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DEVELOPING A PREDICTIVE MODEL TO IMPROVE ROWING PERFORMANCE THROUGHOUT A SEASON

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ABSTRACT

Introduction: Despite a long history of performance testing and modeling, no study has examined the use of performance models over a season. We hypothesize that current performance models of rowing would be incapable of seasonal use and, instead, act as a "snapshot" of performance. A model able to remain valid over the season could allow coaches to better track and modify training and optimize the performance outcomes of athletes. However, previous testing protocols present barriers to implementation since they are often invasive and time-intensive. In response, we identified key factors associated with performance and seasonal variation using systematic review, reviewed testing protocols that characterize the desired physiological performance determinants in a non-invasive and time efficient manner, and proposed rubrics to validate the proposed model and testing scheme. **Systematic Review:** We conducted two systematic reviews. Our first review asked: Which physiological performance determinants are best able to predict performance? We found that performance could be best predicted when anaerobic capacity, aerobic power, sustainable power/fatigue threshold, and mechanical power were included. Our second review asked: How do physiological changes over a season impact rowing performance? Due to a small amount of studies, the question was expanded to include cycling. The quality of evidence found in our second review was low due to inconsistencies across studies, imprecision, and bias since many studies examined only one physiological performance determinant. **Proposed Model:** We created our model with the following goals: 1) remain valid throughout a season; 2) account for physiological changes which affect performance; 3) utilize the least invasive means possible to increase ease of implementation and frequency of assessment; 4) useful to coaches to make training and grouping decisions; and, 5) valid for rowers regardless of age, skill, gender, and weight class. Performance determinants were selected to represent the four areas found in our review (anaerobic capacity, aerobic power, sustainable power/fatigue threshold, and mechanical power) associated with high predictive value. These included maximal aerobic power ($\dot{V}O_{2max}$) ventilator threshold (VT), power at $\dot{V}O_{2max}$, power at VT, max power, critical power (CP), and anaerobic work capacity (W'). All performance determinants could be assessed non-invasively using two tests, which could be administered in approximately 45 minutes over two days. **Implementation Plan:** We present an implementation plan spanning several seasons that would focus on validating the proposed model in the first season and developing a performance "score" with normative values in subsequent seasons to track individual and team changes in physiological status. **Summary:** The model, methods and plan that we have proposed advance performance testing in rowing from theory to practice, encapsulating the physiological determinants of performance.

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ABBREVIATIONS

1-RM .... 1 Repetition-Maximum Force

CP .... Critical Power

CV .... Critical Velocity

La .... Lactate

TTE .... Time to Exhaustion

$\dot{V}O_2$ .... Oxygen Uptake or Aerobic Power

$\dot{V}CO_2$ .... Carbon Dioxide Production

$\dot{V}O_{2max}$ .... Maximal Aerobic Power

VT .... Ventilatory Threshold

W’ .... Anaerobic Work Capacity (joules)

$\dot{W}$ .... Power (Watts)

WEP .... Work End Power

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Chapter 1
Introduction

Performance has been studied in a variety of sports (Brown & Fletcher, 2017; Glazier, 2015; Halson et al., 2002; Lee et al., 2017; Vitale & Weydahl, 2017). In sports less dependent on fine motor skill (e.g., running and cycling, vs. basketball and baseball) the focus of study has been on underlying physiological, biomechanical, and anthropometric performance determinants (Castronovo, Conforto, Schmid, Bibbo, & D'Alessio, 2013; Jarek Maestu, 2005; Jeukendrup & Martin, 2001; J.-R. Lacour, Messonnier, & Bourdin, 2009; Mahler, 1985; Morton, 2009; Rodriguez-Marroyo Ja Fau - Pernia, Pernia R Fau - Villa, Villa Jg Fau - Foster, & Foster, 2017).

Rowing poses an interesting challenge for sport scientists. Indeed, there is less dependence on skill than her individual sports, such as wrestling, swimming, and tennis. Success in rowing is determined by which athlete can produce the most power to move their boat the fastest. Furthermore, while most team sports require athletes to work together by performing different activities, such as passing, dribbling, and shooting in soccer, a team of rowers must synchronize their motion to produce high impulse and high average power to be the fastest boat. Like cross-country skiing, rowing is a whole-body activity with a high cardiac output demand. Most importantly, rowing typically requires athletes to maintain high exercise intensities over a 2000m (2km) course. Athletes, then, must be both powerful and well-adapted to sustain a high-power output for 6-8 minutes in a 2000m race that draws more equally from sustained glycolytic and oxidative metabolism than most other sports. For a 2000m race, the energy needed is estimated to be 65-75% from oxidative phosphorylation and 25-35% from glycolysis and ATP-PCR (Akca, 2015).

Past performance models (Akça, 2014; Cosgrove, Wilson, Watt, & Grant, 1999; S. Ingham, Whyte, GP., Jones, K., & Nevill AM., 2002; Kennedy & Bell, 2000; P. Mikulic, 2009; Mikulić & Ružić, 2008; Nevill, 2011; Riechman, Zoeller, Balasekaran, Goss, & Robertson, 2001; Schranz, Tomkinson, Olds, Petkov, & Hahn, 2012), reviewed in Chapter 2, have considered determinants of a single 2km race but have not related changes in these determinants to changes in performance over a season. Additionally, these models would difficult to implement for tracking seasonal change due to reliance on invasive methods, such as lactic acid collection, and long test times. As a result, past models have acted as a "snapshot" of performance instead of a means to track and monitor performance.

Finally, past models have focused on distinct populations for study and may not be generalizable to other populations. Since rowing performance depends on the same physiological performance determinants, which are weighted differently across skill levels, a performance predictive model should be generalizable to all populations if a categorical variable is added to account for the different weights of performance determinants.

The invasiveness, lengthy time to test, focus on distinct populations, and "snapshot" provided by previous models limit the utility of performance modeling by coaches and athletes to inform training and improve performance. The question we pose are the following:

- Are performance predictors similar across studies in rowing, and are they consistent with the demands of the sport?
- Can the performance determinants related to rowing performance that were identified by past models be used to predict performance across a season?
- Can a performance test be developed with high sensitivity and specificity that does not require large amounts of time or biological samples?

These questions and challenges, helped to define goals for a performance model, enumerated below in unranked order:

1) be specific to the sport of rowing;
2) remain valid throughout a season;
3) account for physiological changes which affect performance;
4) utilize the least invasive means possible to increase ease of implementation and frequency of assessment;
5) have utility for coaches to make training and grouping decisions; and,
6) be generalizable to rowers of different age, skill, gender, and weight class.

In Chapter 2, we used systematic reviews to summarize previous approaches to modeling performance and derive insight to how they could be improved. Based on these reviews, we have proposed a new approach to modeling rowing performance that should be able to account for physiological changes throughout the season, to be used by coaches for tracking team and individual progress, and to help coaches make informed decisions for grouping athletes in boats.

Chapter 2
Systematic Reviews

2.1 Performance predictive models in rowing

Our first review was conducted to identify performance determinants, or clusters of determinants, used to model performance, examine the invasiveness and time required for testing, and analyze the validity of these models (i.e., the proportion of variance in group performance that could be explained by the models).

Figure 1. Predictive Model Selection Process

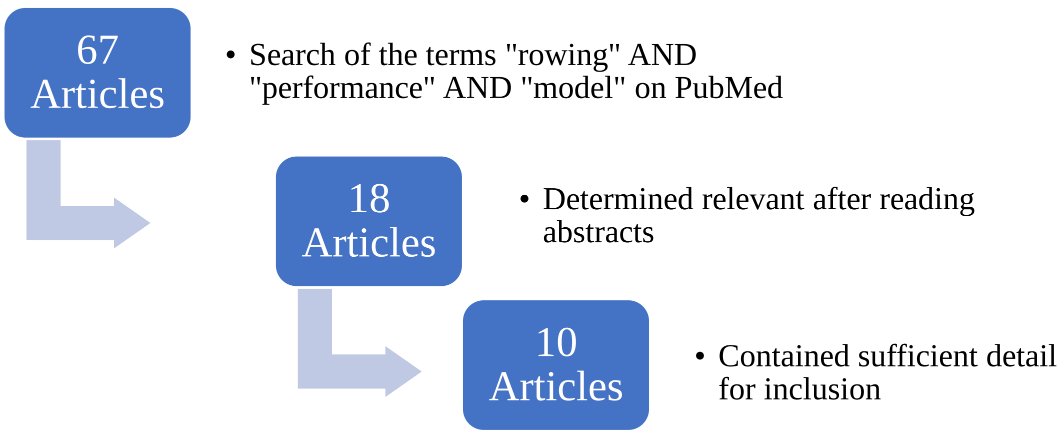


Figure 1 is a schematic of our review strategy. A PubMed search of the words “rowing,” “performance,” and “model” over 40 years produced 67 results. Of those, 39 papers were determined to be not relevant based on their abstract. The remaining18 papers were read and retained if performance was modeled which resulted in 10 papers being included in the review. Table 1 summarizes the 10 studies selected for analysis.

Table 1. Predictive Models and Performance Determinants

Author (Year)	Sample Population	# of Subjects & gender	Model Performance determinants	Model R^2	Performance Outcome
Akça (2014)	Collegiate Males	38	Anthropometric- Height, weight, arm span, leg girth, arm length & leg length	0.83	2000m time (s)
			Strength-bench pull, biceps, leg press 1RM, height & weight	0.80	
			Anaerobic power (Wingate Test average, maximal, and minimal power), height & weight	0.76	
			strength, height, weight, bench pull 1RM, leg press 1RM, & Wingate average & minimal power	0.85	
			Combination of all- Height, weight, bench pull 1RM, arm length, leg length, arm span, Wingate maximal, minimal, and average power, & leg press 1RM	0.92	
Cosgrove et al. (1999)	Club Males	13	$\dot{V}O_{2max}$ & maximal [La] 5 min after performance test	0.87	2000m time (s)
S. Ingham, Whyte, GP., Jones, K., & Nevill AM. (2002)	Elite Heavy-weight and lightweight Males and Females	23 Males & 18 females	Max power, Power @ 4mmol [La], Power @ $\dot{V}O_{2max}$, and $\dot{V}O_2$ @ [La] threshold	0.983	2000m time (s)
Kennedy and Bell (2000)	Male	16	$\dot{V}O_{2max}$	0.865	2000m velocity (m/s)
			Critical Velocity	0.941	

Mikulić and Ružić (2008)	12-13y old males	48	$\dot{V}O_{2max}$, biacromial diameter, thigh girth, body height	0.84	1000m time(s)
P. Mikulic (2009)	Elite Males	25	lean body mass, power output @ VT, power @ $\dot{V}O_{2max}$, body mass, chest girth, relaxed arm girth, forced vital capacity, and arm span	0.722	6000m time (s)
Nevill (2011)	Elite Heavy-weight and lightweight Males and Females	76	Power @ $\dot{V}O_{2max}$, Max power, $\dot{V}O_2$ @ [La] threshold	0.962	2000m time (s)
Riechman et al. (2001)	Collegiate Females	12	Wingate mean power and %fatigue, and $\dot{V}O_{2max}$	0.96	2000m time (s)
Russell, Rossignol, and Sparrow (1998)	Elite schoolboys	19	$\dot{V}O_{2max}$, accumulated oxygen deficit, efficiency	0.49	2000m time (s)
			Subcutaneous fat, height, body mass	0.78	
			Body mass, $\dot{V}O_{2max}$, and subcutaneous fat	0.74	
Schranz et al. (2012)	Junior Males	243	Body morphology (3-dimensional anthropometric scanning)	0.761	Self-reported best 2000m time(s)
	Junior Females	257	Body morphology (3-dimensional anthropometric scanning)	0.723	

2.1.1 Quality of Evidence

Using the GRADE (Grading of Recommendations, Assessment, Development and Evaluations) rubric (BMJ, 2019), we rated the quality of evidence to be moderate. Of the 18 models, five were able to explain greater than 90% of the variance in performance. We downrated the evidence because of imprecision; studies had a large variation in sample size (13 to 500 subjects) and the models which explained the most variance also had the fewest subjects. As a result, small sample sizes could have resulted in the explained variance being inflated. Additionally, inconsistency was found in the determinants used to explain performance across studies.

We clustered the studies into groups based on the performance determinants included for each model. Each cluster is described in greater detail below.

2.1.2 Anthropometric

Four of the models(Akça, 2014; Russell et al., 1998; Schranz et al., 2012) consisted of only anthropometric performance determinants and were able to account for an average of 77% of the variance in performance among these samples. Addition of markers of aerobic power, to two of the models (Mikulić & Ružić, 2008; Russell et al., 1998), explained a similar amount of the variance (79%). In contrast, when Akça (2014) added anaerobic power and strength to anthropometric measures the amount of explained variance increased to 92%.

It should be noted that the sample population for these studies was schoolboys, or junior rowers. The fact that anthropometric performance determinants – limb length in particular – were such important contributors to the model is consistent with the notion that stroke length is an important contributor to rowing performance. Rowers with long arms are able to reach further to “catch” the oar in the water, and long legs allows the rower to finish with a long stroke.

That said, these performance determinants of rowing are fixed and cannot be altered with training. In other words, they are important distinguishing factors for a coach when selecting athletes for a team, but they provide no information about changes in performance over the course of a season. When physiological performance determinants were added to these models, anaerobic power and strength appeared to be better predictors than aerobic power in this population.

2.1.3 Aerobic Power

Two of the models used only measurements associated with oxidative phosphorylation or "aerobic" power to assess performance and had variable results. Russell et al. (1998) were only able to explain 49% of performance variance while Kennedy and Bell (2000) found $\dot{V}O_{2max}$ alone accounted for 86.5% of performance variance. Taken together, the findings suggest that aerobic power is an important contributor to rowing performance as assessed by 2 km ergometer time.

2.1.4 Anaerobic Power

Akça (2014) created the only model which used only performance determinants relying predominately on non-oxidative metabolism energy sources and found that strength (bench pull 1RM, leg press 1RM) and anaerobic power (Wingate Test average & minimal power) explained 85% of performance variance while anaerobic power alone (Wingate average & minimal power) explained 76% of performance variance.

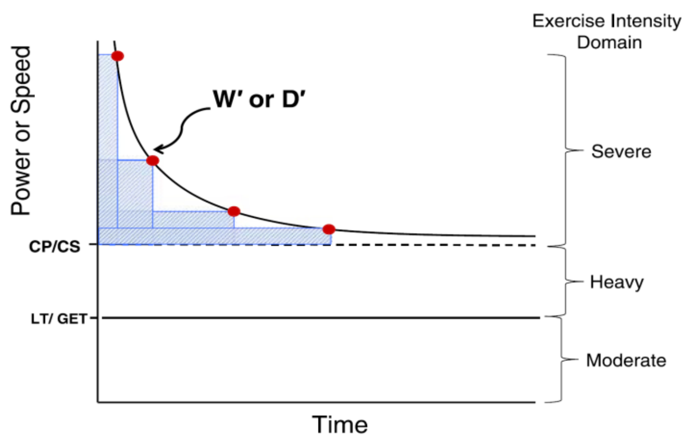
2.1.5 Anaerobic Power, Sustainable Power, and Aerobic Capacity

The best physiological models were those which included performance determinants related to both aerobic and anaerobic power. These models were able to explain 96%, or more, of performance variance (S. Ingham, Whyte, GP., Jones, K., & Nevill AM., 2002; Nevill, 2011; Riechman et al., 2001). Furthermore, some of these models included performance determinants related to sustainable work rates such as lactate threshold (LT), $\dot{V}O_2$@LT, critical power (CP) and velocity@CP in addition to maximal work rates. These models were among the best of the models reviewed, accounting for 96.2% Nevill (2011) and 98.3% S. Ingham, Whyte, GP., Jones, K., & Nevill AM. (2002) of variance. Therefore, sustainable mechanical power appears to be an important predictor of performance in addition to maximal aerobic, anaerobic, and mechanical power.

The concept of critical power and velocity incorporated in the model presented by Kennedy and Bell (2000) requires further explanation. Critical power (and velocity) are defined as, "the greatest metabolic rate that results in wholly oxidative energy provision, where wholly oxidative considers the active organism *in toto* and means that energy supply through substrate-level phosphorylation reaches a steady-state, and that there is no progressive accumulation of blood lactate or breakdown of intramuscular phosphocreatine" (Poole, 2016). This steady-state lies almost equidistant between the lactate/gas-exchange threshold and the power at $\dot{V}O_{2max}$ (Poole, 2016). Therefore, critical power and velocity are the power or velocity which can, theoretically, be maintained "indefinitely."

Historically, critical power and velocity has been calculated from three or more tests which use set powers or speeds and measure the time to fatigue (the inability to maintain the work rate). The power or speed and time to exhaustion are then fitted with a hyperbolic curve where critical power or velocity is the asymptote (Poole, 2016). While able to accurately predict critical power and velocity, time-to-exhaustion (TTE) testing is time consuming and requires at least three days of testing. To decrease the time to test, a 3-min all-out critical power test was developed (Burnley, 2006; Dicks, 2016; Vanhatalo, 2007, 2008). Instead of modeling the work-time relation with several TTE tests, the 3-min test measures power vs time during one test, with the starting power being determined from the power achieved halfway between GET and $\dot{V}O_{2max}$. Critical power is defined the steady-state power achieved during the last 30 seconds of the test.

Figure 2. The Parameters of Critical Power



Each of the points shown on the graph to the left were produced from four TTE tests. W', shown as the blue rectangles to the left, was measured as the work done above critical power for each test.

Two parameters are derived from a critical power test. The first, designated CP, is the critical power. The second, W' is the anaerobic work capacity which is the work done above critical power. For a 3-min all-out test, W' can be calculated from the work end power (WEP) which is the integral of the power-time relation above critical power(Vanhatalo, 2007, 2008). By definition, W' is the total work that can be completed above a steady-state exercise intensity and therefore requires energy from glycolytic metabolism.

Despite its different methods, the critical power calculated from the 3-min all-out test does not differ from TTE tests (Felipe Mattioni Maturana, 2017) and is sensitive to changes in critical power (Vanhatalo, 2008). Therefore, critical power, and velocity, are an important measure of the work rate athletes can sustain and can be measured conveniently and accurately from a 3-min test.

Clustering models lends insight into which determinants have important impacts on performance and what combination of determinants might best predict performance over time. The importance of anerobic power and sustainable power can be seen in the models created by Akça (2014) and Kennedy and Bell (2000). These models did not incorporate aerobic power but were still able to account for more than 90% of the variance in performance.

Expectedly, the importance of anthropometric performance determinants was less in groups of subjects with greater rowing experience. These groups were more similar in their anthropometric characteristics, since they were already self-selected to the sport because of characteristics such as limb length.

Taken together, we concluded that maximum mechanical power, anaerobic power, aerobic power, and indices of fatigue threshold or sustainable power (such as critical velocity or lactate threshold), are essential categories of predictors to be included in a performance model. For aerobic power, however, it appears as if $\dot{V}O_{2max}$ may be less important than the amount of work which can be done at $\dot{V}O_{2max}$ (S. Ingham, Whyte, GP., Jones, K., & Nevill AM., 2002; Nevill, 2011).

2.1.6 Utility in a Field Setting

Our design goals for a rowing performance model placed high value on ease of implementation for its intended audience (coaches and athletes). In particular, we sought to minimize the time and invasiveness of testing. Accordingly, we reviewed the best models (i.e., those with $r^2 \geq 0.9$) with respect to invasiveness, time to test, and how we believe test results could be used to inform training. The analysis was subjective and attempted to emulate the decision-making processes a coach or research team would utilize for field implementation.

The time to test for each model was approximated with the assumption that any test would require 30 minutes, including warmup and cooldown, and that tests requiring maximal efforts (except for 1RM strength tests) would be separated by at least 24 hours. Invasiveness is a binomial variable; testing was considered invasive if collection of biological material from a needle was required (e.g., blood, muscle). Finally, application to training was described as the area of performance that would be meaningful to coaches. A summary of these findings can be found in Table 2.

Table 2. Model Utility

Author (Year)	**# tests**	**Approximate time to test**	**Invasiveness**	**Possible application to training**
Akça (2014)	6	3 hours of tests over 3 days	Noninvasive	Sprint and strength training
S. Ingham, Whyte, GP., Jones, K., & Nevill AM. (2002)	2	1 hour of testing over 2 days	Invasive: Blood collection through catheter or needle	Strength, sprint, and endurance training
Kennedy and Bell (2000)	4	2 hours over 4 days	Noninvasive	Endurance training at highest maintainable power
Nevill (2011)	2	1 hour of testing over 2 days	Invasive: Blood collection through catheter or needle	Strength, sprint, and endurance training
Riechman et al. (2001)	3	1.5 hours of testing over 3 days	Noninvasive	Sprint and endurance training

Analysis of the five models revealed that all were lacking in at least one of the three categories. The two models with the shortest time to test, S. Ingham, Whyte, GP., Jones, K., &

Nevill AM. (2002); Nevill (2011), were invasive, requiring repeated blood samples for determination of lactate threshold. In contrast, the model by Riechman et al. (2001) was noninvasive and only required 1.5 hours of testing but was not comprehensive; it did not include any index related to sustainable power. The remaining two models, Kennedy and Bell (2000) and Akça (2014), are both non-invasive, but required long test times and only included Critical Velocity and anaerobic power, respectively.

2.1.7 Critique

Our analysis found several models capable of accurately predicting performance at a single point. Disregarding anthropometric performance determinants, three clusters of performance determinants were identified: aerobic power, anaerobic power, and sustainable power. However, no model was sufficiently comprehensive to evaluate subjects in all of these dimensions. Moreover, all studies raised concerns regarding invasiveness, and/or length of testing.

To help assure that a performance model would be valid for rowing, we decided *a priori* that all testing would utilize rowing as the mode of activity. However, the models with the best predictive ability (highest r^2) required blood collection throughout testing for determination of blood lactate. For rowing, blood samples would need to be taken from the earlobe or from a catheter because athletes would not be able to release the handle on an ergometer or oar which would violate our design goal for ease of implementation.

Models which were not invasive overlooked important areas of performance and some required a time to test too long to be effective for season long use by coaches. Kennedy and Bell (2000) used critical velocity, measured with time to exhaustion tests, but did not consider anaerobic or aerobic power for their model, even though both were acquired through their testing methods. This exclusion was due to the study's goal of examining the relationship between critical velocity and performance alone. The model created by Akça (2014) focused only on anaerobic power and strength but did not include aerobic power or a sustainable mechanical power. Finally, Riechman et al. (2001) included aerobic power and anaerobic power in their model but did not include a measure of sustainable mechanical power.

With regard to anthropometric measures, several models included these performance determinants with considerable success in predicting performance in novice rowers. However, these are unmodifiable performance determinants (P. Mikulic, 2012). Therefore, anthropometric performance determinants may be important for team selection but not for season long use. This conclusion is supported by Fiskerstrand and Seiler (2004) and Hagerman Fc Fau - Staron (1983) who found that anthropometric values remained constant over a season even though performance changed. Therefore, despite an ability to predict a singular performance, anthropometric values would not be valid to track seasonal performance.

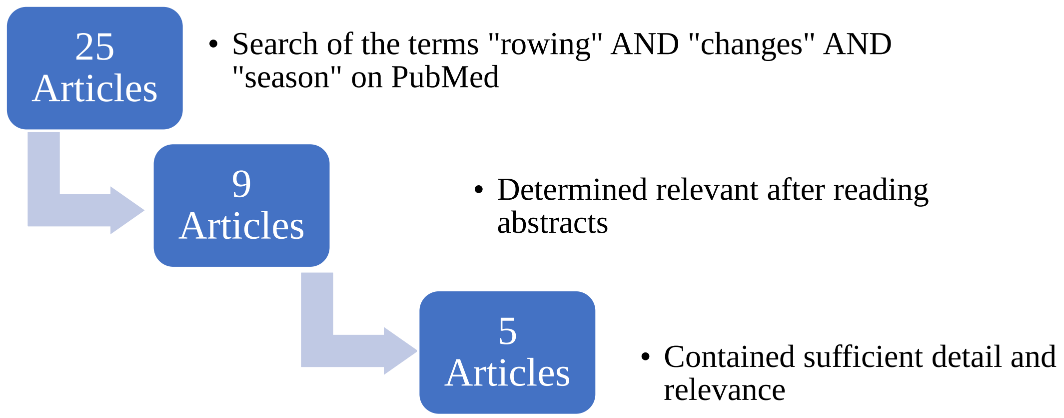
It is useful to restate that, in every model, performance was predicted as a "snapshot" and did not analyze how seasonal changes effected performance, Therefore, it is unknown whether these models would remain valid throughout a season. Additionally, since each model weighted different dimension of performance (anaerobic power, fatigue thresholds, aerobic power, mechanical power) the importance of seasonal variation in one or more dimension could be overlooked. Because this gap could affect model validity and utility over the course of a season, we conducted a second systematic review to determine how physiological performance determinants might be used to predict performance improvements over time.

2.2 The relationship of physiological changes and performance over a season

2.2.1 Selection Process

For a performance model to remain valid over a season, it must include determinants which relate to performance and explain a large fraction of the variance in seasonal performance. Our second review examined whether changes in physiological performance determinants could account for changes in performance.

Figure 3.Selection Process of Rowing Changes Over a Season

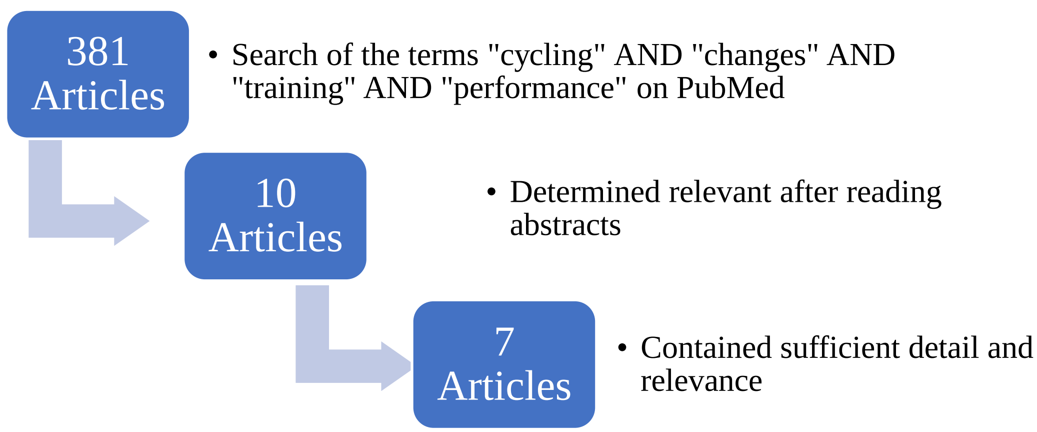


A PubMed search of the words “rowing”, “changes”, and “season” produced 67 results. After reading these abstracts, 9 papers were determined to be relevant to our question based. These 9 papers were reviewed thoroughly and retained if they examined physiological changes and performance, resulting in 5 papers being included for analysis.

Besides the small remaining group of studies, further analysis revealed an additional problem: although physiological changes over the course of the season were reported, authors did not attempt to associate these changes in rowing performance. Consequently, we expanded our search to include cycling, a sport with similar physiological determinants. Cycling was chosen because, like rowing, performance is dependent on maintaining a high-power output over a sustained amount of time. Similar energy sources are required, albeit with a greater reliance on aerobic power and fatigue threshold because the duration of contests are longer than rowing. Therefore, the physiological determinants and changes in performance associated with them should somewhat approximate those seen in rowing. Nevertheless, it should be acknowledged that the modes of locomotion and power production differ between the two sports and comparisons should be made with caution.

A PubMed search of the words “cycling”, “changes”, “training”, and “performance” produced 381 results. Of those, 10 papers were determined to be relevant based on their abstracts. The 10 papers were then read and retained if they examined physiological changes and performance which resulted in 7 papers being added to the review.

Figure 4. Selection Process of Rowing Changes Over a Season



2.2.2 Quality of Evidence

Using the GRADE rubric, we scored a low quality of evidence for physiological changes related to performance over a season. Studies suffered from indirect reporting of performance or failed to statistically examine the relationship between changes in physiology and performance. A risk of bias was found because many of the studies focused exclusively to $\dot{V}O_{2max}$ and did not consider other physiological performance determinants. Finally, the relationship between physiological changes and performance were inconsistent across studies. While Holm, Sattler, and Fregosi (2004) found an increase in performance accompanied an increased $\dot{V}O_{2max}$, Johnson, Sharpe, and Brown (2007) found performance improved without an increase in $\dot{V}O_{2max}$.

2.2.3 Critique

A key finding from this review is that no study related changes in physiological performance determinants to changes in rowing performance. For rowing, seasonal variations in physiological performance determinants were well studied but performance was not; performance, if studied, was defined as place at competitions. However, place in rowing is confounded by multiple external factors (other competitors, weather, race course, location within the race course etc.). For similar reasons, regattas (scored in head-to-head competition) are held separately from head races (where place is based on time).

In cycling, analysis of the training studies demonstrated increases in $\dot{V}O_{2max}$, max power, average power, and power at 4mmol [La] after training as well as an improvement in performance. Again, the physiological changes were not compared statistically to the changes in performance. Instead, as described by Jeukendrup and Martin (2001) the comparisons were between the percentage change of a selected performance determinant, typically $\dot{V}O_{2max}$ or max power, and the percentage change in performance. This inference is weak because percentage changes are influenced by the initial magnitude of the performance determinant of interest, other possible contributors were neither controlled nor measured, and only a single performance determinant was analyzed. Jeukendrup and Martin (2001) noted in their review that an increased lactate threshold training may have impacted performance as much, or more, than changes in $\dot{V}O_{2max}$. Because of this narrow scope, training studies may have overrepresented the importance of changes in max power and $\dot{V}O_{2max}$ to seasonal variation in performance. Similarly, Castronovo et al. (2013); Jarek Maestu (2005); Levin, McGuigan, and Laursen (2009); Smith and Hopkins (2012); Tanaka and Swensen (1998) suggested that performance studies may have overlooked important physiological performance determinants and wrongfully attributed changes in performance to a single determinant.

Table 3. Performance and Physiological Changes over a Season

Author (Year)	**Sport**	**Population & # of subjects**	**Examined Seasonal Variation in Physiological Performance determinants**	**Examined Performance**	**Physiological Changes Related to Performance over season**
Bourgois, Steyaert A Fau - Boone, and Boone (2014)	Rowing	Case Study of 1 elite rower	Yes	No	Not examined
Fiskerstrand and Seiler (2004)	Rowing	28 elite Norwegian men	Yes	Yes	Not examined
Hagerman Fc Fau - Staron (1983)	Rowing	9 elite males	Yes	No	Not examined
J. R. Lacour, Messonnier L Fau - Bourdin, and Bourdin (2009)	Rowing	Case Study of 1 rower	No (Performance determinants examined yearly)	Yes	Not examined
P. Mikulic (2012)	Rowing	4 elite males	Yes	No	Not examined
Halson et al. (2002)	Cycling	8 males	No (training intervention)	No	Not examined
Hardman, Williams, and Wootton (1986)	Cycling	8 males	No (training intervention)	No	Not examined
Holm et al. (2004)	Cycling	20 “fit” cyclists	No (training intervention)	Yes	Not examined
Johnson et al. (2007)	Cycling	18 males	No (training intervention)	Yes	Not examined

Lamberts, Rietjens, Tijdink, Noakes, and Lambert (2010)	Cycling	1 elite male	No (training intervention)	Yes	Not examined
Levin et al. (2009)	Cycling	14 males	No (training intervention)	Yes	Not examined
Rønnestad, Hansen, and Raastad (2010)	Cycling	12 males	Yes	Yes	Not examined

2.3 Gaps in the Literature

While previous rowing performance models have presented several means to predict performance in specific populations, they were neither comprehensive from a physiological perspective (including markers of all physiological performance determinants of rowing) nor generalizable (including athletes of different ability levels). Moreover, our second systematic review revealed that performance has not been modeled across a season. That said, this supported the inclusion of $\dot{V}O_{2max}$ and maximal power output in our proposed approach because they changed over the course of a season and revealed sustainable power to be an important predictor at a specific time point. However, other findings, such as Johnson et al. (2007), revealed that performance improved even though $\dot{V}O_{2max}$ and critical power remained the same and other meta-analyses made by Jarek Maestu (2005); Smith and Hopkins (2012) suggest that other performance determinants must be considered.

In his review, Jarek Maestu (2005) found the physiological characteristics of muscular endurance, aerobic power, anaerobic power and strength to be important performance determinants of competitive rowing. Alternatively, Smith and Hopkins (2012) found “peak incremental power, $\dot{V}O_{2max}$, some measures of lactate threshold power and possibly 30-second power, have measurement properties that make them potentially valuable for assessing rowing performance." In consensus with the findings of our present review, Maestu concluded that previous literature failed to examine physiological and performance changes over the season. Smith and Hopkins (2012) noted that the small sample sizes used to create past models could explain the high explained variance and may have resulted in a substantial underestimate of the true error of the model.

Models made by Akça (2014) and Riechman et al. (2001) which found performance determinants affected by anaerobic power, such as Wingate average power and %fatigue (((Wingate max power-min power)/max power)x100), to be related to performance, further emphasizes the need to expand the study of determinants of seasonal performance beyond $\dot{V}O_{2max}$ and maximal power.

Beyond a narrow scope of study focused on $\dot{V}O_{2max}$ and maximal power, studies of seasonal changes considered physiological changes independent of rowing performance. When there was a change in performance and physiology, authors rarely performed statistical analyses to determine an association between the two.

The models best able to predict performance at a single point in time often relied on invasive testing to determine fatigue thresholds with performance determinants such as lactate threshold. However, seasonal change in fatigue thresholds have not been used to determine seasonal variation in performance. As mentioned previously, invasive tests increase the difficulty of implementation for rowing teams, and the problem is magnified when repeated measures are needed over the course of a season. The problem is surmountable, in our opinion. The close relationship between ventilatory threshold (VT) and lactate threshold, in normal humans, suggests VT may be a noninvasive alternative (Cabo, 2011). Since lactate threshold and

VT reflect the accumulation of lactate and blood in normal physiology, subtle differences in values produced by each measure should be largely irrelevant to performance prediction.

Overall, our review identified models built on sound physiological constructs that warrant changes to increase utility across a season. Finally, previous models were created with specific populations and have not looked at the applicability of the model to other populations or attempted to create a generalizable model to could consider age, weight class, and skill level.

To summarize, the physiological basis for a performance model should include:

- Aerobic power
- Anaerobic power
- Maximal mechanical power
- Sustainable power/fatigue

In contrast, anthropometric performance determinants should be excluded because they remain, for the most part, the same over the course of a season.

Chapter 3
Proposed Model

Our proposed model is based on the knowledge garnered from previous approaches to performance assessment. The new approach to performance testing fills the gaps in the literature; builds upon the strengths of previous approaches; and works to eliminate, or at least minimize, their shortcomings. To reiterate, the goals of the proposed model are:

1) Valid for rowing (although the concepts are applicable to other sports)

2) Remain valid throughout a season

3) Account for physiological changes which affect performance

4) Utilize the least invasive means possible to increase ease of implementation and frequency of assessment

5) Available to coaches to make training and grouping decisions

6) Independent of age, skill, gender, and weight class.

3.1 Performance Determinants and Testing Selection

Our review converged on four areas of performance physiology: Anaerobic power, maximal mechanical power, fatigue/sustainable power thresholds, and aerobic power. Therefore, we reviewed assessments in each of these areas, focusing on methods that were utilized in the models reviewed in Chapter 2. Then, the pros and cons of testing methods for each performance determinant are summarized in Table 4.

Table 4. Assessments and Methods for Chosen Physiological Performance Determinants

Performance Determinant	Assessed by	Method/Protocol		Pros	Cons
$\dot{V}O_{2max}$	Graded Exercise Test (GXT)	Mixing chamber	Ramp	Data are smoothed Ventilatory threshold is easier to identify	Mixing chamber delays measured response
		Mixing chamber	Incremental	Steady states can be achieved for each work rate	Ventilatory threshold is less distinct
		Breath-by-breath	Ramp	No lag time, distinct ventilatory threshold	Large breath-to-breath variation requires more sophisticated data smoothing
			Incremental	No lag time	Ventilatory threshold is less distinct
Mechanical Power Output ($\dot{W}$)	Max pulls	Ave of 5 max pulls		Sport specific	N/A
	GXT	Peak power @ end of GXT		Power@ $\dot{V}O_{2max}$ Easy to obtain	May vary depending on how it is measured/recorded
		Extrapolation to $\dot{V}O_{2max}$ from regression of power and submaximal $\dot{V}O_2$		Easy to determine	Estimate, not a true measurement
		$\dot{W}$@ anaerobic threshold	Power @ Lactate threshold	Widely used	Invasive
			Power @ Ventilatory threshold	Non-invasive	Indirect determination of anaerobic power
Anaerobic power	Wingate	%fatigue= (Start power-end power)/start power		Fatigue as a loss of power	Not a direct measurement of power
		Peak, Average power		Higher than power @$\dot{V}O_{2max}$ indicates reliance on glycolytic metabolism	Requires precise power measurement in 5 sec increments
	Critical power	W' (Area under power curve and above critical power)		Accurate measurement of mechanical power from glycolytic metabolism	Start power is set below maximal
Maximal sustainable power/fatigue threshold	Anaerobic Threshold	Lactic acid threshold	Inflection of Lactate concentration	Used extensively in literature	Invasive; multiple blood samples required
		Gas exchange threshold	V-slope (Pavle Mikulic, Vucetic, &	Non-invasive	Inflection point not always easy to determine

			Sentija, 2011; Siepel, 2015)		
	Critical Power	Multiple performance trials to exhaustion	asymptote of work-time relationship	accurate measure of CP	Time consuming; requires multiple tests to exhaustion over several days
		3’ All-out test	end power = critical power	rapid determination of CP	Not as thoroughly validated; requires prior determination of $\dot{V}O_{2max}$ and lactate threshold

The performance determinants selected were those that encompassed aerobic power, anaerobic power, maximal mechanical power, and sustainable mechanical power with methods and tests which minimized invasiveness and time to test. We found that $\dot{V}O_{2max}$, VT, power at $\dot{V}O_{2max}$, power at VT, max mechanical power, critical power, and anaerobic work capacity (W’, total work that can be completed in excess of critical power) could be assessed non-invasively using two tests, each lasting less than 45 minutes and administered over two days.

The first test would entail a ramp GXT to maximum on rowing ergometer to determine $\dot{V}O_{2max}$, VT, power at $\dot{V}O_{2max}$, power at VT and max mechanical power. The second day of testing would be devoted to determination of critical power and anaerobic capacity assessed by W’, calculated from WEP, from the 3-min test. Two fatigue thresholds, Ventilatory and Critical Power, are determined, defining athletes’ sustainable power over a race which has implications for grouping rowers in boats. Ventilatory threshold is used as a non-invasive surrogate for lactate threshold.

The tests and performance determinants are summarized below:

1) Ramped GXT with breath-by-breath gas exchange
    a. $\dot{V}O_{2max}$ – less than 150 ml/min change in $\dot{V}O_2$ over the final 30 sec of the test (Taylor, 1955)

b. Ventilatory Threshold using $\dot{V}$-Slope method $\dot{V}O_2$ vs $\dot{V}CO_2$ (Siepel, 2015)

c. Power at $\dot{V}O_{2max}$

d. Power at VT

e. Max Power – average power from 5 maximum strokes at the start of test

2) 3-min all-out Critical Power test

a. Critical Power - Average power over last 30s (end test power)

b. Anaerobic Work(W') calculated from total work greater than CP (WEP)

3) Simulated 2km race using a rowing ergometer

a. Time to completion

b. average velocity

A ramped GXT with breath-by-breath analysis was chosen because work rate increases continuously. This type of protocol provides a clear ventilatory threshold, power at this point, can provide power at $\dot{V}O_{2max}$ directly, and is able to provide the information necessary for the 3-min critical power test (power at $\dot{V}O_{2max}$. and power at VT) (Dicks, 2016; Vanhatalo, 2007, 2008). The 3-min all-out critical power test was selected because it requires little time to complete while providing both anaerobic capacity (W') and sustainable mechanical power (Critical Power). These performance determinants are compared to time on the simulated 2km because it is the most commonly compared performance test in rowing. For example, athletes hoping to be selected for US Olympic teams submit 2km times to USA Rowing as part of their portfolio. Moreover, 2km times were used in previous studies which allows our model to be compared to others. However, average velocity was chosen instead of time to complete because of our additional utilization of performance scores, which will be discussed below.

3.2 Model Structure

We propose a multivariate regression model that will, at its inception, include all examined performance determinants. Stepwise regression and/or Principal Components Analysis will be used to reduce the initial set of performance determinants, the logic being that elimination of performance determinants which, at first, appear to not impact performance could be important to determine seasonal variation in performance. Regardless of the performance determinants contributing to the model, the regression will be constrained so that all four categories of performance determinants (aerobic power, anaerobic power, sustainable power, mechanical power) will be included.

To generalize the model to rowers of all skill levels and weight classes we propose the implementation of categorical predictors and separate models for men and women. The choice of gender-specific models is based on the logic that men and women typically do not compete together or against one another, apart from the rare use of mixed boats. Similarly, categorical predictors are planned for skill and weight class. The skill classifications are those already recognized by National and International Rowing organizations: Junior, Collegiate, Elite, and Colt. Skill was chosen rather than age because individuals are similar at the same skill levels than within an age group and some skill levels (e.g., junior) are based on age. For weight class, the categories of open and lightweight will align with the same weight cutoffs currently used by rowing organizations.

In addition to our proposed model components, we have developed new theory to apply the model over multiple seasons.

3.3 Application of Performance Scores to Track Seasonal Changes and Inform Training

The model described above allows us to reduce performance to a single score. By acquiring a large sample, the population distribution can be determined such that changes in performance can be tracked for the individual and compared to the population. Clearly, developing the population distribution is a non-trivial task; it will require multiple samples from multiple teams, different genders, and all skill levels across multiple season. Then, treating each data performance as independent, the distribution of performance can be calculated and defined by typical measures of central tendency and variability (e.g., mean and standard deviation). Because our implementation is based on parametric statistics, an assumption of normality is included. However, if this assumption is violated, data will be transformed appropriately. Outliers will also be identified and eliminated to prevent skewing of data. The score for the athlete would then be calculated as the standard deviations from the population mean (i.e. effect size) and could also be represented to athletes and coaches as a percentile rank.

The use of performance scores has at least three benefits. An advanced implementation strategy based on Bayesian inferential statistics could yield additional benefits and is presented in Chapter 5. First, individual performance could be tracked by comparing scores between tests to reveal how their performance is changing over time. Second, coaches could have rapid feedback to monitor the effectiveness of training and progress between seasons. For example, if a coach sees that all athletes produce low scores (-3) in preseason, they know that offseason training must be adjusted, and training must be improved to reach a competitive level of performance. Alternatively, a marked increase or decrease in performance by an individual or group of athletes could inform the coach of their training status. Furthermore, if a coach sees increased individual performance scores which do not correlate to better race times in a 4 or 8 athlete boat they could examine whether an athlete is holding the boat back or if the athletes are not working together well.

Lastly, like the Athlete Biological Passport Score (ABPS) (Sottas, 2006; Sottas et al., 2006; Thieme, 2010), categories of performance determinants could be presented as subscores that could provide coaches more insight into the training status of their athletes. For example, if a coach notices that the performance of an athlete has not improved, they could examine individual performance predictors such as critical power, max power, or power at $\dot{V}O_{2max}$ to identify areas where the athlete needs to improve. This capability could help coaches individualize training for athletes their athletes.

To summarize, the utility of a performance score lies in the ability to aggregate and compare the score of individuals and populations and to understand how underlying physiological mechanisms contribute to the observed performance. The knowledge garnered from the model should provide better feedback to coaches and enable more informed decisions for training. In Chapter 4 we propose an implementation of this approach, including data collection and testing, model validation, and application in sport settings.

Chapter 4
Implementation plan

4.1 Proposed Testing Procedures

In the previous chapter we outlined a rationale for evaluation that would assess anaerobic capacity, aerobic power, power/fatigue thresholds, and maximal mechanical power in diverse samples of rowers over the course of seasons. In this chapter we consider the implementation plan for these evaluations, including proposed testing protocols and schedule.

4.1.1 GXT

The GXT should be conducted on the first day of testing using a ramp protocol modified from S. A. Ingham, Pringle, Hardman, Fudge, and Richmond (2013) on a Concept 2™ Model D rowing ergometer. To reduce forward-aft motion and to better simulate the feel of open-water rowing, the ergometer will be placed on slides. The drag factor or "load" will be based on gender, weight class, and skill level, to simulate the drag they would feel in an actual boat, based on norms developed by the Australian Institute of Sport (Tanner, 2013). $\dot{V}O_2$ will be determined with open-circuit spirometry on a breath-by-breath basis and heart rate will be monitored from the ECG. Maximum heart rate estimated from the equation (207-0.7*age). Participants will begin with a self-paced 10-minute warmup followed by 3 min of low-load rowing (Damper setting of 1) with a pace of 30 strokes/min. Participants will then perform two build-up strokes followed by five maximal rowing strokes at a rate of 30 strokes/min. Maximum power will be recorded as the average of the five strokes (Nevill, 2011). Participants will then begin to row at their preferred cadence at a power of 100W for 1 minute. After 1 minute, participants will steadily increase their power by 5W/15s (20W/min) until they reach volitional exhaustion, or their power dropped by 10% for 5 strokes(S. A. Ingham et al., 2013). Power at $\dot{V}O_{2peak}$ will be recorded as the average power output the first 30 seconds upon reaching $\dot{V}O_{2peak}$. The first 30s upon reaching $\dot{V}O_{2peak}$ was chosen for calculation to exclude additional power from anaerobic sources (S. A. Ingham et al., 2013). Objective criteria for accepting the test as a maximal effort will include an increase in $\dot{V}O_2$ of less than 150 ml/min during the final minute of test (Taylor, 1955), HR within 10 beat/min of age-predicted maximum, and RER exceeding 1.1. Participants will actively rest 150s with low load rowing before performing a 1-minute self-paced supramaximal effort. $\dot{V}O_2$ will be compared between the ramp test and supramaximal effort and $\dot{V}O_{2peak}$ will be determined to be $\dot{V}O_{2max}$ if the two measures do not differ by 150ml/min or more (Taylor, 1955). Ventilatory threshold (VT) will be calculated by the V-slope method; i.e., regression analysis of $\dot{V}CO_2$ and $\dot{V}O_2$ with breakpoint determined using cumulative sums (changepoint) analysis (Beaver, 1986). The power associated with VT will be recorded as an index of maximal sustainable power.

4.1.2 Critical Power and Velocity

The protocol for determination of critical power has been adapted for rowing by Cheng et al (2012). On a separate day and at least 24 hrs following the maximal GXT, critical power and velocity will be calculated by a 3-min all-out test on a Concept 2™ Model D rowing ergometer on slides with breath-by-breath gas exchange determined with open circuit spirometry. Participants will begin with a self-paced 5-minute warmup followed by 5 minutes of rest. Participants will then perform 3 minutes of low-load rowing (Damper setting of 1) at 133% of their preferred stroke rate (Burnley, 2006; Vanhatalo, 2007, 2008). The damper setting on the ergometer will be adjusted to a drag factor based on their gender, weight class, and skill level based on Australian Institute of Sport norms for rowing (Tanner, 2013). Target power for the test will be calculated as the power midway between power at VT and $\dot{V}O_{2max}$, which is greater than critical power (Dicks, 2016). Concept 2's conversion between power and split ($Split = 500(\frac{2.8}{Power(Watts)})^{\frac{1}{3}}$) will be used to give participants a target split to achieve at their desired stroke rate (Concept2, 2018). Participants will then attempt to maintain this power for 3 minutes. Because this work rate is, by definition, greater than the sustainable work rate, a decrease in power to an asymptotic work rate (i.e. end-test power or critical power) is expected. Power and velocity from the test will be analyzed in 15-second increments and the mean power and velocity over the final 30s will then be used to determine critical power and critical velocity respectively (Burnley, 2006; Dicks, 2016; Vanhatalo, 2007, 2008). $\dot{V}O_2$ was analyzed over the final 30s to determine if $\dot{V}O_{2max}$ was achieved at critical power(Burnley, 2006; Jones, 2010).

4.1.3 Simulated 2km

The simulated 2km will be performed on a Concept 2 Model D rowing ergometer on slides, with a drag factor set based on gender, weight class, and skill level using Australian Institute of Sport norms (Tanner, 2013), under "race conditions" as an objective indicator or competitive performance. Participants will begin with a self-paced 5-minute warmup followed by a 2-minute rest. After the 2-minute rest, participants will row 2000m as fast as possible while encouraged by teammates to ensure maximal effort. Time, power and velocity will be recorded in 500m increments throughout the race. At the completion of 2000m, participants' time, average power, and average velocity will be recorded (Nevill, 2011).

4.2 Model Data Collection

To develop a performance model that will remain valid throughout a season, data must be included over the course of at least one season, including periods when performance might change acutely (e.g., brief periods of high and low training, illness, etc.). To avoid bias from repeated measures on each athlete, a large sample size is needed, and the data points collected for individuals should be collected throughout the season. In this way, the multiple data points provided by athletes could be considered "quasi-independent" because the athletes have changed since the previous test. Data collection should be extended to offseason periods to capture additional variation in performance. We recommend that testing occur at least once a month and separated by at least two weeks except at the start of preseason. The first round of testing serves as a baseline for athletes while the second round serves to determine test-retest repeatability and should be conducted within one week of the first.

Depending on the length of the preseason, the third test should be conducted at the middle and/or at the end of the preseason to identify physiological improvements and efficacy of preseason conditioning. Subsequent testing periods during the competitive season would be conducted monthly with at least one day between the end of testing and competitions to avoid testing related fatigue. Ideally, tests would be conducted the week before important competitions. Here the emphasis should be placed on athletes who might be grouped together in a boat with the experimental goal of determining which class of performance determinants (aerobic capacity/power, anaerobic capacity/power, mechanical power, sustainable power) is most similar in high-performing crews. The final test would occur immediately after the season to provide "end-season" data which should represent each athlete's peak performance and physiological capability.

4.2.1 Proposed Test Schedule:

Preseason

Week 1: Monday: GXT, Wednesday: 3-min Critical Velocity test, Friday: Simulated 2km

Week 2: Monday: GXT, Wednesday: 3-min Critical Velocity test, Friday: Simulated 2km

Week3: No testing

Week 4: Monday: GXT, Wednesday: 3-min Critical Velocity test, Friday: Simulated 2km

Competitive Season

Week 5: Competition week

Week 6: No testing or competition

Week 7: Monday: GXT, Wednesday: 3-min Critical Velocity test, Friday: Simulated 2km

Week 8: Competition week

Week 9: No testing

Week 10: No testing

Week 11: Monday: GXT, Wednesday: 3-min Critical Velocity test, Friday: Simulated 2km

Week 12: Competition week

Week 13: No testing

Week 14: No testing

Week 15: Monday: GXT, Wednesday: 3-min Critical Velocity test, Friday: Simulated 2km

Week 16: Final competition

Post Season

Week 17: Monday: GXT, Wednesday: 3-min Critical Velocity test, Friday: Simulated 2km

4.3 Building the Model

Initially, two models will be developed. The first, a "snapshot model", will be created from the data collected during the first and second rounds of testing. Multivariate regression, with all performance determinants included, will be conducted to produce a prediction equation for performance and weights for each physiological determinant and categorical variable. The aims are threefold: first, to establish test-retest repeatability; second, to examine whether "snapshot" models could remain valid throughout the season; and third, to relate seasonal changes in competitive performance to seasonal changes in physiological performance.

The second model, a seasonal model, will be created from an entire season of data. Multivariate regression with all performance determinants will be used to produce a prediction equation for performance and weights for each physiological determinant and categorical variable. The snapshot and seasonal models would be compared in two ways: first, by the weights assigned to each performance determinant and second, by the fitted scores. The aim of this analysis is to determine whether or not the snapshot model is valid over a season.

4.4 Model Validation

To validate the model, we selected the “leave-one-out cross-validation” method ("Applied Regression Analysis," 2019; "Regression Methods," 2019). An advantage of this approach is that it does not require an additional season of testing for validation. Instead, leave-one-out cross-validation trains data sets without including one subject and then tests the model’s predictive capability with that subject. The process is repeated for all subjects and a prediction sum of squares (PRESS) is generated using Equation 1, where n equals the size of the data set, y_i is the actual value and $\hat{y}_{i(i)}$ is the omitted response value.

$$PRESS = \sum_{i=1}^{n}(y_i - \hat{y}_{i(i)})^2 \qquad \text{Equation (1)}$$

Then, the following equation is used to produce an R^2 where SSTO is the total sum of squares.

$$R^2_{Pred} = 1 - \frac{PRESS}{SSTO} \qquad \text{Equation (2)}$$

If the R^2_{Pred} is low, the model may have too many performance determinants which are adding noise. The models would then need to be regenerated to reduce the number of included performance determinants. Candidate methods include Cluster or Principal Components analysis (to aggregate similar performance determinants) and/or with stepwise regression (to eliminate non-contributing performance determinants).

Despite a similar form, R^2 and R^2_{Pred} cannot be directly compared because the values have slightly different meanings (variance of the model vs variance of deviations). It is possible for model R^2 to be relatively higher than R^2_{Pred} ("Applied Regression Analysis," 2019). So, the primary use of leave-one-out cross-validation will be to determine if R^2 for the initial model decreases significantly when season long data is introduced. Such a hypothesized reduction would support the null hypothesis that the snapshot model is unable to account for seasonal changes.

Another criterion should be analyzed to examine potential differences between the snapshot and seasonal model. The composition and weights of each performance determinant should be compared between each model. If the season long model includes different weights and/or different predictive performance determinants, it is likely that the snapshot model was unable to adequately account for seasonal changes.

These hypothetical approaches are provided to illustrate how snapshots of performance should be evaluated in the context of seasonal change. Hybrid approaches are likely. For example, if a category of performance determinants (e.g. anaerobic capacity) contributes to the prediction of performance at a single point in time but another category of determinants (e.g., aerobic power) accounts for a large proportion of seasonal change, then the models may be reconciled by forcing all categories into the model. Preliminary statistical analyses will therefore be required before the final model can be specified.

4.5 Implementation of Performance Scores

Once the seasonal model has been constructed and validated, the implementation of performance scores is simple in concept but difficult in execution. First, from the data used to create model, a distribution of predicted performances could be generated to produce the population mean and standard deviation. Equation 3 illustrates that an individual's score is the same as a Z-score the calculation:

$$Performance\ Score = \frac{Predicted\ 2k\ Average\ Velocity_{Athlete} - Mean\ Predicted\ 2k\ Average\ Velocity_{Pop}}{Standard\ Deviation_{pop}}$$

Then, if desired, a percentile could be calculated. The scores provided to athletes could then be compared between tests to monitor performance changes. After examination of how the score of the athlete changes, or fails to change, coaches should then consider the physiological determinants to understand why a change occurred.

4.6 Physiological Determinants

In conjunction with a performance score, presentation of the physiological contributors to performance is important because it should help inform athletes, coaches and researchers why a change in performance occurred. Furthermore, physiological performance determinants should be presented so that changes can be tracked and compared within and between athletes. Between athlete comparisons could consider, for example, population distributions of rowers or team distributions of rowing performance.

To track individual changes, changepoint analysis could be implemented to examine if the value of any physiological performance determinant is increasing, decreasing, or remaining the same over time. Individual changes could be compared to the whole team by using the individual's data points and the percentile score relative to the team distribution. A graphical representation of the for each test along with the value of the individual allows the athlete would make visual comparisons easy.

Box plots could be another useful visualization tool because it reduces the presentation of distributions to a few standardized points (e.g., quintiles or standard deviations). For each test, a box plot could be created for the desired performance determinant set to cover 90% of those tested. The advantage of this approach is that it is that the visual influence of outliers is less obvious.

4.7 Sample Size and Statistical Power

The required sample size cannot be calculated at this time. Since the model is conceptual, no previous studies are available to identify meaningful differences in physiological performance when all relevant categories of performance (mechanical power, aerobic capacity/power, anaerobic capacity/power, fatigue thresholds) are considered. We propose to calculate power for each category, and to define sample size on the most variable category of performance. The validation procedures described in the implementation plan will provide replicates of each performance determinant on each subject so that statistical power (sensitivity) to identify a change can be determined during the season when the model is developed.

When calculated, we recommend the use of a desired power (sensitivity) of 80% (β=0.20) and a significance level of 5% (α=0.05). The desired power may be increased with larger samples sizes, but the significance level should be constrained to control the probability of a type 1 error. The test-retest variability of each test will be obtained from the first and second rounds of testing. The change we have chosen to be minimally important is a 2% change in performance (i.e., velocity or 2 km race time). For an assumed average velocity of 4m/s (8-minute 2km time), a 2% change would result in a 10 second change in performance. At elite level regattas, less than 10 seconds often separates first place from last place. Although a finer level of discrimination may be desirable, it may not be practical because other performance determinants are beyond the scope of this thesis (e.g., variations in current across the width of a river, social-behavioral dynamics, etc.) could account for differences of this magnitude.

Chapter 5
Summary

The model and methods we have proposed represent a more holistic approach to performance testing and modeling. When setting design goals for this program, we adopted a user-centric framework that would help coaches and athletes know where physiological improvements could impact performance. Our research has shown that the utility of previous models for this purpose is unproven since they did not consider seasonal changes when physiological performance determinants were modeled. Hypothetically, if used by coaches, previous models might incorrectly emphasize training areas, such as $\dot{V}O_{2max}$, overlooking the importance of improving VT, CV, and max power.

Testing time was another important consideration in our user-centric framework. To be feasible and meaningful, testing should require a minimal amount of time and conducted frequently so changes can be tracked. The invasiveness and long test times for published protocols could hamper coaches' ability to implement performance models. Our analysis of these protocols suggest that they could require coaches to forgo a week of training for testing. Testing that would interfere with training would be burdensome for athletes. The goal of testing is to promote better performance, not prevent it.

Invasive measures would not only increase the difficulty of testing and probably decrease athlete compliance with testing. Although blood sampling for lactate determination is minimally invasive, if a rower were required to have their ear lanced multiple times in a single session, testing could be viewed more as burden than a benefit. Consequently, we selected a non-invasive substitute – ventilatory threshold – as a more acceptable means of testing for athletes. To summarize, our proposed strategy for performance testing could provide more useful information for coaches and athletes and minimize the "human costs" of testing.

We used systematic review to identify four areas of performance relevant to sports similar to rowing (mechanical power, aerobic power/capacity, anaerobic power/capacity, and fatigability threshold/sustainable power). Each area can be integrated with a family of performance determinants, but we were able to identify six ($\dot{V}O_{2max}$, VT, power at $\dot{V}O_{2max}$, power at VT, max power, critical power, and anaerobic capacity or W') that represented all four areas and could be evaluated non-invasively over two days. Furthermore, the proposed model can serve as the basis of future research to fill the gaps in the literature about the impact of physiological changes over a season on performance; test the null hypothesis that "snapshot" models do not remain valid over a season and a "seasonal" physiological model is needed to account for seasonal or career improvements in performance.

The non-invasive and time-efficient testing strategy that we have proposed should enable coaches to track athletes and training throughout the season. It should reduce the time-to-test to three visits (GXT, CP, 2km) and about one hour of actual testing per athlete. With a well-validated model, the simulated 2km could be eliminated which would reduce test time to less than one hour over two days.

With this user-centric design the performance determinants chosen for the model could be used by coaches for both training assessment, boat grouping decisions, and race strategies. One example is critical velocity, which could provide coaches with the maximum pace that athletes can maintain during a race. Therefore, coaches do not need to make grouping decisions based only on predicted 2km times but could examine how athletes achieved their performance. For example, an athlete who maintains a high velocity over the entire race without a "kick" at the start or finish could be contrasted with an athlete who maintains a lower velocity for a majority of the race but has a strong "kick" at the end of the race. These very different racing strategies might produce boats that highlight the respective weaknesses of its athletes. Instead, critical velocity could be utilized to group individuals who have similar fatigue thresholds and sustainable power outputs. A coxswain could use this information to set an appropriate pace for their boat.

5.1 Future Directions

While our research focused on physiological performance determinants, future research could benefit from expanding performance models to include other performance determinants which impact performance. Particularly, areas worthy of consideration are nutritional performance determinants such as meal pattern and food intake (type and amount); and psychosocial performance determinants such as sleep quantity, sleep quality, and athlete mood.

Finally, future research should consider the implementation of Bayesian inference to personalize performance. The steps used for implementation would be similar to those used for the Athlete Biological Passport, except for the included performance determinants.

Briefly, the application of Bayesian inference follows three steps (Gelman, 2013). The first is to establish a full probability model with the joint probability of both the observable and unobservable performance determinants. The second step is to condition the model observed data so that the posterior distribution can be calculated and interpreted using the observed data. The last step is an evaluation of the fit: The model is critiqued on how well it fits the data, how reasonable the conclusions (posterior distributions) are and how sensitive the model is to the assumptions in step one.

The advantage of Bayesian inference for performance tracking is in subsequent evaluation and modification of the posterior distributions. These distributions begin as a population distribution, but individual data can replace the population data to create a score distribution *unique to a specific athlete*. This “adaptive model” application of Bayesian inference is the basis of the World Anti-Doping Agency’s Athlete Biological Passport Score (ABPS) (Sottas, 2006; Sottas et al., 2006). Similarly, a Bayesian performance model could replace a population posterior distribution for performance with performance data unique to a specific athlete. If a test fell outside of the athlete’s distribution then it could then be flagged as an “out of norm” performance, helping coaches make evidence-based decisions to individualize testing and training.

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Academic Vita

John Arnold

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Education

The Pennsylvania State University, University Park, PA May 2019

Schreyer Honors College

Bachelor of Science in Kinesiology (Movement Science)

Minor in Sociology

Dean's List (All semesters)

Relevant Courses

Anatomy	Exercise Physiology	Chemical Principles I & II
Functional Anatomy	Health Policy & Issues	Organic Chemistry
Physiology	Programming for Business and Agencies	

Relevant Business Project

Created a business proposal which detailed the goals, marketing plan, financing, and maintenance of an Integrated Physical Therapy Clinic and Fitness Center

Work Experience

Personal Trainer, *Penn State Fitness and Wellness* January, 2018– Present

- Gathered clients through marketing on campus, designed workout programs to achieve clients goals, led clients through programs, tracked client progress, set performance goals, and prepared clients to be able to exercise independently.

DJ, *Showtime Entertainment* June, 2017– Present

- Organized and facilitated entertainment for weddings, bars, fundraisers, etc. and collaborated with businesses to plan future events and expand the services provided.

Raft Guide, *WISP Resort* May, 2016– August, 2017

- Conducted rafting and kayaking trips, oversaw the safety of guests on the river, and informed guests of other activities available at the resort.

Research

Undergraduate Thesis *Dr James Pawelczyk, The Pennsylvania State University-University Park, PA*

Development of a Predictive Model to Improve Rowing Performance Throughout a Season

- Performed a standardized review of performance modelling and physiological determinants of performance
- Worked with Penn State's statistical department to create a Bayesian based performance model
- Determined which variables would be included in the model and created an implementation plan for testing

Activities

Penn State Club Track and Field– Competitive Sports team

Penn State Club Track and Field THON– Fundraising subgroup of club T&F

ServeState Students for Philanthropy– Community Service Organization

Licenses and Certificates

CPR and First Aid

ACSM Certified Personal Trainer

Awards

President's Freshman Award, The Pennsylvania State University

Junior and Senior Evan Pugh Scholar Award, The Pennsylvania State University