompassing HRV analysis, and a deep learning model, specifically Long Short-Term Memory (LSTM). An overview of analysis framework used in this study are shown in the figure 2.

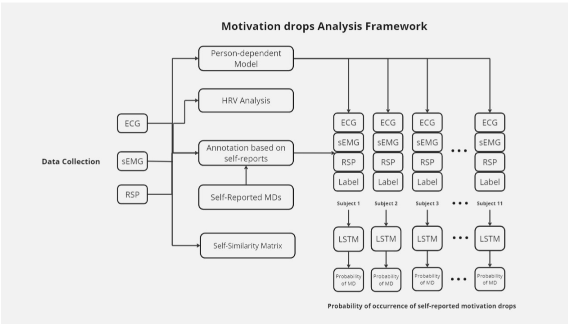

Figure 2: The framework for investigating relationship between self-reported Motivation drops and biosignals.

4.1 HRV Analysis

HRV consists of great value in sports due to the synergy between the heart and numerous systems. Heart rate variability is often mentioned by exercisers after exercise, and this feedback is also reflected in the post-questionnaire. HRV may be recognized as the response of the heart towards any kind of stimuli so that it compensates the situations accordingly, and thus, its variation may be used as warning signs of cardiac diseases (ChuDuc et al., 2013). If a person quits exercising because of decreased motivation, he or she often complains of cardiac distress, such as tachycardia, chest tightness, etc.

HRV is one of the means to find out the state of the automatic nerve system (ANS). The variation between heartbeat is low in sympathetic activation and high in parasympathetic mode. It has been observed that low HRV indicates cardiovascular diseases such as hypertension, whereas high HRV shows higher cardiac fitness (Tiwari et al., 2021). Abnormalities in HRV analysis can be used as a basis for abnormal physiologic signals.

4.2 Self-Similarity Matrix Anlysis

The purpose of the Self-Similarity Matrix (SSM) is to compare each sample of the signals with all the other samples. To calculate the SSM, the dot product between the transposed Feature Matrix (FM) and itself is performed. Hence, each column of the matrix is compared with every other column, yielding a similarity score (Santos et al., 2021). Columns sharing common feature values exhibit higher similarity scores, while those with diverging feature values manifest lower similarity scores (Paulus et al., 2010) (Bello et al., 2018). Each column of the matrix signifies the characterization of each segment of the signal selected during the sliding window process.

The value of the principal diagonal represents the highest similarity value. Block structures signify homogeneous regions in the signal, and when a block structure transitions to a different one along the diagonal, it indicates a change in the signal's behavior. The presence of additional diagonals in the matrix, aside from the primary diagonal, suggests that the columns and rows divided by the secondary diagonal share similar properties.

It's worth noting that, a widely used biomedical signal, ECG, has testified to the feasibility of SSM (Rodrigues et al., 2022). This analysis enables the scrutiny of the correlation between decreased motivation for autonomous reporting and abnormal physiological signals. Detailed results of the self-similarity matrix analysis are elucidated in the Results section.

4.3 LSTM Model

The choice of LSTM was inspired by research "Robust ECG R-peak detection using LSTM". This study discusses the use of LSTM models to learn long-time dependencies in temporal signal ECGs and to identify R-peaks(Laitala et al., 2020). LSTM networks are known for their ability to capture long temporal dependencies, to learn complex pattern and their robustness to irregularity. LSTM has the processing power before or without feature extraction (Wang et al., 2024). The data employed in this study consist entirely of time-series signals, with motivation levels characterized by changes over time. In the case of complex and elusive signal patterns, the LSTM model excels in learning the structural features of intricate signals through supervised learning on pre-labeled segments.

4.3.1 Annotation Based on Self-Reported

Using a sampling frequency of 1000Hz, the moment of rubber duck squeezing as the central point was considered. Subsequently, we marked 500 adjacent sampling points to this moment as 1, while the remaining points were labeled as 0. The conceptualization of motivation drop occurrence extends beyond a singular moment, viewing it as a process with a specific duration. It's also important to note that the act of squeezing the rubber duck lags behind the moment of perceiving the motivation drop, and the drop does not immediately dissipate upon squeezing.

4.3.2 Time Series Data Splitting and Cross Validation

The training approach adapts to individual motivational profiles, employing an individual-dependent model due to motivational variations. A sliding window approach is employed for homogeneous cross-

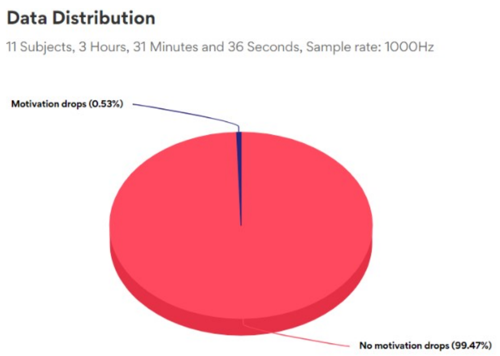

Figure 3: Data proportion (Motivation Drops (MDs)).

validation, initially dividing each subject's data into 80% training, validation, and 20% test sets. Subsequently, 80% of the training set undergoes a four-segment division, with the initial 80% forming training sets and the remaining 20% constituting validation sets, resulting in a 4-fold cross-verification.

4.4 Motivation Drop Prediction: LTSM Model

The bidirectional LSTM layer and a dense layer of the constructed sequence model. Each layer has 64 units, and the final dense layer contains only one output unit. The hyperbolic tangent is used as the activation function of all other layers, except that the final output layer uses sigmoid as the activation function. This model, which has proven effective in the study of R-peak recognition, serves as a reference for training in this study (Laitala et al., 2020) aiming to derive initial conclusions using a relatively compact network structure. The model was not optimized in this phase, as the primary objective of this study was to identify the presence of physiological abnormalities. The input sequence is three channels, respectively ECG, RSP and sEMG. The data length of each sequence is 4000, and the overlap between each two sequences is 50%.

5 RESULTS AND DISCUSSION

5.1 Questionnaire

As evident from the post-questionnaire statistics in figure 4, the three most frequently reported physiological discomforts during motivational drops are shortness of breath, rapid heartbeat, and profuse sweating. Among the 11 subjects, 6 mentioned experiencing shortness of breath, 8 reported a rapid heartbeat, and 9 noted an increase in sweating during self-reported motivation drops. This implies that the chosen ECG and respiratory signals for the experiment are apt for describing the physiological discomfort associated with declining motivation.

However, it's worth noting that increased sweating, mentioned by the majority of subjects, was not captured by relevant physiological signals such as Electrodermal Activity (EDA), which can measure skin changes. EDA is a common feature integrated into many healthcare monitoring devices, including smartwatches.

Additionally, only one person reported muscle soreness and fatigue during the autonomous debriefing of motivation drops. Interestingly, vertigo and inattention were more frequently mentioned. This provides a rationale for subsequent analysis focusing on neurologically related indicators.

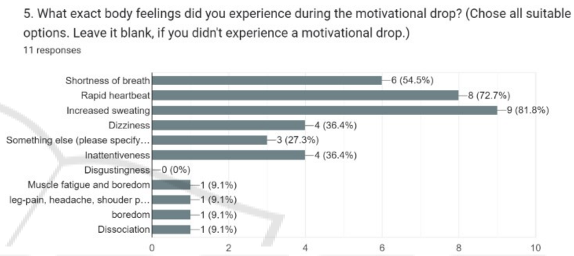

Figure 4: Results from post-questionnaire about how subjects felt when motivation drops happened.

5.2 RR-Interval, Instantaneous Heart Rate (IHR) and LF/HF Ratio

5.2.1 RR-Interval

Heart rate variability (HRV) is one of the health indicators used worldwide (Litscher et al., 2014). It is important to assess the variation in heart rate for evaluating cardiac conditions by studying the fluctuation in RR intervals (Tiwari et al., 2021). RR intervals (R-wave peak to R-wave peak in electrocardiograms, RRI) represent the measurements of the sinus heart period in chronological or heartbeat order (Electrophysiology, 1996). RR-Interval and IHR were generated in real-time by Heart Rate Variability (HRV) Add-on while acquisition [1]. The fluctuation interval of RR-Interval is depicted in the figure 5 through box plots, wherein the RR-Interval at the moment (s) of motivational drops is highlighted as a red dot. The results illustrate variations in the fluctuation range and magnitude of RR-Interval among different subjects, highlighting the individual independence

[1] https://www.pluxbiosignals.com/products/heart-rate-variability-hrv-add-on (accessed 13.Jan.2024)

of RR-interval data. Among the RR-intervals corresponding to moments of motivational drops, only one fell within the range of outliers, while the data for the remaining self-reported motivation drop instances were distributed between the maximum and minimum values. This suggests that RR-interval did not exhibit observable anomalies when individuals became aware of motivational drops.

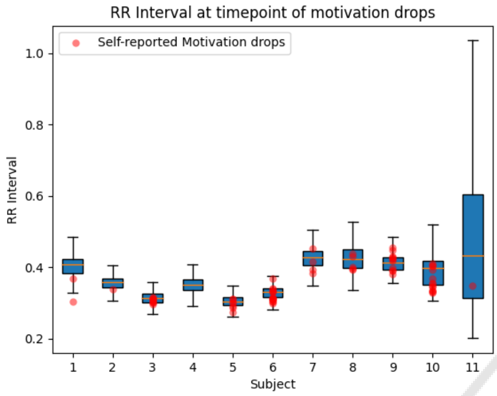

Figure 5: Box plots of the range of variation in subjects' RR-interval, and the RR-interval corresponding to the onset of motivational drops.

5.2.2 Instantaneous Heart Rate (IHR)

HRV helps not only in identifying the risk of cardiac diseases but also in the state of ANS (Tiwari et al., 2021). Instantaneous heart rate provides a direct measure of vagal nerve and sympathetic nervous system activity and is of substantial use in a number of analyzes and applications (Jarchi and Casson, 2017). Initially, the box plot in figure 6 illustrates the time-domain distribution of IHR for each subject, providing insight into the range of IHR distribution. Concurrently, the IHR at the onset of motivational drops is denoted by a red dot in the plot. Similar to the RR-Interval distribution plot, the distribution interval varied for each subject, underscoring the individual independence of the data. Notably, the IHR corresponding to the moment of motivational drops did not qualify as an outlier for all subjects, despite rapid heartbeat being was reported as a physiological discomfort in the Post-questionnaire by eight subjects.

5.2.3 LF/HF Ratio

Empirical evidence suggests that the activity of theSympathetic Nervous System (SNS) influences the low frequency band (LF) of the HRV, from 0.04 to 0.15 Hz, while the Parasympathetic Nervous System (PNS) is predominantly reflected in the high frequency band (HF), from 0.15 to 0.4 Hz, and

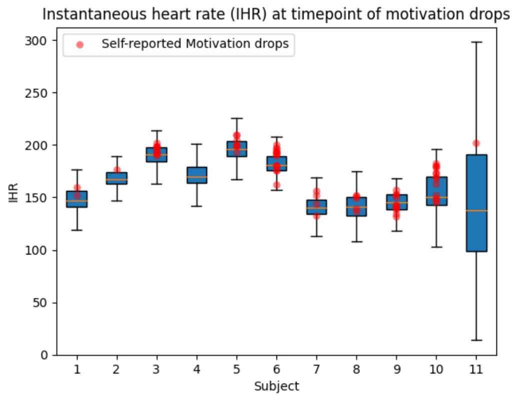

Figure 6: Box plots of the range of variation in subjects' IHR, and the IHR corresponding to the onset of motivational drops.

also possibly in a proportion of LF (Malik et al., 1996). By comparing the timepoint at which the subjects reported in the experiment that the Motivation drop occurred (i.e., the point in time at which they felt a physical or psychological change) with the changes in sympathetic-vagal balance that were found through the HRV analysis. The low-Frequency power/ high-Frequency power (LF/HF) ratio assumes that a low LF/HF ratio reflects parasympathetic dominance. This is seen when we conserve energy and engage in tend-and-befriend behaviors. In contrast, a high LF/HF ratio indicates sympathetic dominance, which occurs when we engage in fight-or-flight behaviors or parasympathetic withdrawal (Shaffer and Ginsberg, 2017). Pagani proposed to combine low frequency band (LF) and high frequency band (HF) into the low-to-high frequency ratio (LF/HF) as an index for the sympathovagal balance between the two nervous systems (Pagani et al., 1986). But this theory also received some criticism. Such as in a comprehensive study by Billman, it was conclusively shown that sympathovagal balance cannot be quantified by a single number, the LF/HF, which assumes a simplistic linear relationship between the activity of the nervous systems and the frequency bands (Billman, 2013). From the results of HRV analysis in frequency domain, among the 68 reported motivation drops, 44 occurred when the LF/HF ratio was below 0.5. In healthy adult, during rest ratio (LF/HF) is 1:2 (Tiwari et al., 2021). However, not all instances of self-reported motivation drops coincide with a low LF/HF ratio. Subject 4 exhibited a consistent absence of motivation drops during running, concomitant with the sustained maintenance of an LF/HF ratio below 0.5. Unfortunately, these findings in the ECG signal do not form a consistent indicator that directly points to the occurrence of decreased motivation.

5.3 sEMG and RSP Analysis and Observation

During jogging, the frequency of breathing and the motion state of the upper and lower limb muscles often play a crucial role in determining whether to cease exercise. The time nodes of self-reported motivation drops were marked on the respiration rate graph and the thigh sEMG signal graph. Through observation, it was noted that the peak physiological signals, namely the peak respiration rate and muscle signal, did not consistently align with the self-reported motivation drop points. Despite subjects repeatedly reaching the peak of the biological signal, interpreted as the physiological limit value for the current exercise (defined here as the highest peak value not breached during exercise), they did not report a decrease in motivation each time the limit value was reached. This suggests a lack of significant association between respiration signals and sEMG signals on motivation drops.

The respiration rate chart clearly illustrates that subjects proactively adjust their respiration rate after reporting motivation drops, reducing it through conscious modulation. This aligns with the subject's definition of decreased motivation, and the decrease in breathing rate aids in continuing the exercise. Conversely, excessive breathing rate or shortness of breath may induce a sense of decreased motivation.

However, in sEMG from the thigh, this modulation consciousness is less evident. This observation may be linked to the experimental environment, as jogging on the treadmill aligns the running rhythm closely with the treadmill setting, limiting the variability in thigh muscle movement.

5.4 Self-Similarity Matrix Analysis Results

Self-similarity matrix reports abnormal segments of physiological signals and segments with similar pattern or features through diagonal and blocks showed in matrix in Figure 7. This results are produced by subject 6 who has 4 self-reported motivation drops time interval 800s-900s out of the whole 20min jogging. In total, subject 6 reported 15 times motivation drops in 20min jogging. The top row shows the raw data of ECG, sEMG and RSP, the middle part is the self-similarity matrix and in the bottom row, those peak values represents changes happened in signals. The self-similarity matrix of ECG presents clearly the periodicity, in contrast, the matrix of sEMG point to non-periodicity and very little similarity. And the matrix of respiration indicates respiration system stayed in a stable state.

However, all three analysis (diagonal matrix, blocks and secondary matrix) mentioned in last section shows that there isn't some significant abnormal pattern when participants self-reported motivation drops. Peak values can suggests certain changes, but the difference between the peak and the mean is not significant. Not enough to reveal an abnormal signal fragment. Also, the frequency of peaks was much higher than the number of participant complaints, so changes in physiological signals could not be recognized as antecedents or consequences of motivation drops.

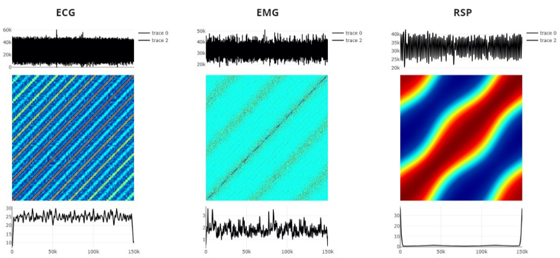

Figure 7: Subject 6: Self-Similarity Matrix (SSM) of ECG, sEMG, RSP, Window length: 2s, overlap: 50%.

5.5 LSTM Prediction

The predicted probability of motivation drops based on labeled data by self-reported motivation drops during jogging is shown in Figure 8. Firstly, the generally low predicted values (ranging from 0 to 1) stem from the extreme imbalance within the database. . Secondly, the occurrence frequency of time points predicted to have relatively high probabilities significantly surpasses the frequency of subjects experiencing motivation drops. This suggests that, according to the LSTM learning results, signal fragments resembling the characteristics of the fragment labeled at the time of motivation drops occur much more frequently than autonomously reported motivation drops. This also indicates that the pattern of the signal corresponding to autonomously reported motivation drops is not rare in the LSTM model's learning results.

Meanwhile, in both the validation and test sets, only a limited number of signal segments at the time points labeled as motivation drops were predicted to share similar characteristics with those labeled as 1 in the training set, and this occurred with higher probability. This illustrates that the commonality between the labeled segments is not apparent. However, it is essential to note that the extreme imbalance in the database and the person-dependent nature of the research methodology might hinder definitive conclusions regarding whether the lack of commonality is intrinsic to the signals or if it results from insufficient data at the labeled motivation drop, thereby impacting optimal learning. An observable periodicity is evident, potentially linked to the periodic nature of ECG and respiration signals. Remarkably, this periodicity remains unaffected by the presence or absence of motivation drops. Partial findings indicate that the aggregate predicted value tends to be lower than instances of self-reported motivation drops during segments when no motivational drops is reported.

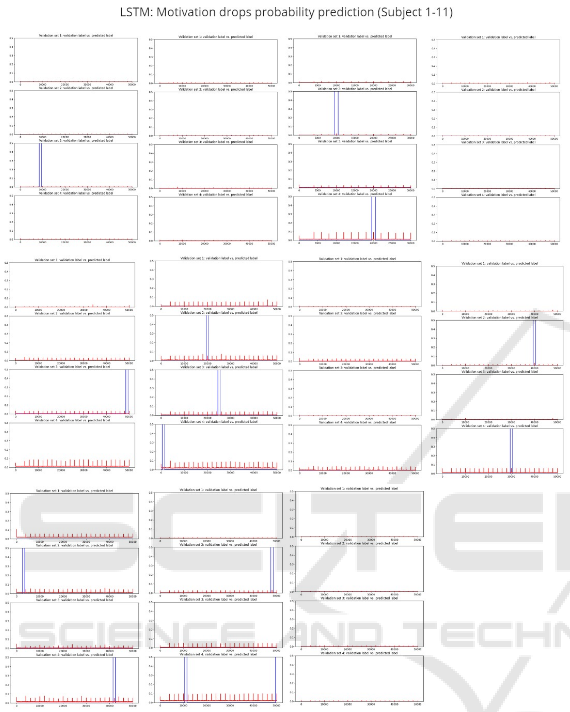

Figure 8: Left to right: Subject1-4 (row 1), Subject 5-8 (row 2), Subject 9-11 (row 3), windowlength: 4000, overlap 50%, Predicted results on validation set. Blue square: self-reported motivation drops. Left: y-scale: 0-1, Right: y-scale: 0-0.5.

5.6 Discussion

This study aimed to explore whether the discomforts reported and triggered by decreased motivation had discernible effects on monitored physiological signals. A comprehensive analysis framework was proposed in this study which inlcudes data acquisition, pre-/post- questionnaire, HRV analysis, self-similarity matrix analysis and machine leanring with LSTM model. ECG and RSP serve as representative signals in the experiments, enabling the characterization of the proposed main physiological discomforts. These signals can be collected in real-time without interfering with exercise, making them justified for studying motivation drops during physical activity. Although EDA, mentioned several times as a physiological discomfort, was not explored in the experiments, its widespread use in health monitoring devices suggests potential applications in motivation-related studies, opening avenues for integrating motivation-related functions into health monitoring devices.

In HRV analysis, ECG signal segments corresponding to the onset of autonomously reported motivation decrements were analyzed in both time and frequency domains. The resulting indicators (RR-Interval, IHR, LF/HF ratio) fell within the normal range, indicating that these signal segments lacked observable abnormalities. On the contrary, the self-similarity matrix focused on detecting mutated abnormal segments in the three signals (ECG, sEMG, RSP). Results demonstrated significant pattern changes in all three signals at the moment of motivation drops. However, compared to motor segments without reported motivation decrements, the signals corresponding to the onset of self-reported motivation decrements showed no observable pattern changes, suggesting that no abnormal physiological signals were generated alongside motivation decrements.

The prediction results of the LSTM were not highly convincing, attributed to database size and balancing issues. For a single subject, the LSTM model did not sufficiently learn features of physiological signal segments corresponding to autonomous reporting of motivation drops. Improvements could be made by increasing single-subject data length and balancing the database. Nonetheless, the learning results still indicate that signal fragments with high similarity to those labeled as motivation drops appear frequently and at non-subject-mentioned time points. The difficulty in discriminating the model when signal fragments labeled as motivation drops appeared in the test set was due to low similarity of representative features between these fragments.

The experimental design did not account for gender differences in the autonomous expression of motivational decrements, with male subjects reporting them twice as often as female subjects. Females tended to hesitate in reporting and employed positive mental cues, while males exhibited a stronger need for communication when bored, potentially influencing the frequency of reported motivation drops. Despite efforts to control the experimental environment, self-reported data's highly subjective nature reveals significant variability in subjects' processing and reaction to the environment and decision-making.

6 CONCLUSION AND FUTURE WORK

Contrary to hyphothesis, our findings reveal the absence of a direct link between self-reported motivation and biological signals. Specifically, biological signals prove inadequate as reliable indicators of personalized motivation drops. Instances of motivation drops do not elicit abnormal biological signals, and certain biological signals peak without corresponding to motivation drops.

While diminished motivation prompts exercise cessation, it does not manifest in discernible alterations in biological signals. Our study introduces a pioneering hypothesis, aiming to explore whether motivation drop elicits abnormalities in biological signals or self-comparative irregularities. Future investigations should also prioritize database equilibrium, striving to achieve a balanced representation. Addressing the data balancing issue before training may enhance the interpretability and credibility of the predicted results. The focus ought to shift from singularly scrutinizing predictive probability values to emphasizing trends foreseen by the algorithm. In essence, attention should pivot towards instances when the probability of motivation drop exhibits continuous or relatively substantial escalation, rather than fixating on discrete probability values at isolated time points.

Assessing the trustworthiness of self-reporting is challenging due to the strongly subjective nature of self-reported motivation drops. In future studies, objective descriptions of motivation drops can mitigate the effects of personal dependence brought about by subjective awareness in studies exploring whether motivational drop causes abnormal physiological signals. Natural facial expressions (Bian et al., 2023; Veldanda et al., 2024), as an auxiliary to physiological signals, also have the potential to provide another dimension of information.

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