ÇUKUROVA UNIVERSITY
INSTITUTE OF NATURAL AND APPLIED SCIENCES

PhD THESIS

Shahaboddin DANESHVAR

PREDICTING THE PERFORMANCE OF CROSS-COUNTRY SKIERS USING MACHING LEARNING METHODS

DEPARTMENT OF COMPUTER ENGINEERING

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ABSTRACT

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The purpose of this thesis is to develop new regular and feature selection-based models for predicting the racing times of cross-country skiers by using machine learning and feature selection methods. Particularly, six popular machine learning methods including Optimized-General Regression Neural Network (OPGRNN), General Regression Neural Network (GRNN), Support Vector Machine (SVM), Multilayer Perceptron (MLP), Radial Basis Function Neural Network (RBFNN), and Single Decision Tree (SDT) have been used, whereas Relief-F has been employed as the feature selector. Several models have been developed to predict the racing time of cross-country skiers using physiological data along with a rich set of survey-based data. By performing 10-fold cross-validation, the prediction errors of the models have been calculated using root mean square error (*RMSE)*. The results emphasize that OPGRNN-based prediction models show superior performance and can be categorized as a feasible tool to predict the racing time of cross-country skiers. Furthermore, significant advantages such as the non-exercise-based usage and the applicability to a broader range of cross-country skiers make the prediction models proposed in this study easy-to-use and more valuable.

Key Words: Machine learning, racing time, cross-country skiers, prediction

ÖZ

DOKTORA TEZİ

MAKİNE ÖĞRENME YÖNTEMLERİ KULLANILARAK KROS KAYAKÇILARIN PERFORMANS TAHMİN EDİLMESİ

Shahaboddin DANESHVAR

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Bu tezin amacı, makine öğrenimi ve nitelik seçme yöntemlerini kullanarak kros kayakçılarının yarış sürelerini tahmin etmek için yeni regüler ve nitelik seçimine dayalı modeller geliştirmektir. Optimize Edilmiş Genel Regresyon Sinir Ağı (OPGRNN), Genel Regresyon Sinir Ağı (GRNN), Destek Vektör Makinesi (SVM), Çok Katmanlı Algılayıcı (MLP), Radyal Temel Fonksiyon Sinir Ağı (RBFNN) ve Tekli Karar Agacı (SDT) olmak üzere altı popüler makine öğrenme yöntemi kullanılırken, özellik seçici algoritma olarak Relief-F uygulanmıştır. Zengin bir anket tabanlı veri seti ile birlikte fizyolojik verileri kullanarak kros kayakçılarının yarış sürelerini tahmin etmek için çeşitli modeller geliştirilmiştir. 10 kat çapraz doğrulama uygulanarak, modellerin tahmin hataları ortalama kare hatası (*RMSE*) hesaplanarak değerlendirilmiştir. Sonuçlar, OPGRNN tabanlı tahmin modellerinin üstün performans gösterdiğini ve kros kayakçılarının yarış süresini tahmin etmek için uygun bir araç olarak kategorize edilebileceğini göstermektedir. Ayrıca, egzersize dayalı olmayan kullanım ve daha geniş bir kros kayakçı grubuna uygulanabilirlik gibi önemli avantajlar, bu çalışmada önerilen tahmin modellerini kullanımı kolay ve daha değerli kılmaktadır.

Anahtar Kelimeler: Makine Öğrenmesi, Yarış Zamanı, Kros Kayakçılar, Tahmin

EXTENDED ABSTRACT

In cross-country skiing, skiers utilize their own condition to move across snow-covered terrain, instead of utilizing ski lifts or other kind of special equipment. For the foremost decade of the 20th century, solely traditional styles were used for cross-country ski racing, where the cross-country skis stay along each other within parallel tracks prepped into the snow. For this kind of skiing, different techniques exist including kick double-pooling, herringbone, diagonal stride which are used as a function of different factors such as steepness of terrain, skier's fitness and skiing speed. During the mid of 1980's, a competitive skiing style named as "skating" was introduced among the skiers for better competition. The skating style is a movement looking like to ice skating.

Independent of the type of skiing, the racing time of cross-country skiers is influenced by multiple parameters, such as the upper body power (UBP), maximum oxygen uptake (VO_2max), maximum heart rate (HRmax), sex, age, height, weight and body mass index (BMI). The effort accomplished by the different parts of the body like shoulder, arm and trunk muscles is known as the UBP rate. The force delivered by the chest area during cross-country skiing is passed on through the poles and aids forward movement. VO_2max is interpreted as top ability to move and absorb oxygen while performing strenuous endurance exercise. Even though the direct measurement of UBP and VO_2max utilizing laboratory-based experimental setup is the most precise strategy, it includes a few constraints. As a matter of first importance, the equipment for measuring UBP and VO_2max is not yet normally available because of its significant expense. Particularly, the direct determination of UBP relies on special ergometers which, in general, are only found in specific sports research facilities. Moreover, the direct measurement does not allow to test more than one subject at once. Consequently, in the case of higher number of subjects, it is not feasible to conduct the measurement tests for all subjects. Additionally, measuring UBP and VO_2max is a tedious procedure which necessitates the attendance of a qualified and experienced staff.

In corresponding with the sport's development and expanding popularity as a recreational sport, it is necessary to understand the physiological, biomechanical, and neurological elements that are responsible for better performance prediction of skiers. Given the difficulty of conducting conventional laboratory-based physiological and biomechanical evaluations with respect to an enormous number of skiers, particularly when these testing resources are not even easily accessible, it is important to devise alternative ways to indirectly estimate the racing time of cross-country skiers via machine-learning models. Non-exercise prediction models dependent on self-declared demographics, training and racing habits, just as past experience can give an advantageous way to estimate the performance of cross-country skiers. This methodology does not need a direct measurement of UBP and VO_2max, is reasonable, time-proficient, and feasible for large groups. Despite the fact that there exist a few studies attempting to estimate the racing time in other sports, the number of studies for predicting the racing times of cross-country skiers is exceptionally constrained and none of these previous works leverage machine learning strategies. Besides, the larger part of previous works utilizes measurement-based variables to predict the racing time of cross-country skiers instead of creating non-exercise regression models relying on survey information.

The purpose of this thesis is to develop new regular and feature selection-based models for predicting the racing times of cross-country skiers by using machine learning and feature selection methods. Particularly, six popular machine learning methods including Optimized-General Regression Neural Network (OPGRNN), General Regression Neural Network (GRNN), Support Vector Machine (SVM), Multilayer Perceptron (MLP), Radial Basis Function Neural Network (RBFNN), and Single Decision Tree (SDT) have been used, whereas Relief-F has been employed as the feature selector algorithm. Several models have been developed to predict the racing time of cross-country skiers using physiological data along with a rich set of survey-based data. By performing 10-fold cross-validation, the prediction errors of the models have been calculated using root mean square error (*RMSE)*.

The results reveal that among the evaluated machine learning methods, Optimized GRNN (OPGRNN) exhibits the best prediction performance and can be considered as a feasible tool to predict the racing time of cross-country skiers from survey-based data with acceptable RMSEs. The GRNN-based models yield the second lowest RMSEs. There is no strict order between SVM-based and MLP-based prediction models, but the RMSEs related to SVM-based and MLP-based prediction models are always higher than those of GRNN-based prediction models, and lower than those of RBFNN-based prediction models. The age and wave variables have been found to be the most relevant attributes in predicting the racing time of cross-country skiers. Among the set of all prediction models built by using various machine learning methods, it is seen that the OPGRNN-based model including age, height, weight, gender, number of BMT races completed within the past 5 years and 10 years (BMT5 and BMT10), average number of hours of cross-country skiing during preceding 6 weeks (HrsXC), average number of hours of strength and power training (SP) during preceding 6 weeks (HrsSP), number of ski races completed that season prior to the 2013 BMT race (RaceComp), number of ski races planned for the entire season (RacePlnd), and wave comparatively gives the lowest RMSE value with 10.77 min for prediction of racing time of cross-country skiers.

GENİŞLETİLMİŞ ÖZET

Kros kayağında kayakçılar, telesiyej veya diğer özel ekipman kullanmak yerine karla kaplı arazide hareket etmek için kendi kondisyonlarını kullanmaktadırlar. 20. yüzyılın ilk on yılında, karda hazırlanan paralel pistlerde kros kayaklarının yan yana durduğu arazi yarışları için sadece geleneksel stiller kullanılmıştır. Bu tür bir kayak için, arazinin dikliği, kayakçının kondisyonu ve kayak hızı gibi farklı faktörlerin bir fonksiyonu olarak kullanılan kick double-pooling, balıksırtı, çapraz adım gibi farklı teknikler mevcuttur. 1980'lerin ortalarında, rekabeti geliştirmek için kayakçılar arasında "paten" adı verilen rekabetçi bir kayak stili tanıtıldı. Paten, buz patenine benzeyen bir harekettir.

Kayak türünden bağımsız olarak, kros kayakçılarının yarış süresi, üst vücut gücü (UBP), maksimum oksijen tüketimi (VO_2max), maksimum kalp atış hızı (HRmax), cinsiyet, yaş, boy, ağırlık ve vücut kitle indeksi (BMI) gibi birçok parametreye bağlıdır. Omuz, kol ve gövde kasları gibi vücudun farklı bölgelerinin gerçekleştirdiği efor UBP oranı olarak bilinmektedir. Kros kayağı sırasında göğüs bölgesi tarafından verilen kuvvet kayak direklerden geçirilir ve ileriye doğru harekete yardımcı olur. VO_2max, yorucu dayanıklılık egzersizi yaparken hareket etme ve oksijeni absorbe etme konusunda en iyi yetenek olarak tanımlanır. UBP ve VO_2max'ın laboratuvar tabanlı deney düzeneği kullanılarak doğrudan ölçümünün en kesin strateji olmasına rağmen, birkaç sınırlama içermektedir. Öncelikle UBP ve VO_2max'ı ölçmek için kullanılan ekipman, önemli masrafı nedeniyle henüz her yerde mevcut değildir. Özellikle, UBP'nin doğrudan belirlenmesi, genel olarak yalnızca belirli spor araştırma tesislerinde bulunan özel ergometreler kullanılarak yapılmaktadır. Ayrıca doğrudan ölçüm aynı anda birden fazla deneğin test edilmesine izin vermemektedir. Sonuç olarak, denek sayısının daha fazla olması durumunda, tüm denekler için ölçüm testlerini yürütmek mümkün olmamaktadır. Ek olarak, UBP ve VO_2max ölçümü, nitelikli ve deneyimli personelin katılımını gerektiren sıkıcı bir prosedürdür.

Sporun gelişmesi ve rekreasyonel bir spor olarak artan popülaritesi ile bağlantılı olarak, kayakçıların daha iyi performans tahminiyle ilişkili olan fizyolojik, biyomekanik ve nörolojik unsurları anlamak gerekmektedir. Çok sayıda kayakçı için geleneksel laboratuvar tabanlı fizyolojik ve biyomekanik değerlendirmeler yapmanın zorluğu göz önüne alındığında, özellikle bu test kaynaklarına kolayca erişilemediğinde, kros kayakçıların yarış zamanını makine öğrenme modelleri aracılığıyla dolaylı olarak tahmin etmek için alternatif yollar geliştirmek önemlidir. Egzersiz dışı tahmin modelleri, kayakçıların beyan ettiği demografik özelliklere, antrenmana, yarış alışkanlıklarına ve geçmiş deneyimlere bağlıdır. Bu metodoloji, doğrudan bir UBP ve VO_2max ölçümüne ihtiyaç duymaz, zaman açısından ve büyük gruplar için uygundur. Diğer spor branşlarındaki yarış süresini tahmin etmeye çalışan birkaç araştırma olmasına rağmen, kros kayakçılarının yarış sürelerini tahmin etmeye yönelik yapılan çalışmaların sayısı son derece kısıtlıdır ve önceki çalışmaların hiçbiri makine öğrenimi stratejilerini kullanmamaktadır. Ayrıca, önceki çalışmaların büyük bir kısmı, anket bilgilerine dayanan egzersiz dışı regresyon modelleri oluşturmak yerine kros kayakçılarının yarış sürelerini tahmin etmek için ölçüm temelli değişkenler kullanmaktadır.

Bu tezin amacı, makine öğrenme ve özellik seçme yöntemlerini kullanarak kros kayakçılarının yarış sürelerini tahmin etmek için yeni klasik ve özellik seçimine dayalı modeller geliştirmektir. Özellikle, Optimize Edilmiş Genel Regresyon Sinir Ağı (OPGRNN), Genel Regresyon Sinir Ağı (GRNN), Destek Vektör Makinesi (SVM), Çok Katmanlı Algılayıcı (MLP), Radyal Temel Fonksiyon Sinir Ağı (RBFNN) ve Tekli Karar Ağacı (SDT) dahil olmak üzere altı popüler makine öğrenme yöntemi kullanılırken, özellik seçici algoritma olarak Relief-F kullanılmıştır. Fizyolojik veriler ve zengin bir anket tabanlı veri seti kullanarak kros kayakçılarının yarış sürelerini tahmin etmek için çeşitli modeller geliştirilmiştir. 10 katlı çapraz doğrulama yapılarak, modellerin tahmin hataları, ortalama kare hatası (RMSE) kullanılarak hesaplanmıştır.

Sonuçlar, değerlendirilen makine öğrenme yöntemleri arasında OPGRNN'nin en iyi tahmin performansını sergilediğini ve kros kayakçıların yarış sürelerini kabul edilebilir RMSE'lerle anket tabanlı verilerden tahmin etmek için uygun bir araç olarak kabul edilebileceğini ortaya koymaktadır. GRNN tabanlı modeller ikinci en düşük RMSE'leri üretmiştir. SVM tabanlı ve MLP tabanlı tahmin modelleri arasında kesin bir sıralama yoktur, ancak SVM tabanlı ve MLP tabanlı tahmin modellerinin ürettiği RMSE'ler her zaman GRNN tabanlı tahmin modellerininkinden daha yüksek ve RBFNN tabanlı tahmin modellerininkinden daha düşüktür. Yaş ve dalga değişkenlerinin, kros kayakçılarının yarış süresini tahmin etmede en alakalı özellikler olduğu gözlemlenmiştir. Çeşitli makine öğrenimi yöntemleri kullanılarak oluşturulan tüm tahmin modelleri seti arasında yaş, boy, kilo, cinsiyet, son 5 yıl ve 10 yıl içinde tamamlanan BMT yarışlarının sayısı (BMT5 ve BMT10), önceki 6 hafta boyunca ortalama kros kayağı saati (HrsXC), önceki 6 hafta boyunca ortalama güç antrenmanı saati sayısı (HrsSP), 2013 BMT yarışından önce o sezon tamamlanan kayak yarışlarının sayısı (RaceComp), tüm sezon için planlanan kayak yarışı sayısı (RacePlnd) ve dalga değişkenlerini içeren OPGRNN tabanlı modelin kros kayakçılarının yarış süresinin tahmini için 10.77 dakika ile en düşük RMSE değerini ürettiği görülmüştür.

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LIST OF ABBREVIATIONS

BMI	:	Body Mass Index
BMT 5	:	Number of BMT races completed within the past 5 years (2009-2013)
BMT10	:	Number of BMT races completed within the past 10 years (2004-2013)
CI	:	Confidence Interval
DLT	:	Distributed Ledger Technology
DTF	:	Decision Tree Forest
GE	:	Gross Efficiency
GNSS	:	Global Navigation Satellite Systems
GRNN	:	Generalized Regression Neural Networks
GXT	:	Graded Exercise Test
HR		Heart Rate
HRmax		Maximal Heart Rate
HrsOther	:	Average number of hours for all other types of training during preceeding 6 weeks
HrsSP	:	Average number of hours of strength & power training (SP) during preceeding 6 weeks
HrsTot	:	Average total number of hours of training during preceeding 6 weeks?
HrsXC	:	Average number of hours of cross country skiing (XC) during preceeding 6 weeks
MAE	:	Mean Absolute Error
MAPE	:	Mean Absolute Percentage Error
MFANN	:	Multi-layer Feed-forward artificial Neural Network
MLP	:	Multilayer Perceptron

MLR	:	Multi Linear Regression
MSE	:	Mean Squared Error
NMN	:	Normethanephrine
η2p	:	Partial Eta Squared
PXC	:	Cross-country Skiing Performance
R	:	Multiple Correlation Coefficient
RaceComp	:	Number of ski races completed that season prior to the 2013 BMT race?
RacePlnd	:	Number of ski races planned for the entire season, including the 2013 BMT race
RBF	:	Radial Basis Function
RMSE	:	Root Mean Square Error
SDT	:	Single Decision Tree
SRM	:	Structural Risk Minimization
SS	:	Skiing Speed
STC	:	Skiing Time Coefficient
SVM	:	Support Vector Machine
SVM-Sigmoid	:	Support Vector Machine with the sigmoid kernel function
SVM-Linear	:	Support Vector Machine with the linear kernel function
SVM-Poly	:	Support Vector Machine with the polynomial kernel function
SVR	:	Support Vector Regression
UBP	:	Upper Body Power
VO_2max	:	Volume Oxygen Maximum
XC	:	Cross-country
YRS10	:	Number of years of ski racing during the past 10 years

YRSALL	:	Number of years of ski racing experience throughout your lifetime

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1. INTRODUCTION

1.1. Overview of Cross-Country Skiing

The sport of cross-country skiing is thought to have originated over 4,000 years ago in Northern Europe. In cross-country skiing, skiers utilize their own condition to move across snow-covered terrain, instead of utilizing ski lifts or other kind of special equipment . For the most part of the twentieth century, cross-country ski racing consisted only of the classical style, in which the skis remain parallel to each other within parallel tracks groomed into the snow. In this style of skiing, there are several distinct techniques (i.e., diagonal stride, double-poling, kick double-pole, and herringbone) that are preferentially used as a function of terrain steepness, skiing speed, as well as skier fitness. By the mid-1980s, a new crosscountry skiing style called “skating” had become popular among competitive ski racers. The skating style is a motion similar to ice skating (Alsobrook, 2005). Figure 1 and Figure 2 show typical examples of classic style and skate skiing, respectively.

Figure 1.1. The example for classic style of cross-country skiing

Cross-country skiing is a very strenuous sport because the cross-country skiers intensively use all of upper and lower body musculature (Heil and Camenisc, 2014). Regardless of the style of skiing, the most important component that determines the performance of a cross-country skier in a race is his/her ability to utilize the upper body power (UBP) (Marsland et al., 2012).

Figure 1.2. The example for skate skiing of cross-country skiing

Cross-country ski racing consisted only of the classical style, in which the skis remain parallel to each other. In this style of skiing, the skier strides uphill by springing from one ski to another while pushing with the opposing pole in a motion similar to running. The double pole technique is used while classical skiing in flat terrain; the skier pushes on both poles simultaneously while bending slightly at the waist, which allows assistance by the trunk muscles. By the mid-1980s, a new skiing style called “skating” had become popular in cross-country ski racing. Ski-skating is a motion similar to ice skating: the skis are turned outward in a V shape, and the skier moves laterally from ski to ski while pushing with both poles. Today, skating and classical races are held as separate events, and most racers participate in both events (Alsobrook, 2005).

1.2. Performance of Cross-Country Skiers

There are several parameters that affect the performance of cross-country skiers in races. These parameters include racing Time , maximal oxygen uptake (VO2max),maximal heart rate (HRmax), gender, age, height, weight and body mass index (BMI), upper body power (UBP) cross skiing performance.

UBP is the rate at which work can be performed using the arm, shoulder, and trunk muscles. Power generated by the upper body during cross-country skiing is transmitted through the poles and assists in forward motion. For instance, the upperbody has been appeared to contribute as much as half to the aggregate propellingforce during uphill skating and 15% to 30% during uphill classical skiing. Although measurement using experimental setup is the direct and most accurate method to determine UBP, this method involves several limitations. First of all, the equipment for measuring UBP is not yet usually accessible due to its high cost. The tests of UBP have all been based upon custom-designed ergometers which can only be found in specific sports research laboratories. In addition, the measurement of UBP hasn't got standardized as it is still a relatively new physiological construct. Also, measuring UBP is a time-consuming process and it requires the presence of a qualified and experienced staff.

VO_2max is defined as the maximum ability to transport and consume oxygen during strenuous endurance exercise and is considered the single best measure of cardio-respiratory fitness. The direct measurement of VO_2max during a maximal graded exercise test (GXT) is accepted as the most accurate method for the assessment of aerobic power. Cycle ergometer or treadmill graded exercise tests (GXT) are commonly used for accurate measurement of VO_2max. Maximal tests require costly laboratory equipment, trained staff and are labor intensive.

Also, when the number of subjects is large, it is not practical to apply VO_2max tests for all subjects .

Given the impracticality of performing traditional laboratory-based physiological and biomechanical assessments on a large number of skiers, especially when these testing resources are not even available, it is necessary to develop alternative models to predict the performance of cross-country skiers

Non-exercise regression models based on self-reported demographics, training and racing habits (both past and present), as well as past experience can provide a convenient means to predict the performance of cross-country skiers. This approach does not require a direct measurement of UBP and VO_2max, is inexpensive, time-efficient and realistic for large groups (Abut et al., 2017).

The sport's evolution and increasing popularity as a recreational sport is the desire by sports scientists to better understand the physiological, biomechanical, and neurological factors that best predict cross skiing performance. Given the impracticality of performing traditional lab-based physiological and biomechanical assessments on a large number of skiers, especially when these testing resources are not even available, it is necessary to develop alternative models to predict the performance of cross-country skier .

1.3. Motivation, Purpose and Contributions of the Thesis

Although there exist some studies in literature that try to predict racing times in different sports [8–10], the number of studies on prediction of racing times of cross-country skiers is very limited and none of these studies benefits from the power of machine learning methods. Most of the studies employ measurement-based variables to predict the performance of cross-country skiers [11–13]. In fact, to the best of our knowledge, there is a single study in literature [14] that uses the non-exercise predictor variable "lean mass" to predict the race performance of elite cross-country skiers using linear regression.

Abut et al. (Abut, 2017) the first time used machine learning methods and survey-based data for predicting the racing times of cross-country skiers. Particularly, three popular types of artificial neural networks (ANN) including Multilayer Feed-Forward Artificial Neural Network (MLP), General Regression Neural Network (GRNN) and Radial Basis Function Neural Network (RBFNN) have been used for model development. The utilized dataset is made up of samples related to 370 cross-country skiers with heterogeneous properties, and includes physiological variables such as gender, age, height, weight and body mass index (BMI) along with a rich set of survey-based data. The performance of the three ANN-based methods on prediction of racing time of cross-country skiers has been found to be comparable to each other. Particularly, the *RMSE*s of MLP based prediction models change from 19.43 min to 22.82 min. Similarly, the *RMSE*s of GRNN-based prediction models vary between 18.58 min and 23.24 min. Finally, the *RMSE*s of RBFNN-based models are between 20.70 min and 25.36 min.

The major differences between the current research and the studies from related literature can be summarized as follows:

- This is the first study in literature that proposes to use machine learning methods and survey-based data for predicting the race times of cross-country skiers.
- This is the first study in literature that applies feature selection in order to reveal the discriminative features of the race times of cross-country skiers. The Relief-F algorithm combined with a ranker search has been used to perform the feature selection operations.
- This is the first study to include heterogeneous sample of cross-country skiers in the dataset. The past studies focused on predicting the performance of elite cross-country skiers only.

- The number of samples in the dataset that will be used in this thesis is 370, which is way higher than the ones used in the past studies.
- Six types of machine learning methods including Optimized-General Regression Neural Network (OPGRNN), General Regression Neural Network (GRNN), Support Vector Machine (SVM), Multilayer Feed-Forward Artificial Neural Network (MLP), Single Decision Tree (SDT), and Radial Basis Function Neural Network (RBFNN) have been used for model development. Several race time prediction models have been developed using different data sets and combination of the predictor variables. By performing 10-fold cross-validation, the prediction errors of the models have been calculated calculated using root mean square error (*RMSE).*

1.4. Overview of the Dataset

The dataset that will be used in this thesis has been obtained from Dan Heil, who is a professor at Health and Human Development Department of Montana State University, Bozeman, MT, USA. The details of dataset generation is given below.

Participants in the 2013 Boulder Mountain Tour (BMT) cross country skiing race (February 2; Sun Valley, Idaho, USA) were recruited using an E-mail list-serve a week after the race. The BMT is a 32 km point-to-point skate ski race with a net elevation drop of 335 m from 2231 m (starting line) to 1901 m (finishing line) and often attracts the fastest professional and age-group skiers in North America. After providing informed consent to the purpose and methodology of the study, participants were asked a series of self-report questions about BMT ski racing background, personal ski training and racing history, as well as demographic information. Completion of the entire survey required answers for 18 questions. The survey responses were then matched to official race completion times that were published on-line and publicly available. These methods were approved by the Institutional Review Board of Montana State University (Bozeman, MT, USA).

1.5. Demographic Information

Participants were asked to self-report their gender (male or female), their age on the day of the 2013 BMT race (years), as well as body height (m) and body mass (kg). Body height and mass were then used to calculate the BMI.

1.6. Training and Racing Habits

It is generally assumed that those who race more frequently will tend to have a higher quality and quantity of training both within a given season, as well as across successive racing seasons. Thus, two questions asked how many of the past 10 years had the participant competed in at least one local or national caliber ski race, as well as how many years over their lifetime. For the current 2012-2013 ski racing season, participants were also asked the number of ski races in which they had competed before the 2013 BMT race, as well as the total number of ski races for which they were planning in the entire 2012-2013 ski season. Several additional common metrics of training amongst skiers is hours of training per week, as well as hours of training per year. Hours of weekly training was broken into three separate questions that asked for typical training habits over the six weeks preceding the 2013 BMT: (1 Weekly hours spent cross country skiing? 2) Weekly hours spent doing strength or power specific activities (e.g., weight lifting)? 3) Weekly hours spent doing any other traditional forms of training (e.g., running, cycling, swimming). These three answers were then summed to represent the average total weekly hours of training self-reported for the weeks just prior to the race.

1.7. BMT Race Experience

Given several fairly unique characteristics of the BMT race course (i.e., point-to-point with a net elevation drop of 335 m from start to finish), it seemed necessary to assess the experience level of each participant with racing the BMT course. Thus, participants were asked how many past BMT races within the past 5 years, as well as the past 10 years, that they had competed

Brief statistical of the predictor variables and target variable of the dataset is given in Table 1.1. Figure 1.1 shows an image of the first 20 rows from the dataset.

Table 1.1. Statistical information about the dataset

Predictor Variables	**Minimum**	**Maximum**	**Mean**	**Standard Deviation**
Wave	1	7	4.20	1.91
Age (years)	43	86	47.56	13.19
Height (m)	1.72	2.05	1.74	0.10
Weight (kg)	74.09	115.90	70.00	12.79
BMI	24.83	36.20	22.91	2.73
Gender	0	1	0.62	0.48
BMT5	1	5	1.83	1.86
BMT10	1	10	3.06	3.45
YRS10 (years)	1	11	7.16	3.58
YRSALL (years)	1	46	12.32	10.40
HrsXC (hours)	0	17	5.70	3.26
HrsSP (hours)	0	15	1.83	1.83
HrsOther (hours)	3	30	3.40	3.60
HrsTot (hours)	2	5	2.95	0.89
RaceComp	0	20	2.29	3.29
RacePlnd	1	40	5.14	5.48
RaceTime (min)	69.14	214.09	106.19	24.84

	A	B	C	D	E	F	G	H	I	J	K	L	M	N	O	P	Q	R	S
1	RaceTime			Age	SRBH	SRBM	BMI	Gender1	Gender2	BMT5	BMT10	YRS10	YRSALL	HrsXC	HrsSP	HrsOther	HrsTot	RaceComp	RacePlnd
2	(hrs)	AG	Wave	(yrs)	(m)	(kg)	(kg/m^2)	(0/1)	(F/M)	(yrs)	(yrs)	(yrs)	(yrs)	(hrs)	(hrs)	(hrs)	(cat)	(numb)	(numb)
3	1,15241833	M 25-29	1	57	1,73	74,09	24,84	0	M	1	1	1	1	11	3	3	3	20	31
4	1,15264417	M 25-29	1	25	1,85	80,91	23,53	1	M	0	0	11	15	12	1	2	5	20	40
5	1,15265972	M 25-29	1	28	1,75	67,27	21,90	1	M	3	3	11	20	12	2	2	5	17	32
6	1,1527075	M 18-24	1	24	1,75	77,27	25,16	1	M	2	2	11	13	13	1	2	4	14	28
7	1,15293306	M 25-29	1	28	1,83	77,27	23,10	1	M	0	0	11	15	16	2	1	5	15	27
8	1,15296194	M 18-24	1	19	1,91	81,82	22,55	1	M	1	1	7	12	13	2	2	5	10	23
9	1,15331361	M 25-29	1	25	1,85	75,00	21,81	1	M	1	1	11	12	10	3	2	5	8	20
10	1,15351833	M 25-29	1	26	1,85	77,27	22,48	1	M	1	1	11	13	17	2	1	5	11	20
11	1,15600222	M 25-29	1	29	1,75	70,45	22,94	1	M	3	3	11	14	8	1	1	4	6	18
12	1,16655028	M 35-39	1	38	1,83	75,00	22,42	1	M	1	1	6	12	6	0	1	3	4	8
13	1,18006361	M 35-39	1	40	1,83	86,36	25,82	1	M	0	1	11	33	15	0	0	4	3	8
14	1,18997194	M 30-34	1	34	1,93	100,00	26,84	1	M	0	2	11	25	5	1	7	3	4	8
15	1,19007806	M 40-44	1	43	1,83	76,36	22,83	1	M	5	10	11	13	8	2	2	3	5	10
16	1,19017583	M 45-49	1	45	1,70	65,91	22,76	1	M	3	8	11	32	6	1	2	4	7	11
17	1,20487667	M 30-34	1	33	1,83	75,00	22,42	1	M	1	1	5	16	9	2	7	3	2	6
18	1,20517889	M 18-24	1	24	1,70	54,09	18,68	1	M	1	1	11	13	5	2	3	3	7	14
19	1,20618667	M 25-29	1	29	1,78	72,73	23,01	1	M	5	8	8	7	8	2	1	3	4	10
20	1,21342639	M 40-44	1	41	1,80	70,45	21,66	1	M	4	9	11	25	2	0	3	2	2	8

Figure 1.3. Image of the first 20 rows from the dataset

1.8. Literature Review

Reid et al. (2020) aimed to measure ski movement characteristics using 3-dimensional kinematic data set collected on highly skilled skiers during slalom racing simulations and to compare these measurements with theoretical predictions based primarily on ski geometric properties. In middle steepness (19 °) slalom turns, ski edge angles reached maximum 65.7 ± 1.7 ° and 71.0 ± 1.9 ° values for 10 and 13 m doorways. Turning radii reached the minimum values of 3.96 ± 0.23 and 4.94 ± 0.59 m for 10 and 13 m tracks. These values are in good agreement with the theoretical estimates of the turning radius based on the edge angle by Howe (2001). Other results of the study support recent advances in understanding the role ski scoop plays in groove formation during carving, and also point to the need for further study of how ski geometric and physical properties interact to determine the trajectory of skiing, especially at low levels, for example edge angles. These results have important implications for understanding the implications that ski design can have for skier technique and tactics in competitive slalom skiing [1].

Supej et al. (2020) aimed to summarize published research by the GNSS on the methodological and practical aspects of evaluating alpine ski performance. Methodologically, in conjunction with trajectory analysis, it has been proven that a resolution of 1-10 cm, achievable with the most advanced GNSS systems, provides acceptable accuracy. The antenna should be positioned to follow the trajectory of the skier's center of mass (CoM) as closely as possible, and the prediction of this trajectory can be further improved by applying advanced modeling and / or other computerized approaches. From a practical point of view, effective evaluation requires consideration of a large number of performance-related parameters, including gate-to-door times, trajectory, speed and energy distribution. The video footage should be synchronized with GNSS data for analysis, both more comprehensive and more accessible to coaches / athletes. In summary, recent advances in GNSS technology allow, at least to some extent, precise biomechanical analysis of performance in real time on an entire Alpine ski racetrack [2].

Ekström (2020) attempted to estimate future timings in Vasaloppet using timings from past and present controls. Linear regression predictions were made using deep neural networks and supported vector machine regression. The current control and timings up to now are used as input data. The timing to be predicted into the future was used as output data. This resulted in 28 estimated functions made for each start row. With 11 initial rows, the final number of estimated transfer functions is 308. All methods have significantly improved the estimation with up to six times lower average error compared to the currently used method. It has been found that deep neural networks have the ability to make the best predictions, but the training time required is unrealistic given the available resources. Support vector regression performed almost as well as deep neural networks but was trained much faster. Linear regression had the worst performance of machine learning algorithms and the fastest training time. Improvement ranged from the lower average hourly error up to six times the average hourly error to 1.3 times the average hourly error depending on the evaluated transfer function estimate. The improvements made for the predictions from the first check, where the absolute error was by far the largest, yielded the best results. Therefore, the worst predictions about the original model are most developed [3].

Biathlon performance consists of ski speed, shooting accuracy (ShAcc) and shooting time (ShT). For coaches, it is very important to evaluate the performance level for the selection of biathletes to specific events. Dzhilkibaeva et al. (2019) aimed to compare two different approaches (relative ski speed, SS% and ski time coefficient, STC) to analyze the ski performance of biathletes and to analyze the relationship between different performance parameters between the two competition levels (World Cup, WC). Data from four competitive seasons were analyzed, including 166 male and 184 female biathletes. The correlation between SS% in IC and WC was similar for both genders (males $r = .81$; females $r = .78$ compared to the correlation between STC in IC and WC (males $r = .80$; females $r = .75$).) ($p <.001$), whereas the mean absolute percent error is higher for STC (1.2% and 1.8% versus 18% and 22%). In IC, SS%, ShAcc, and ShT explained 54% and 45% ($p <.001$) of the overall WC rank for males and females, respectively. For this reason, it is recommended to use SS% to evaluate the ski performance of biathletes [4].

Nilsson (2019) correlated physiological and anthropometric test results (X variables) with FIS points (Y variables) to investigate the predictive power of physiological and anthropometric variables for competitive performance in skiing. The significance of the included test results was examined using bivariate and multivariate data analysis. As a result, it was found that the inclusion of aerobic test results, neither alone nor in combination with anthropometric variables, did not predict competitive performance of young elite mountain skiers. Major component analysis shows that male and female young mountain skiers can be distinguished based on test results, but none of the tests included are significant for sport-specific performance [5].

Jonsson et al. (2019) investigated the biomechanical differences in double poling (DP) between gender and performance level were investigated in female and male cross-country skiers during a classical race (10/15 km). Skiers were divided into faster and slower according to race performance: women faster ($n = 20$), women slower ($n = 20$), men faster ($n = 20$), and men slower ($n = 20$). DP on a straight section of the track, joint and pole angles at the pole plant (PP) and pole exit, loop characteristics, and the use and coordination pattern of heel raising (heel elevation higher body position in PP) were analyzed. Faster women and men had 4.3% and 7.8% higher DP rates than slower ones (both $P < 0.001$). Faster men had 6.5% longer cycles than slower men ($P < 0.001$). Faster skiers then stopped heel raising than slower skiers. (women: $1.0 \pm 3.5\%$ versus $2.0 \pm 3.4\%$, $P < 0.05$; men: $3.9\% \pm 2.4\%$ of cycle time versus PP, P 0.8 ± 3.2 of <0.001). At PP, faster skiers and male skiers had a smaller pole angle than the vertical and a larger ankle-to-hip and ankle-to-shoulder angle, resulting in a more pronounced forward body inclination. However, they thought that most of the differences were likely due to the higher DP rate [6].

Bunker et al. (2019) aimed to provide a critical analysis of Machine Learning literature with a focus on the application of Artificial Neural Network (ANN) to prediction of sports outcomes. In doing so, he identified the learning methodologies used, data sources, appropriate model assessment tools, and specific difficulties in predicting sports outcomes, which later led to the proposal for a new sports prediction framework in which machine learning can be used as a learning strategy [7].

Windhaber et al. (2019) sought to evaluate whether spiroergometry performance in adolescent Alpine ski racers could predict progress into a professional career later. For over 10 years in a row, adolescent skiers of the regional Austrian Youth Skiers Association (local level) have been subjected to annual medical examinations, including extensive bicycle spirergometry. Performance was determined at constant (2 and 4 mmol / l serum lactate) and individual (individual anaerobic threshold (IAT) and lactate equivalent (LAE)) thresholds. Data from the last available test were compared between skiers who later progressed to the professional level (Austrian national ski team) and those who did not. Ninety-seven mountain skiers ($n = 51$ men; $n = 46$ women); mean age 16.6 (range 15-18) was included. Of these, 18 adolescents ($n = 10$ men; $n = 8$ women) started a professional career. No significant difference was found for maximum oxygen uptake (VO2max). Athletes progressing to the professional level had significantly higher performance and VO2 at the LAE. In addition, male professionals had significantly higher performances at fixed thresholds and IAT. Performance and VO2 in LAE and thus the ability to generate power at a certain metabolic threshold has been determined as the optimal spiroergometric parameter to predict a later professional career [8].

Stöggl et al. (2018) reviewed the scientific literature to determine the effects of pacing strategy on the performance of elite XCS racers. Four electronic databases were searched using relevant topics and keywords. All 27 articles reviewed applied correlative designs to examine the effectiveness of different speed strategies. None of the articles include the use of an experimental design. Also, potential changes in external conditions (eg weather, ski characteristics) were not taken into account. A comparable number of studies have been found focusing on ice skating or classical technique. In most cases, a positive pacing rate was observed with some indication that higher level athletes and those with more endurance and strength were using a more even pace strategy. The ability to achieve and maintain a long cycle length across all terrain types was an important determinant of performance in all studies included, but not for cycle rate. In general, uphill performance has been closely related to overall race performance, uphill performance has been most associated with the success of female skiers, and performance on flat terrain has been found to be more important for male skiers. As a result, they suggested that skiers of all levels could improve their performance with more specific training in techniques (i.e., sustaining long cycles and choosing appropriate techniques without sacrificing cycle rate), along with training for endurance and greater strength [9].

Nilsson et al. (2018) investigated the predictive power of aerobic test results and anthropometric variables in the FIS ranking of young elite mountain skiers. Twenty-three male and female adolescent elite mountain skiers' results for two seasons were included in multivariate statistical models. Physical work capacity was determined by V̇O2 peak, blood lactate concentration ([HLa] b) and heart rate (HR) during the ergometer cycle. Anthropometric variables were body height, body weight and calculated BMI. There was no significant relationship between competitive performance and aerobic working capacity or anthropometric data in neither male nor female skiers. Pre-season physical tests and anthropometric data could therefore not predict the end of season FIS rankings. The best regression ($R2$) and prediction ($Q2$) models of the FIS slalom (SL) and giant slalom (GS) rank reached $R2 = 0.51$ to 0.86, $Q2 = -0.73$ to 0.18, showing that it is not a valid model. This study failed to establish V̇O2peak and other included variables as determinants of competitive performance [10].

Supej et al. (2018) investigated the relationship between slope and initial strategy during mountain skiing. Eight FIS skiers performed starts on a flat (3°) and steep (21°) incline employing five different strategies. Their times, trajectories and velocities were monitored with a GNSS system and video. A significant interaction was observed between slope incline and start strategy with respect to the skier's exit velocity ($p < 0.001$, $\eta 2p = 0.716$), but not for the start section time ($p = 0.732$, $\eta 2p = 0.037$). On the almost flat incline, both section time ($p = 0.022$, $\eta 2p = 0.438$) and exit velocity ($p < 0.001$, $\eta 2p = 0.786$) were influenced significantly by start strategy, with four V2 skate-pushes being optimal. On the steep incline, neither section time nor exit velocity was affected significantly by start strategy, the fastest section time and exit velocity being attained with four and two V2 skate-pushes, respectively. In conclusion, these findings demonstrate that the start strategy exerts considerable impact on start performance on almost flat inclines, with strategies involving three or more V2 skate-pushes being optimal. In contrast, start performance on the steep incline was not influenced by strategy [11].

To date, there is no evidence of the relationship between competitive performance and 'acute stress response' markers. Danese et al. (2018) this study; (i) acute sympatho-adrenergic activation during endurance exercise in recreational runners by measuring free metanephrine (MN) and normetanephrine (NMN) plasma levels before and after the half-marathon run; (ii) designed to investigate the relationship between metanephrine levels and duration of work. 26 amateur runners (15 men, 11 women) aged 30 to 63 years were recorded. Quantification of MN and NMN was done by LC-MS / MS. Anthropometric, ergonomic and routine laboratory data were recorded. Statistical analysis included paired T-test, univariate and multivariate regressions. Post-run values of MN and NMN increased approximately 3.5 and 7-fold compared to baseline values, respectively. ($p < 0.0001$ for both). NMN pre-run values and pre / post-run delta values showed a significant direct and inverse relationship ($p = 0.021$ and $p = 0.033$, respectively) with running performance. No correlation was found for MN values. NMN is a reliable marker of sympatho-adrenergic activation by exercise and is thought to be predictive of endurance performance of each athlete. Adaptation phenomena that do not occur only in the adrenal medulla may represent the biological mechanism underlying this relationship. Further study of sympatho-adrenergic activation, competitive performance, and educational status should consider measuring these metabolites rather than their unstable precursors [12].

Hållmarker et al. (2018) examined the relationship between participation in a long-distance skiing race and the incidence of cardiovascular diseases (CVD) to address the hypothesis that lifestyle reduces incidence. A cohort of 399 630 subjects in Sweden, half were skiers in the world's largest ski race, and half were non-skiers. Non-skiers were frequency matched for gender, age, and year of race. Individuals with severe diseases were excluded. The endpoints were death, myocardial infarction, or stroke. The subjects were followed up for a maximum of 21.8 years and median of 9.8 years. We identified 9399 death, myocardial infarction, or stroke events among non-skiers and 4784 among the Vasaloppet skiers. The adjusted hazard ratios (HRs) comparing skiers and non-skiers were 0.52 [95% confidence interval (CI) 0.49–0.54] for all-cause mortality, 0.56 (95% CI 0.52–0.60) for myocardial infarction and 0.63 (95% CI 0.58–0.67) for stroke and for all three outcomes 0.56 (95% CI 0.54–0.58). The results were consistent across subgroups: age, gender, family status, education, and race year. For skiers, a doubling of race time was associated with a higher age-adjusted risk of 19%, and male skiers had a doubled risk than female skiers, with a HR 2.06 (95% CI 1.89–2.41). The outcome analyses revealed no differences in risk of atrial fibrillation between skiers and non-skiers. This large cohort study provides additional support for the hypothesis that individuals with high level of physical activity representing a healthy lifestyle, as evident by their participation in a long-distance ski race, have a lower risk of CVD or death [13].

Fornasiero et al. (2017) for the first time examined a vertical competition that investigated the relationship between laboratory measurements and uphill performance through multiple regression analysis. Nine high-level ski mountaineers (20.6 ± 3.0 years old, VO2max 69.3 ± 7.4 mL / min / kg). Performed an anthropometric assessment for the laboratory and the ski-mountaineering grade exercise test (GXT) for VO2max, gross efficiency (GE), ventilation thresholds (VTs), blood lactate thresholds (LTs) and power output with these indices were examined. News of vertical gain, length and average slope are as follows: 460 m, 3 km, 15.3% for young men and older women; 600 m, 3.5 km, 17.1% for the elderly. According to the reviews, the average race time was 23:35 ± 01:25 (min: sec). Learning power output during the race is 3.40 ± 0.34 W / kg, equal to 79.0 ± 3.5% of the maximal calculated at GXT and 95.3 ± 5.2% of VT2. The most variable with performance is VO2 (mL / min / kg) in VT2 (R = 0.91, $p < 0.001$) with 80% of the performance variation (Probable R 2 = 0.80, p = 0.001). When GE was included in the analysis, the regression model was significantly improved (improved R2 = 0.90, p = 0.031). The study showed that the power output maintained during a vertical race is close to talking power with VT2 and is related to the physiological characteristics of the athletes. In particular, two variables, VT2 and VO2 in GE, which can be measured with a particular GXT, account for 90% of the performance variation in a ski-mountaineering vertical race. Training programs, according to

Fornasiero et al., Should focus on increasing the GE with technical development as well as the maximum development of VT2 [14].

Stöggl et al. (2017) attempted to analyze whether specific skating tests and cycling length are determinants of cross-country skiing (XC) performance of youth and to evaluate gender-specific differences. The data set includes data from 41 subjects, 33 men and 16 women. Each subject has completed the wheeled ski tests of both short (50 m) and long (575 m) periods. Test results were correlated with on snow XC skiing performance (PXC) based on 3 skating and 3 classical distance competitions (3 to 6 km). The main findings of the current study were: 1) Anthropometrics and maturity status were related to boys', but not to girls' PXC; 2) Significant moderate to acceptable correlations between girls' and boys' short duration maximal roller skiing speed (double poling, V2 skating, leg skating) and PXC were found; 3) Boys' PXC was best predicted by double poling test performance on flat and uphill, while girls' performance was mainly predicted by uphill double poling test performance; 4) When controlling for maturity offset, boys' PXC was still highly associated with the roller skiing tests [15].

Table 1.2. Overview of studies for prediction of racing time – Part 1

Study	Purpose of the Study	Dataset	Method	Metric	Result
Reid et al. (2020)	to measure the ski movement properties collected on the skiers during the slalom race simulations	3D kinematic data set	DLT, Challis residual autocorrelation algorithm, genlock	*RMSE*	27.2-44.5 m
Supej et al. (2020)	to summarize published research by the GNSS on the methodological and practical aspects of evaluating alpine ski performance	Not available	GNSS	Position accuracy	1-10 cm
Ekström (2020)	to predict timings in Vasaloppet using supervised machine learning	Twelve rows and 117.682 columns of data were used between 2012 and 2019.	SVR, Linear Regression	MAE, MSE	MAE: 0.1- 0.85 min (Linear Regression) MSE: 2-8 min (SVR)
Dzhilkibaeva et al. (2019)	to compare two different approaches to analyse biathletes' skiing performance	166 male and 184 female biathletes	Multiple Linear Regression	MAPE	18% for males and 22% for females
Nilsson (2019)	to identify physiological and anthropometric variables valid for prediction of competitive performance in alpine skiing	twenty-three young elite male and female alpine skiers.	Multiple Linear Regression	R^2	0.51-0.86

Table 1.3. Overview of studies for prediction of racing time – Part 2

Study	Purpose of the Study	Dataset	Method	Metric	Result
Jonsson et al. (2019)	To investigate the biomechanical differences in double poling (DP) between gender and performance level	80 skiers, 40 men and 40 women	Linear Regres-sion	R^2	0.799
Bunker et al. (2019)	to provide a critical analysis of the literature in the field of Machine Learning with a focus on the application of Artificial Neural Network to prediction of sports outcomes	Not available	ANN	Not available	Not availab le
Windhaber et al. (2019)	to evaluate whether spiroergometry performance in adolescent alpine ski racers can predict later advancement to a professional career	ninety-seven mountain skiers data (51 men, 46 women)	Non-parametr ic Mann-Whitney-U-Test	p-value	0.005-0.160 for males, 0.096-0.921 for females
Stöggl et al. (2018)	to review the scientific literature in an attempt to determine the effects of pacing strategy on the performance of elite racers	Not available	Four electro-nic data-bases were searche d using relevant subject head-ings and key-words	Not available	Athlete s with greater endura nce and strengt h can utilize more pacing

Table 1.4. Overview of studies for prediction of racing time – Part 3

Study	Purpose of the Study	Dataset	Method	Metric	Result
Nilsson et al. (2018)	to investigate the predictive power of aerobic test results and anthropometric variables on ranking of junior elite alpine skiers	twenty-three elite junior alpine skiers,	Multi-variate data analysis; principal compo-nent analysis	R^2	0.51- 0.86
Supej et al. (2018)	to explored the relation-ship between incline and start strategy during skiing	seven male and one female member of the Swedish alpine ski team	Linear Regression	η2p	Between slope incline and start strategy with respect to the skier's exit velocity (η2p = 0.716), On the almost flat incline, both section time (p = 0.022, η2p = 0.438) and exit velocity (p < 0.001, η2p = 0.786) were influenced significantly by start strategy
Danese et al. (2018)	to predict an athlete's perfor-mance	26 amateur runners (15 males, 11 females)	Univariate and Multivariate Linear Regression	Pearson's correlation coefficient	0.66 for NMN variation and VO2max

Table 1.5. Overview of studies for prediction of racing time – Part 4

Hållmarker et al. (2018)	to investigate relationship between taking part in a long-distance ski race and incidence of cardiovascular diseases	A cohort of 399.630 subjects	Cox regression models	Hazard ratios	0.52 for all-cause mortality, 0.56 for myocardial infarction, and 0.63 for stroke
Fornasiero et al. (2017)	to explore the association between laboratory measures and uphill performance by means of multiple regression analysis	nine (seven men, two women) high-level ski-mountaineers	Linear Regression	R^2	0.90 when GE was included in the analysis
Stöggl et al. (2017)	to analyze whether specific roller skiing tests and cycle length are determinants of youth cross-country (XC) skiing performance	Forty-nine young XC skiers (33 boys, 16 girls)	Stepwise Multiple Linear Regression	Pearson's Product Moment Correlations	0.52- 0.74 for anthropometrics, age and maturity status, 0.80-0.85for single tests

2. OVERVIEW OF METHODS

In this section, the theoretical foundations of machine learning and feature selection algorithms used to develop the prediction models are given.

2.1. Generalized Regression Neural Network

A GRNN architecture includes four layers, the names of which are given in Figure 2.1.

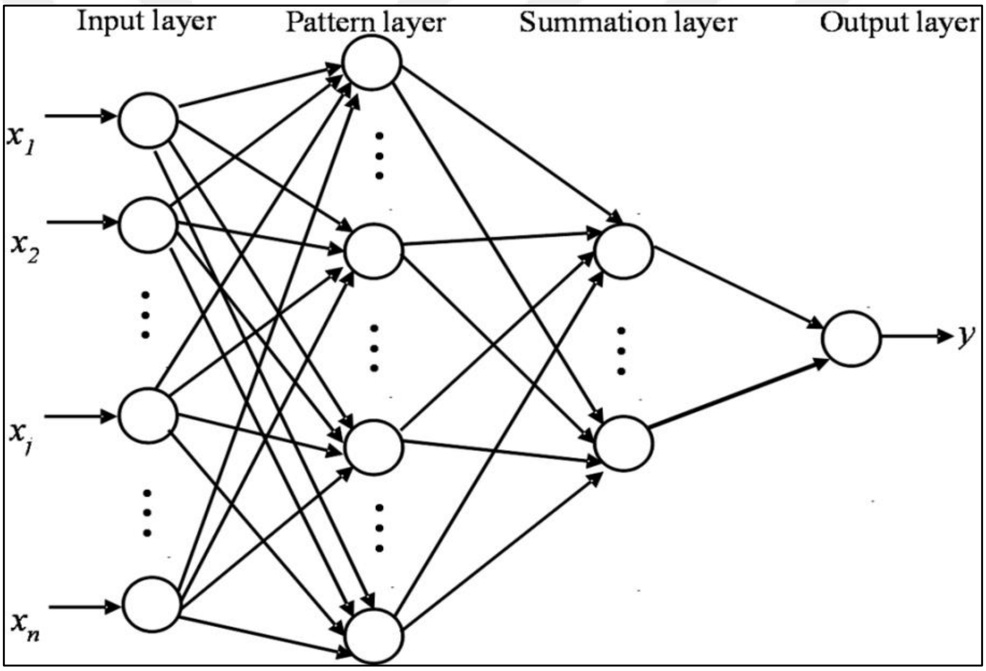

Figure 2.1. A typical GRNN architecture

Total number of features specifies the number of input structures. As shown in Figure 2.1, each layer is directly connected to next layer without having any feedback loops. The summation layer is comprised of a single division unit and summation units. A normalization of the output set is performed by both the summation and output layer.

GRNN can be considered as a technique to predict the joint pdf of *x* and *y*, when only a training set is given. Let *f (x, y)* represent the joint pdf of a vector random variable, *x* and a scalar random variable, *y*. In this case, the conditional expected value of *y* given X, is calculated by (2.1.).

$$E[y|X] = \frac{\int_{-\infty}^{\infty} y f(X,y) dy}{\int_{-\infty}^{\infty} f(X,y) dy} \tag{2.1.}$$

In case *f (x, y)* is not known, a sample of observations of x and *y* has to be used to predict *f (x, y)*. Let *f'(X, Y)* (given by (2.2.)) be the probability estimator. *f'(X, Y)* includes sample values X^i and Y^i of the random variables x and *y*. In (2.2.), *n* is the number of sample observations, σ is the width and *p* is the dimension of the vector variable x.

$$f'(X,Y) = \frac{1}{(2\pi)^{(p+1)/2}\sigma^{(+1)}} \frac{1}{n} \sum_{i=1}^{n} \exp[-\frac{(X-X^i)^T(X-X^i)}{2\sigma^2}] \exp[-\frac{(Y-Y^i)^2}{2\sigma^2}] \tag{2.2.}$$

The scalar function D_i^2 *is* given by (2.3.) and (2.4.) is obtained after carrying out the necessary integrations.

$$D_i^2 = (X - X^i)^T (X - X^i) \tag{2.3.}$$

$$Y'(X) = \frac{\sum_{i=1}^{n} Y^i \exp(-\frac{D_i^2}{2\sigma^2})}{\sum_{i=1}^{n} EXP(-\frac{D_i^2}{2\sigma^2})} \tag{2.4.}$$

It should be noted that the final equation given by (2.4.) is applicable to problems involving numerical data.

2.2. Optimized Generalized Regression Neural Network

Much of the success of machine learning has come from building larger neural networks. This allows these models to perform better on various tasks, but also makes them more expensive to use. Larger models take more storage space which makes them harder to distribute. Larger models also take more time to run and can require more expensive hardware.

Model compression aims to reduce the size of models while minimizing loss in accuracy or performance. In machine learning, pruning is removing unnecessary neurons or weights.

One of the disadvantages of GRNN models compared to multilayer perceptron networks is that GRNN models are large due to the fact that there is one neuron for each training row. This causes the model to run slower than multilayer perceptron networks when using scoring to predict values for new rows.

The optimized GRNN offers neuron pruning option, as illustrated in Figure 2.2., to remove unnecessary neurons from the model after the model has been created. Removing unnecessary neurons has three benefits:

1. The size of the stored model is reduced.
2. The time required to apply the model during scoring is reduced.
3. Removing neurons often improves the accuracy of the model.

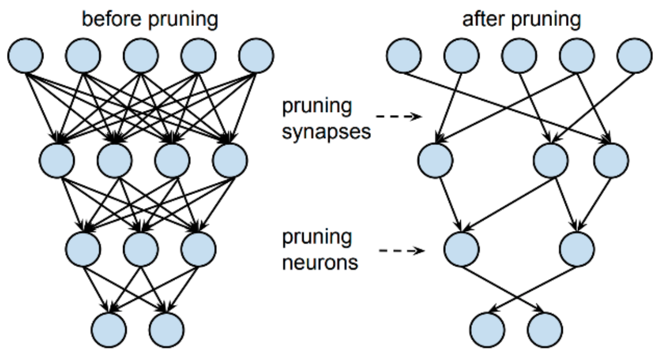

Figure 2.2. The pruning process used by OPGRNN

2.3. Support Vector Machines

SVM is one of the most promising statistical learning methods for classification and regression. (Vapnik, 1995) developed the principles of SVM. Since then, SVM have gained enormous popularity owing to the fact that SVM having many effective features, and providing good performance. Instead of the ERM principle, which is used by artificial neural networks, SRM has been adopted in SVM (Gunn et al., 1997). The error in the training set is minimized in the ERM, whereas the expected risk is minimized in SRM. The generalization ability, which is one of the main aims of statistical learning, of SVM comes from this difference. Although SVM were originally designed to solve classification problems, they have been lately restructured to solve regression problems (Vapnik et al., 1997).

2.3.1. Linear SVM

We are given the training data $(x_i, y_i), (i = 1, ..., \ell)$, where x is a d-dimensional input vector with $x \in \Re^d$ and the output vector is $y \in \Re$. (2.5.) shows the linear regression model (Vapnik, 2000):

$$f(x) = \langle \omega, x \rangle + b, \qquad \omega, x \in \Re^d, \; b \in \Re, \tag{2.5.}$$

In (2.5.), the target function is represented by $f(x)$ and $\langle .,. \rangle$ gives the dot product in $\Re^d$.

To measure the empirical risk, some sort of loss function definition is required. The ε-insensitive loss function, which is proposed by Vapnik (Vapnik, 2000), is the most frequently used function. (2.6.) defines the ε-insensitive loss function:

$$L_\varepsilon(y) = \begin{cases} 0 & \text{for } |f(x) - y| \le \varepsilon \\ |f(x) - y| - \varepsilon & \text{otherwise} \end{cases} \tag{2.6.}$$

The optimization problem given in (2.7.) (Gunn, 1998) should be solved to find out the optimal $\bar{\omega}$ and $\bar{b}$ values

$$\min \ \frac{1}{2}\|\omega\|^2 + C\sum_{i=1}^{\ell}(\xi_i^- + \xi_i^+) \tag{2.7.}$$

with constraints:

$$\begin{aligned} &\mathrm{y_i} - \langle \omega, x_i \rangle - b \le \varepsilon + \xi_i^+, \\ &\langle \omega, x_i \rangle + b - \mathrm{y_i} \le \varepsilon + \xi_i^+, \\ &\xi_i^+, \xi_i^- \ge 0, \quad \mathrm{i}=1,........,\ell \end{aligned} \tag{2.8.}$$

In (2.8.), there exists toleration for the deviations larger than ε and the tradeoff between the flatness of $f(x)$ is determined by *C*. The deviations from the ε-tube are represented by the variables ξ^- and ξ^+.

The dual optimization problem given in (2.9.)

$$\max_{\alpha,\alpha^*} -\frac{1}{2}\sum_{i=1}^{\ell}\sum_{j=1}^{\ell}(\alpha_i^* - \alpha_i)(\alpha_j^* - \alpha_j)\langle x_i, x_j\rangle - \sum_{i=1}^{\ell} y_i(\alpha_i^* - \alpha_i) - \varepsilon\sum_{i=1}^{\ell}(\alpha_i^* + \alpha_i) \tag{2.9.}$$

with constraints:

$$0 \le \alpha_i, \alpha_i^* \le C, \qquad i = 1,...,\ell \ ,$$
$$\sum_{\mathrm{i}=1}^{\ell}(\alpha_i - \alpha_i^*) = 0 \tag{2.10.}$$

has to be solved, which in turn gives the optimum values of the Lagrange multipliers α and α^*, while $\overline{\omega}$ and $\overline{b}$ are given by

$$\overline{\omega} = \sum_{i=1}^{\ell}(\alpha_i^* - \alpha_i)x_i \quad ,$$
$$\overline{b} = -\frac{1}{2}\left\langle \overline{\omega},(x_r + x_s)\right\rangle \ , \tag{2.11.}$$

where x_r and x_s are support vectors (Gunn, 1998).

2.3.2. Nonlinear SVM

Nonlinear SVM can be constructed using a nonlinear mapping ϕ of the input space onto a higher dimension feature space. (2.12.) shows the nonlinear regression model

$$f(x) = \langle \omega, \phi(x)\rangle + b, \quad \omega, x \in \Re^{\mathrm{d}} \ , b \in \Re \ , \tag{2.12.}$$

Where

$$\overline{\omega} = \sum_{i=1}^{\ell} (\alpha_i - \alpha_i^*)\phi(x_i),$$
$$\left\langle \omega, \overline{\phi}(x) \right\rangle = \sum_{i=1}^{\ell} (\alpha_i - \alpha_i^*) \langle \phi(x_i), \phi(x) \rangle = \sum_{i=1}^{\ell} (\alpha_i - \alpha_i^*) K(x_i, x),$$
$$\overline{b} = -\frac{1}{2} \sum_{i=1}^{\ell} (\alpha_i - \alpha_i^*)(K(x_i, x_r) + K(x_i, x_s)) \tag{2.13.}$$

the support vectors are represented by x_r and x_s . A Kernel function *K* satisfying Mercer's conditions has been used to explain dot products (Vapnik, 2000).

After $\overline{b}$ is integrated into the kernel function, (2.12.) becomes:

$$\sum_{i=1}^{\ell} (\alpha_i - \alpha_i^*) K(x_i, x) \tag{2.14.}$$

Many different kernel functions including the radial basis function (RBFNN), the polynomial function and the sigmoid function exist. However; RBFNN, as defined in (2.15.) is the most commonly used Kernel function:

$$K(x, x') = \exp\left(-\frac{\|x - x'\|^2}{2\rho^2}\right). \tag{2.15.}$$

In (2.15.) the width of the RBFNN function is defined by ρ.

2.4. Multilayer Perceptron

Neural networks are composed of simple elements operating in parallel. These elements are inspired by biological nervous systems. As in nature, the network function is determined by the connections between elements. A neural network can be trained to perform a particular function by adjusting the values of the connections (weights) between the elements. Commonly neural networks are adjusted, or trained, so that a particular input leads to a specific target output. Such a situation is shown in Figure 2.1. Here, the network is adjusted, based on a comparison of the output and the target, up to the network output matches the target. Typically many such input/target output pairs are used to train a network. Batch training of a network proceeds by making weight and bias changes based on an entire set (batch) of input vectors. Incremental training changes the weights and biases of a network as needed after presentation of each individual input vector. Incremental training is sometimes referred to as ‘‘online’’ or ‘‘adaptive’’ training. Neural networks have been trained to perform complex functions in various fields of application including pattern recognition, identification, classification, speech, and vision and control systems. Today neural networks can be trained to solve problems that are difficult for conventional computer programs or human beings (Saltan, 2008).

Considering the geometry of the network, there are several types of neural networks: Hopfield, Hamming, Campenter and Grossberg, Kohonen, multi-layer feed forward neural network and others (Lippmann, 1987). Neural networks with different geometry are used for solving various problems.

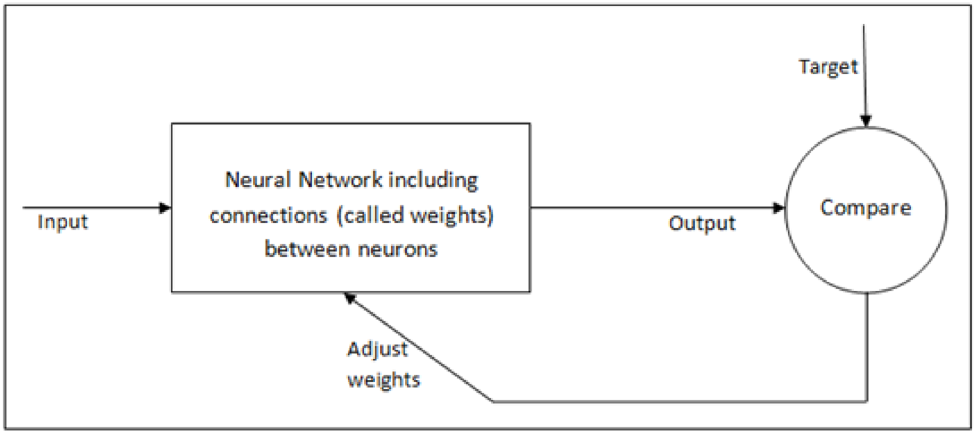

Figure 2.3. Concept of an artificial neural network

The fist three types of neural networks are usually used for binary input data and with problems of classification into classes. The last two types of neural networks are appropriate for the approximation of an unknown function (Ambrozic, 2003).

The geometry of a multilayer feed-forward neural network is shown in Figure 2.3. Input units are connected to the first layer of hidden units which are further connected to the units of the second hidden layer. The units of the last hidden layer are connected to the output units. The input units represent the input data, and the output units represent the output data. The hidden layers may be considered as a black box which performs the necessary transformations of the input data so that the target output data are obtained.

Each unit is represented by its value y_i^k : Each connection between the units is represented by its weight w_{ij}^k ; where index i corresponds to the unit number of the k^{th} layer, while index j corresponds to the unit number of the $(k\text{-}1)^{th}$ layer. The input layer is denoted by 0, whereas the output layer is denoted by n_1: The signals travel in one direction only, i.e. from the input layer towards the output layer.

The value of a unit is multiplied by the corresponding weight and added to the value of the signal in the unit of the next layer. In addition, the value of bias neuron or threshold ϑ_i^k is added to the equation, which is given in (2.18) (Ambrozic & Turk, 2003).

$$y_i^k = f\left(\sum_{i=1}^{n_{k-1}} w_{ij}^k y_i^{k-1} + \vartheta_i^k\right) \tag{2.18}$$

Activation function *f (.)* enables the modeling of an arbitrary nonlinear relation between input and output variables. Different functions could be used as an activation function. The usual choices of activation function are a sigmoid function, Gaussian and radial basis function.

The behavior of the neural network depends on the values of weights w_{ij}^k and thresholds ϑ_i^k which have to be determined by the training procedure. The supervised training is in fact a general optimization problem in which the minimum of error E_p is sought

$$E_p = \frac{1}{2}\sum_{i=1}^{n_0}\left(t_{pi} - y_{pi}^{nl}\right)^2 , \tag{2.19}$$

where t_{pi} are the target output values, y_{pi}^{nl} are the values of neurons in the output layer, i.e. the output values evaluated by neural network, n_0 is the number of neurons in output layer, i.e. the number of output variables (Ambrozic, 2003).

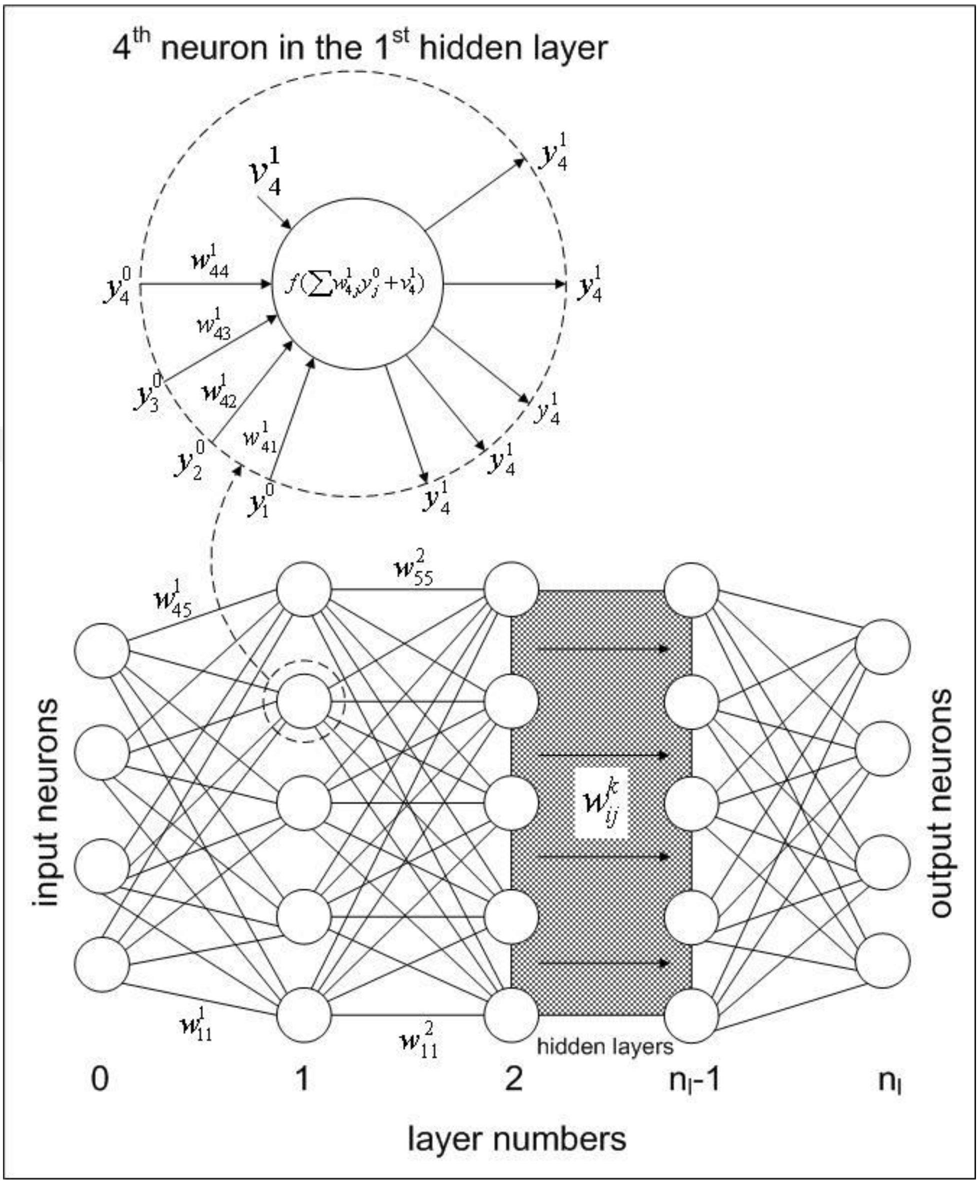

Figure 2.4. Geometry of a multilayer feed-forward neural network

2.5. Single Decision Trees

SDT is differentiated from other regression techniques in two aspects which are its simplicity and potential effectiveness in making decisions. Experiments with SDT in various domains show that it performs well even with large enough samples [18]. The values for minimum rows in a node, minimum size node to split and maximum tree levels determine the quality of SDT on prediction models. Unlike linear regression models that calculate the coefficients of predictors, tree regression models calculate the relative importance of predictors. The relative importance of predictors can be computed by summing up the overall reduction of optimization criteria like RMSE. The main difference between a regression tree and a classification tree is the how you measure the "badness" of a node. There are various ways to do it for both regression and classification trees. For regression trees, you could use sum of squared error or median absolute deviation or some other function

2.6. Radial Basis Function Network

RBFNN's appeared as a variant of artificial neural network in the last years of 1980. Nonetheless, their roots are settled in much more pattern recognition techniques. These techniques can be clustering, mixture models, potential functions, spline interpolation and functional approximation.

RBFNN network includes several layers and the first layer has input neurons. These neurons feed the feature vectors into the network. The second one is the hidden layer that calculates the result of the main functions. The last layer is the output layer that calculates a linear combination of the main functions (Park and Sanberg, 1991). Simple structures of these networks give a decreasing for training time and make possible learning in stages.

RBFNN has the feed-forward structure. It has one layer that consists of hidden units. These units are completely adjusted with the output units. (2.18) indicates the output units (ψ_j) from a linear combination of the main functions (Ghosh-Dastidar et al., 2008).

$$\psi_j(x) = K\left(\frac{\left\| x - c_j \right\|}{\sigma_j^2}\right) \tag{2.18.}$$

$f : R^n \rightarrow R^1$ is estimated by using an RBFNN network. $x \in R^n$ is an input, $\psi(x, c_j, \sigma_j)$ is the j^{th} function with centre $c_j \in R^n$, width σ_j, and $w = (w_1, w_2, ..., w_m) \in R^M$ is the vector of linear output weights. M represents the main number function. The M centres $c_j \in R^n$ are connected to obtain $c = (c_1, c_2, ..., c_m) \in R^{nM}$. Lastly, the widths are connected to obtain $\sigma = (\sigma_1, \sigma_2, ..., \sigma_M) \in R^M$. The output of the network for $x \in R^n$ and $\sigma \in R^M$ is shown by (2.19).

$$F(x, c, \sigma, \omega) = \sum_{j=1}^{M} (\omega_j \psi(x, c_j, \sigma_j)) \tag{2.19.}$$

Suppose that $y = (y_1, y_2, ..., y_n)$ is the weighted output vector and $(x_i, y_i) : i = 1, 2, ..., N$ is a series of training pairs. For each $c \in R^{nM}$, $\omega \in R^M, \sigma \in R^M$ and for random weights $\lambda_{i,} i = 1, 2, ..., N$, which are taken as positive numbers to point out importance of definite domains of the input space, set (2.20) (Wright et al., 2013).

$$E(c, \sigma, \omega) = \frac{1}{2} \sum_{i=1}^{N} \left[\lambda_i (y_i - F(x_i, c, \sigma, \omega)) \right]^2 \tag{2.20.}$$

2.7. Relief-F Algorithm

The algorithm of Relief-F is given in Pseudocode 1. Relief-F randomly selects an instance R_i (line 3), but then searches for k of its nearest neighbors from the same class, called nearest hits H_j (line 4), and also k nearest neighbors from each of the different classes, called nearest misses $M_j(C)$ (lines 5 and 6). It updates the quality estimation $W[A]$ for all attributes A depending on their values for R_i, hits H_j and misses $M_j(C)$ (lines 7, 8 and 9). The update formula is similar to that of Relief, except that the contribution of all the hits and all the misses are averaged. The contribution for each class of the misses is weighted with the prior probability of that class $P(C)$ (estimated from the training set). Since the contributions of hits and misses in each step should be in [0,1] and also symmetric it should be ensured that misses' probability weights sum to 1. As the class of hits is missing in the sum, each probability weight has to be divided with factor $1-P(class(R_i))$ (which represents the sum of probabilities for the misses' classes). The process is repeated for m times.

Input: for each training instance a vector of attribute values and the class value
Output: the vector W of estimations of the qualities of attributes

1. set all weights $W[A] := 0.0$;
2. **for** i := 1 **to** m **do begin**
3. randomly select an instance R_i;
4. find k nearest hits H_j;
5. **for** each class $C \neq class(R_i)$ **do**
6. from class C find k nearest misses $M_j(C)$;
7. **for** A := 1 **to** a **do**
8. $W[A] := W[A] - \sum_{j=1}^{k} \text{diff}(A, R_i, H_j)/(m \cdot k) +$
9. $\sum_{C \neq class(R_i)} [\frac{P(C)}{1-P(class(R_i))} \sum_{j=1}^{k} \text{diff}(A, R_i, M_j(C))]/(m \cdot k)$;
10. **end**;

Pseudocode 1. The algorithm of Relief-F

Selection of k hits and misses is the basic difference to Relief and ensures greater robustness of the algorithm concerning noise. User-defined parameter k controls the locality of the estimates. For most purposes it can be safely set to 10.

3. DEVELOPMENT OF PREDICTION MODELS

3.1. Methodology

This section first introduces the methodology of regular model creation. Then, the methodology for creating feature selection based models is presented.

3.1.1. Regular Model Creation

Various models habe been developed based on Optimized Generalized Regression Neural Networks (Optimized-GRNN), GRNN, Support Vector Machines (SVM), Multilayer Perceptron (MLP), Single Decision Tree (SDT) and Radial Basis Function Network (RBFN) to predict the race time prediction models. By using 10-fold cross-validation, the performance of the prediction models has been assessed using the *RMSE*. By using the unique, double, triple, quadruple, quintuple, sextuple, septuple, octuple, nonuple, decuple and undecuple combinations of the predictor variables, a total of 11, 55, 165, 330, 462, 462, 330, 165, 55, 11 and 1 prediction models have been formed, as given in Table A.3.1 through Table A.3.187[1] respectively.

3.1.2. Feature Selection Based Model Creation

For feature selection, 2 separate versions of the data set are taken into account. The first version, referred as racing-time-set-(1), contains the personal variables sex, age, height, and weight as well as all other survey data except the assigned starting wave of cross-country skiers. The second version, referred to as racing-time-set-(2), consists of the same variables as in racing-time-set-(1) plus the assigned starting wave of cross-country skiers to investigate its effect on prediction of racing time.

[1] Due to space constraints, all regular prediction models along with their predictor variables are included in the appendix.

By running the Relief-F attribute evaluator on racing-time-set-(1) and racing-time-set-(2), the importance rank of each predictor variable has been determined using 10-fold cross-validation, as illustrated in Table 3.1 and Table 3.2. As the next step, the predictor variables have been arranged by decreasing order of importance based on their scores. By iteratively eliminating the variable with the most irrelevant rank from the data sets, several different prediction models for racing-time-set-(1) and racing-time-set-(2) have been created. All prediction models for racing-time-set-(1) and racing-time-set-(2) together with the predictor variables included in any model are shown in Table A.3.1 and Table A.3.2[2], respectively.

Table 3.1. Average Relief-F ranks of predictor variables for racing-time-set-(1) using 10-fold cross-validation

Predictor Variable	Average Relief-F Rank
Age	1 ± 0
Weight	2.50 ± 0.67
HrsSP	2.90 ± 0.94
HrsTot	4.60 ± 0.92
Height	4.80 ± 1.08
YRSALL	7.60 ± 2.46
HrsXC	7.70 ± 2.37
HrsOther	7.90 ± 1.51
Sex	8.10 ± 1.37
YRS10	9.20 ± 1.40
RacePInd	10.50 ± 1.28
BMT5	11.70 ± 1.68
BMT10	12.80 ± 0.87
RaceComp	13.70 ± 0.64

[2] Due to space constraints, all fetature selection based prediction models along with their predictor variables are included in the appendix.

Table 3.2. Average Relief-F ranks of predictor variables for racing-time-set-(2) using 10-fold cross-validation

Predictor Variable	Average Relief-F Rank
Wave	1.00 ± 0
Age	2.00 ± 0
Weight	3.60 ± 0.49
HrsSP	3.60 ± 0.80
Height	5.40 ± 1.02
Sex	5.70 ± 0.64
HrsTot	7.40 ± 1.28
HrsOther	7.80 ± 0.87
YRS10	9.30 ± 0.78
HrsXC	9.40 ± 0.80
RacePlnd	11.40 ± 0.49
YRSALL	11.50 ± 1.02
BMT5	13.30 ± 0.78
RaceComp	14.20 ± 0.75
BMT10	14.40 ± 0.66

3.1.3. Model Evaluation Metrics

The generalization error of the prediction models has been assessed by performing 10-fold cross-validation, and the prediction errors have been calculated using *RMSE*, the formula of which is shown in (3.1).

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}\left(Y - Y'\right)^2} \quad , \tag{3.1.}$$

In Eq. (3.1.), Y represents the measured racing time value value, Y' represents the predicted racing time value, $\bar{Y}$ represents the mean of the measured values of racing time value and n represents the number of samples in a test subset.

The *RMSE* metric is the most widely used evaluation measure in the field of sport physiology, and also most of the studies related to prediction of racing time value utilize this metric for performance and accuracy evaluations of prediction models. Particularly, *RMSE* measures the difference between predicted and measured values, which are squared and then averaged over the number of total samples.

3.2. Details of Prediction Models

This subsection introduces the details of GRNN-based, OPGRNN-based, SVM-based, MLP-based, SDT-based, and RBFNN-baed models.

3.2.1. GRNN-based Prediction Models

GRNN was devised by (Specht, 1991) and is also known to be widely effective for modeling and prediction. Structurally, the GRNN resembles the MLP. However, unlike MLP, the GRNN does not require an iterative training procedure, leading to much faster training times than other back propagation networks. Also, it has recently been shown that GRNN’s have the potential to often exhibit more satisfactory prediction performance (Celikoglu and Cigizoglu, 2007; Kim et al., 2004; Parojčić et al., 2007).

The GRNN approximates any arbitrary function between input and output vectors, drawing the function estimate directly from the training data. Particularly, GRNN works by measuring how far a given sample pattern is from patterns in the training set in N dimensional space, where N is the number of inputs in the problem. When a new pattern is presented to the network, that input pattern is compared in N dimensional space to all of the patterns in the training set to determine how far in distance it is from those patterns. The output that is predicted by the network is a proportional amount of all of the outputs in the training set. The proportion is based upon how far the new pattern is from the given patterns in the training set. In addition, it is consistent that as the training set size becomes large, the estimation error approaches zero, with only mild restrictions on the function (Kim et al., 2004).

For a GRNN-based model, the minimum and maximum values for sigma, search step and the type of kernel function influences the performance of GRNN-based models. Table 3.3. shows the ranges for the utilized values of parameters for GRNN-based prediction models.

Table 3.3. Values of the utilized parameters for the GRNN-based models

Parameter	Value
Minimum Sigma	0.0001
Maximum Sigma	10
Search Step	20
Kernel function	Gaussian function

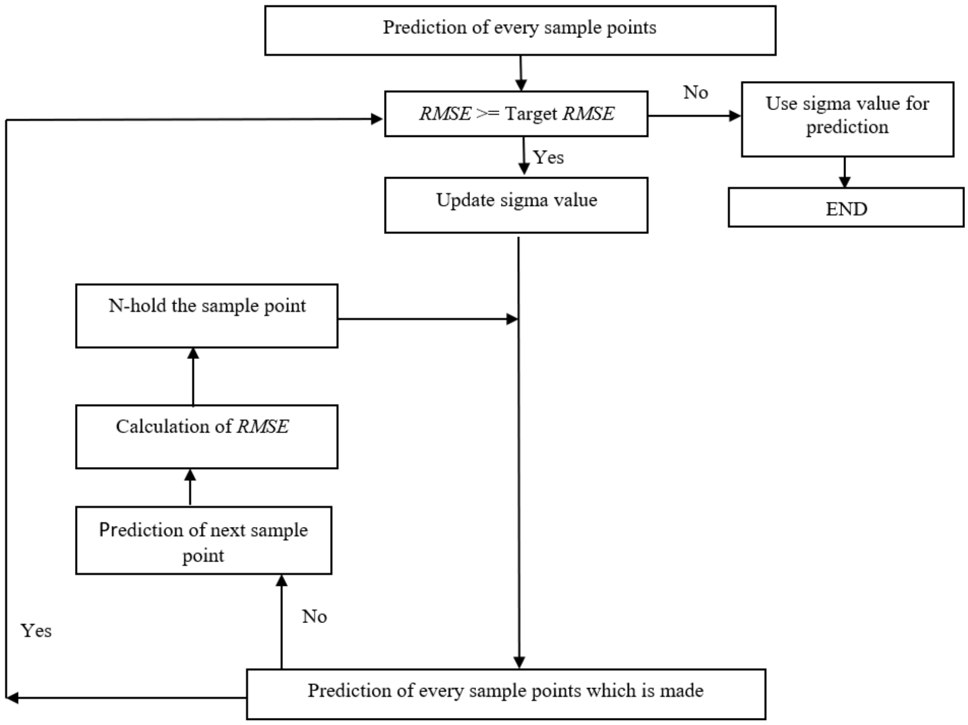

Figure 3.1. Flow chart of GRNN-based model

3.2.2. OPGRNN-based Prediction Models

The biggest challenge in pruning used by OPGRNN is determining what to prune. When removing nodes from a model, the removed parameters should be less useful. There are different heuristics and methods that determine which nodes are less important and can be removed with minimal impact on accuracy.

The process of removing unnecessary neurons is an iterative process. Leave-one-out validation is used to measure the error of the model with each neuron removed. The neuron that causes the least increase in error (or possibly the largest reduction in error) is then removed from the model. The process is repeated with the remaining neurons until the stopping criterion is reached.

There are three criteria that can be selected to guide the removal of neurons:

1. Minimize error – If this option is used, then it removes neurons as long as the leave-one-out error remains constant or decreases. It stops when it finds a neuron whose removal would cause the error to increase above the minimum found.
2. Minimize neurons – If this option is used, it removes neurons until the leave-one-out error would exceed the error for the model with all neurons.
3. # of neurons – If this option is used, it reduces the least significant neurons until only the specified number of neurons remain.

With pruning, there is a tradeoff between model performance and efficiency. You can prune heavily and have a smaller more efficient network, but also less accurate. Or you could prune lightly and have a highly performant network, that is also large and expensive to operate. This trade-off needs to be considered for different applications of the neural network. Table 3.4. lists the intervals for values of the utilized parameters for OPGRNN-based prediction models.

Table 3.4. Values of the utilized parameters for the OPGRNN-based models

Parameter	Value
Minimize error	Enabled
Minimize neurons	Enabled
# of neurons	[10, 100]

3.2.3. SVM-based Prediction Models

The prediction accuracy of SVM largely relies on the values of model parameters such as the value of epsilon (*ε)* for the *ε*-insensitive loss function, the value of *C*, and the type and parameters of the utilized kernel function. In literature, the RBFNN kernel has often been reported to present satisfactory generalization capabilities (Campbell, 2002; Kavzoglu and Colkesen, 2009). Accordingly, RBFNN is utilized as the kernel function in this study, which requests the optimization of the function parameter γ.

Before building an SVM model, it is to be revealed which values of the triple of (C, ε, γ) are the most convenient for a given prediction problem and thus should be worked out accordingly. For this purpose, an appropriate parameter search and optimization technique needs to be utilized to find the optimal values of (C, ε, γ) so that the *RMSE* is minimized over the testing data as much as possible. A variety of such searching and optimization techniques has been proposed in literature including grid search (Hsu and Lin, 2002), cross validation (Jung and Hu, 2015), particle swarm optimization (Guo et al., 2006) and genetic algorithm (Friedrichs and Igel, 2005). The grid search technique can be very convenient for medium-sized problems, so it is implemented in this study to find the optimal values of (C, ε, γ). The grid search technique works by looking for values of every parameter using pre-determined geometric steps across a search range. The lower and upper limit values of the search range have been chosen according to the recommendations made in (Hsu et al., 2003). Particularly, in (Hsu et al., 2003) it has been reported that trying exponentially growing sequences of C and γ is an effective way to determine the optimal values. Similarly, as proposed in (Mattera and Haykin, 1999), the ε-values were chosen so that the percentage of support vectors in the respective SVM-based models is about 50% of the number of total samples. Table 3.5. lists the intervals for values of the utilized parameters for SVM-based prediction models. As already mentioned previously, for testing the generalizability of the prediction models, 10-fold cross-validation has been conducted.

Table 3.5. Values of the utilized parameters for the SVM model

Parameter	Value Ranges
Cost (C)	[0.1, 5000]
Gamma (γ)	[0.0001, 50]
Epsilon (ε)	[0.001, 100]

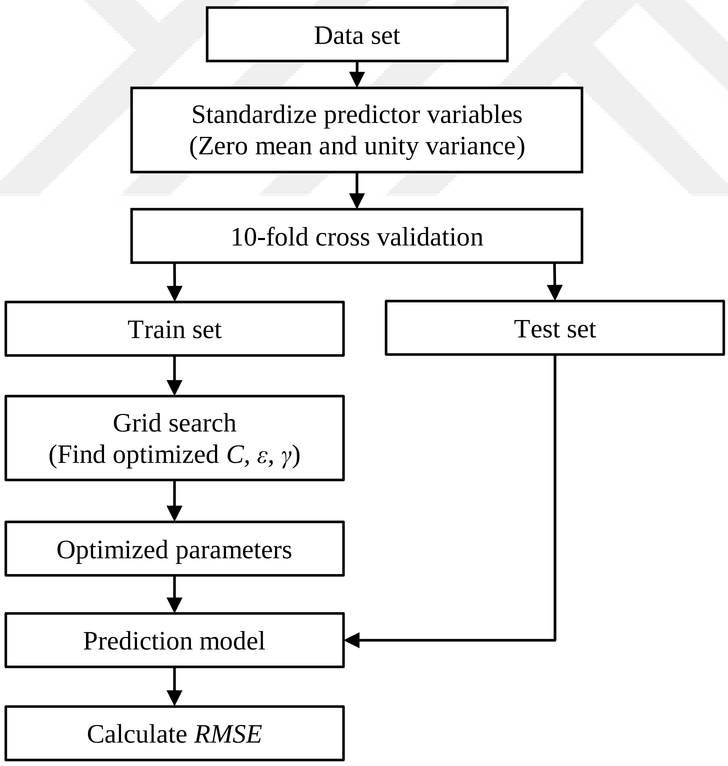

Figure 3.2. Flow chart of SVM-based model

3.2.4. MLP-based Prediction Models

A classical ANN method, the MLP neural network, has been utilized to verify the utility of the proposed prediction models. Back-propagation MLP has been employed for training the MLP network. The number of neurons in every hidden layer is of significant importance for the performance of an MLP. Utilizing less neurons may cause obtaining less information, whereas utilizing many neurons can enhance the local minimum, which reduces the accuracy of the network. As there is no exact to reveal the number of neurons in a hidden layer, the optimal number of neurons is empirically chosen based on the experience of the user and the physical complexity of the problem. In this study, the number of neurons in the hidden layer has been identified by comparing the performance of different cross-validated networks, with 3-11 hidden neurons, and choosing the number that yielded the lowest prediction error. Regarding the selection of activation functions, logistic and linear functions have been applied in the hidden and output layer, respectively.

The search intervals for values of the parameters for the MLP models are given in Table 3.6.

Table 3.6. Values of the utilized parameters for the MLP models

Parameter	**Value**
Number of hidden layers	[1, 3]
Hidden layer activation function	logistic
Output layer activation function	Linear

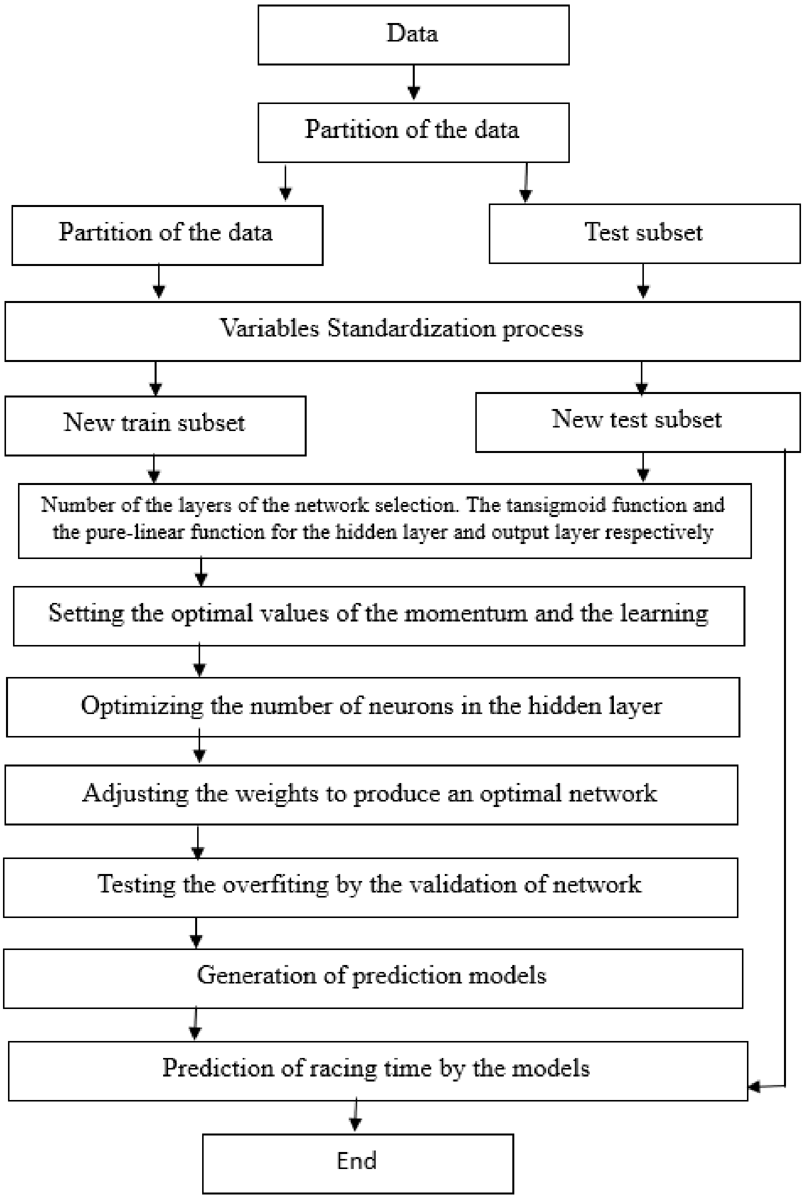

Figure 3.3. Flow chart of MLP-based model

3.2.5. SDT-based Prediction Models

There are three important parameters that affect the performance of SDT-based prediction models. One of the parameters is known as the minimum rows in a node and the others are known as the minimum size node to split and maximum tree levels. The list of intervals for values of the utilized parameters for SDT-based prediction models is shown in Table 3.7.

Table 3.7. Values of the utilized parameters for the SDT models

Parameter	**Value**
Minimum rows in a node	5
Minimum size node to split	10
Maximum tree levels	10

3.2.6. RBFNN-based Prediction Models

RBFNN's are composed of a single hidden and a single output layer, which work faster compared to multilayer feed forward neural networks having multiple hidden layers. One kernel function is associated with each hidden node in the RBFNN. The Gaussian function has been used as a kernel function of the hidden nodes to develop the VO_2max prediction models.

Several steps are gone through in building an RBFNN-based prediction model. Firstly, after reading all information from the dataset, the network standardization of predictor variables is simulated and initialized. Then, a new neuron is added to RBFNN and after adjusting the weight for the output layer, the error at output of network is computed. In case the error is not acceptable, the RBFNN is enriched by inclusion of an additional neuron and the error check is repeated again. Otherwise, the performance of the network for the test and training data is measured and it is investigated whether the network exhibits satisfactory performance. In case the performance is not acceptable, the process turns back to the stage where a further new neuron is added to the RBFNN and the acceptance checks of the error rates are repeated. The regularization parameter (λ), population size, radius of the RBFNN and the maximal number of neurons are the main parameters impacting the performance of an RBFNN-based model. The list of intervals for values of the utilized parameters for SDT-based prediction models is shown in Table 3.8.

Table 3.8. Values of the utilized parameters for the RBFNN models

Parameter	**Value**
Number of neurons	100
Radius	[0.01 , 400]
Lambda	[0.001, 10]

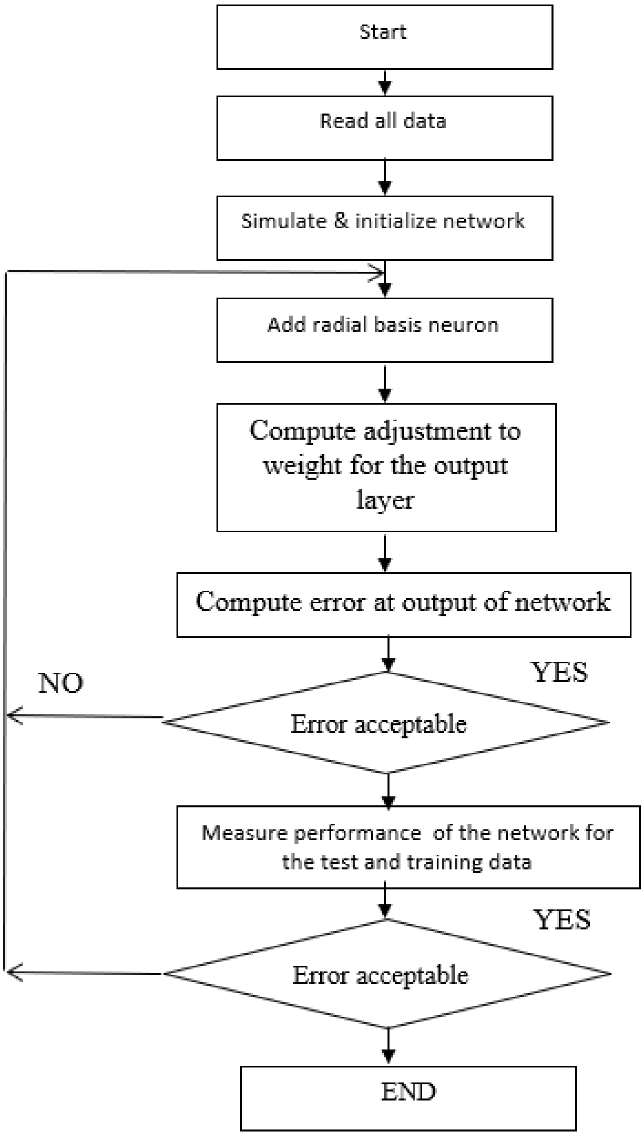

Figure 3.4. Flow chart of RBFNN-based model

4. RESULTS AND DISCUSSION

By using the unique, double, triple, quadruple, quintuple, sextuple, septuple, octuple, nonuple, decuple and undecuple combinations of the predictor variables, a total of 11, 55, 165, 330, 462, 462, 330, 165, 55, 11 and 1 prediction models have been formed, respectively. Due to space limitations, only the twenty models that yield the lowest and *RMSE*'s have been given in this thesis. Table 4.1 through Table 4.21 show *RMSE*'s of all prediction models developed based on Optimized-GRNN, GRNN, SVM, MLP, SDT, and RBFN, respectively.

4.1. Results for Prediction Models Using Unique Combinations of the Predictor Variables

Table 4.1. shows the *RMSE* values for race time models along with unique combinations of the predictor variables.

Table 4.1. *RMSE* for race time models along with unique combinations of the predictor variables

Models	*RMSE*					
	OPGRNN	GRNN	SVM	MLP	SDT	RBFNN
Model 11	12.71	13.68	13.77	14.14	13.95	14.92
Model 10	16.47	18.58	18.89	19.43	20.877	24.32
Model 9	17.49	19.70	19.19	19.82	21.70	20.87
Model 4	17.68	20.62	19.71	20.82	22.90	21.03
Model 3	18.11	19.95	19.91	20.81	23.32	20.9
Model 5	18.19	20.85	20.41	20.69	22.86	24.1
Model 1	18.62	21.72	21.25	21.47	24.13	23.09
Model 8	18.72	21.44	21.05	20.9	23.37	20.7
Model 2	19.32	21.27	21.19	21.48	24.04	21.41
Model 7	19.87	22.08	21.86	21.96	24.19	23.05
Model 6	19.94	22.44	22.04	21.92	23.89	25.36

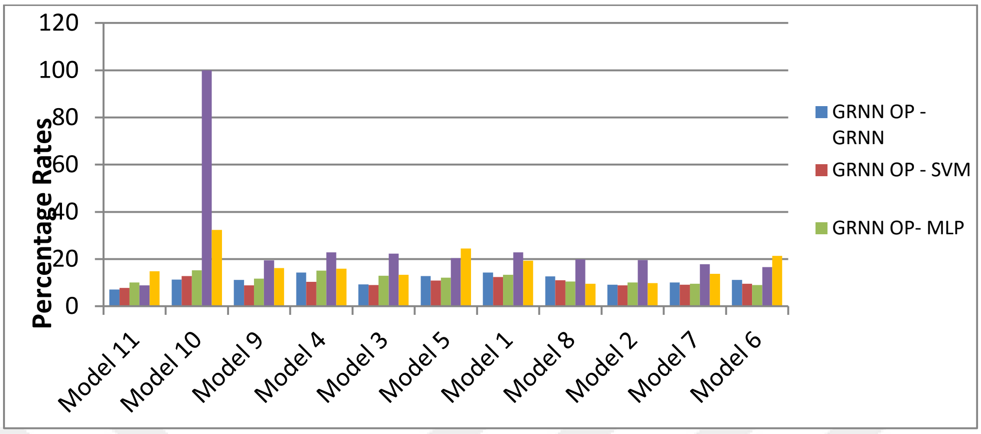

Figure 4.1. Percentage decrease rates in *RMSE* values of race time for OPGRNN-based models compared to *RMSE* values obtained by GRNN, SVM, MLP, SDT, and RBFNN-based models for unique combinations

4.2. Discussion for Prediction Models Using Unique Combinations of the Predictor Variables

The following comments regarding the results can be made for prediction of racing time and the relevant features affecting the quality of prediction models developed using a combination of (1) :

- When the average of the method results for each model is taken, it is seen that the best model is Model-11 with 14.09 *RMSE* value and the worst Model is Model-6 with 23.13 *RMSE* value.
- When the prediction models are analyzed, it is seen that the relationship between the wave predictor variable and racing time has a high correlation.
- When the prediction models are analyzed, it is seen that the relationship between HrsSp predictor variable and racing time has a low correlation.
- When the average of the *RMSE* values of the methods based on models is taken, the best method is found to be SVM with 19.93

RMSE value. It is observed that the worst method is SDT with 22.29 *RMSE* value.

- It is observed that SVM based prediction models produce 1.87% lower *RMSE* value on average compared to that of MLP based prediction models.
- It is observed that SVM based prediction models produce 1.38% lower *RMSE* value on average compared to that of GRNN based prediction models.
- It is observed that SVM based prediction models produce 8.57% lower *RMSE* value on avarage compared to that of RBFNN based prediction models.
- It is observed that SVM based prediction models produce 10.58% lower *RMSE* value on average compared to that of SDT based prediction models.
- It is observed that MLP based prediction models produce 0,49% higher *RMSE* value on average compared to that of GRNN based prediction models.
- It is observed that MLP based prediction models produce 6.83% lower *RMSE* value on average compared to that of RBFNN based prediction models.
- It is observed that MLP based prediction models produce 8.88% lower *RMSE* value on average compared to that of SDT based prediction models.
- It is observed that GRNN based prediction models produce 7.29% lower *RMSE* value on average compared to that of RBFNN based prediction models.

- It is observed that GRNN based prediction models produce 9.33% lower *RMSE* value on average compared to that of SDT based prediction models.
- It is observed that RBFNN based prediction models produce 1.87% lower *RMSE* value on average compared to that of SDT based prediction models.
- It is observed that Optimized-GRNN based prediction models produce 10.08% lower *RMSE* value on average than that of SVM based prediction models.
- It is observed that Optimized-GRNN based prediction models produce 11.76% lower *RMSE* value on average than that of MLP based prediction models.
- It is observed that Optimized-GRNN based prediction models produce 17.79% lower *RMSE* value on average than that of RBFNN based prediction models.
- It is observed that Optimized-GRNN based prediction models produce 19.60% lower *RMSE* value on average than that of SDT based prediction models.
- Average training time of Optimized-GRNN based prediction models is 459.56 seconds.

4.3. Results for Prediction Models Using Double Combinations of the Predictor Variables

Table 4.2. and 4.3. show the *RMSE* values for race time models along with double combinations of the predictor variables.

Table 4.2. *RMSE* for race time models along with double combinations of the predictor variables

Models	*RMSE*					
	OPGRNN	GRNN	SVM	MLP	SDT	RBFNN
Model 10	11.86	13.58	13.78	14.09	13.95	15.26
Model 45	11.93	13.83	13.81	14.07	13.95	40.41
Model 54	12.04	13.78	13.83	13.83	13.53	16.23
Model 40	12.05	13.46	13.65	13.93	13.69	13.90
Model 27	12.07	13.72	14.01	14.10	13.95	14.57
Model 55	12.09	13.52	13.46	13.92	13.26	15.01
Model 19	12.16	13.67	13.52	14.08	13.95	16.23
Model 49	12.17	13.71	13.95	14.07	14.30	15.46
Model 34	12.21	13.72	13.93	14.06	13.95	14.87
Model 52	12.32	13.71	13.51	13.98	13.95	16.37

Table 4.3. *RMSE* for race time models along with double combinations of the predictor variables

Models	*RMSE*					
	OPGRNN	GRNN	SVM	MLP	SDT	RBFNN
Model 33	15.74	18.11	17.77	19.54	20.84	20.72
Model 9	15.83	18.30	18.61	19.99	20.87	23.28
Model 26	15.84	18.23	18.25	19.18	21.25	29.51
Model 18	15.98	18.91	18.37	19.36	21.31	20.93
Model 39	16.00	18.39	18.75	20.20	21.19	23.77
Model 25	16.13	18.89	18.34	19.28	21.65	20.73
Model 48	16.23	18.77	19.12	20.56	20.87	23.04
Model 51	16.25	18.56	19.19	19.65	20.78	25.42
Model 32	16.28	18.93	17.75	19.61	20.77	19.46
Model 53	16.63	18.56	18.87	20.12	21.61	34.99

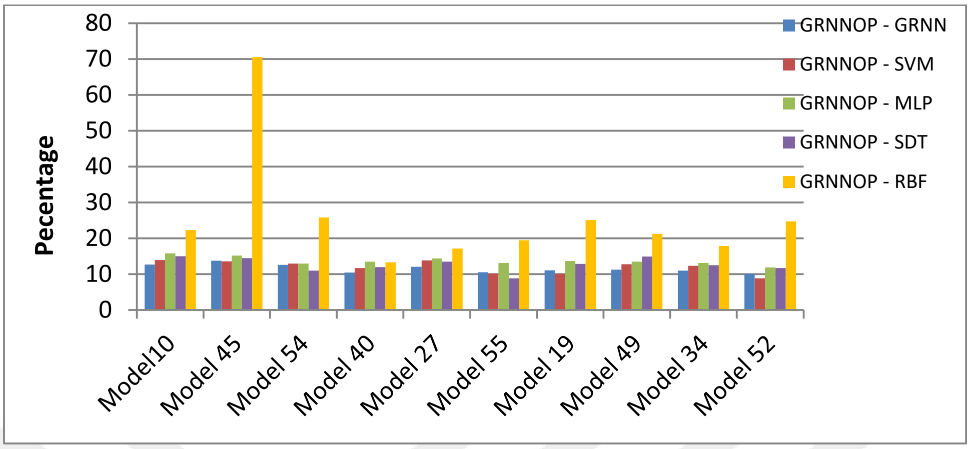

Figure 4.2. Percentage decrease rates in *RMSE* values of race time for OPGRNN-based models compared to *RMSE* values obtained by GRNN, SVM, MLP, SDT, and RBFNN-based models for double combinations

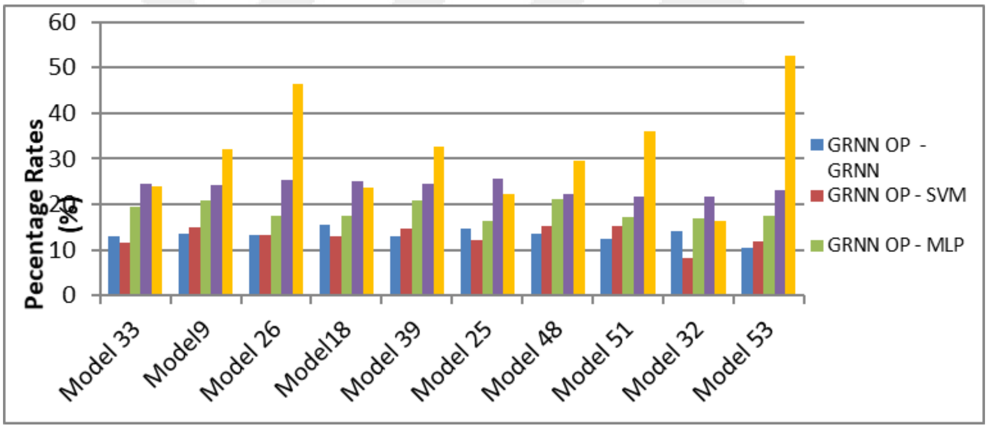

Figure 4.3. Percentage decrease rates in *RMSE* values of race time for OPGRNN-based models compared to *RMSE* values obtained by GRNN, SVM, MLP, SDT, and RBFNN-based models for double combinations

4.4. Discussion for Prediction Models Using Double Combinations of the Predictor Variables

- When the average of the method results for each model is taken, it is seen that the best model is Model-40 with 13.73 *RMSE* value and the worst model is Model-43 with 26.08 *RMSE* value.
- When the prediction models are analyzed, it is seen that the relationship between HrsXC and Wave predictor variables and racing time has a high correlation.
- When the prediction models are analyzed, it is seen that the relationship between HrsSP and RaceComp prediction variables and racing time has a low correlation.
- When the average of the *RMSE* values of the methods based on models is taken, the best method is found to be SVM with 18.53 *RMSE* value. It is observed that the worst method is RBFNN with 23.64 *RMSE* value.
- It is observed that SVM based prediction models produce 4.08% lower *RMSE* value on average compared to that of MLP based prediction models.
- It is observed that SVM based prediction models produce 1.64% lower *RMSE* value on average compared to that of GRNN based prediction models.
- It is observed that SVM based prediction models produce 21.61% lower *RMSE* value on average compared to that of RBFNN based prediction models.
- It is observed that SVM based prediction models produce 11.04% lower *RMSE* value on average compared to that of SDT based prediction models.

- It is observed that MLP based prediction models produce 2.48% higher *RMSE* value on average compared to that of GRNN based prediction models.
- It is observed that MLP based prediction models produce 18.27% lower *RMSE* value on average compared to that of RBFNN based prediction models.
- It is observed that MLP based prediction models produce 7.24% lower *RMSE* value on average compared to that of SDT based prediction models.
- It is observed that GRNN based prediction models produce 20.30% lower *RMSE* value on average compared to that of RBFNN based prediction models.
- It is observed that GRNN based prediction models produce 9.55% lower *RMSE* value on average compared to that of SDT based prediction models.
- It is observed that RBFNN based prediction models produce 11.88% lower *RMSE* value on average compared to that of SDT based prediction models.
- Average training times of SVM, GRNN, MLP, RBFNN and SDT based prediction models are 30.55, 14.93, 1.67, 29.45, 0.71 seconds, respectively.
- An average of 12.53% improvement is observed in the *RMSE* values of the Optimized- GRNN based prediction models.
- It is observed that Optimized-GRNN based prediction models produce 12.15% lower *RMSE* value on average than that of SVM based prediction models.

- It is observed that Optimized-GRNN based prediction models produce 16.13% lower *RMSE* value on average than that of MLP based prediction models.
- It is observed that Optimized-GRNN based prediction models produce 23.29% lower *RMSE* value on average than that of RBFNN based prediction models.
- It is observed that Optimized-GRNN based prediction models produce 18.69% lower *RMSE* value on average than that of SDT based prediction models.
- The average training time of Optimized-GRNN based prediction models is 516.95 seconds.
- The average training time of Optimized-GRNN based prediction models is 91.01% higher than the average training time of GRNN based prediction models.

4.5. Results for Prediction Models Using Triple Combinations of the Predictor Variables

Table 4.4. and 4.5. show the *RMSE* values for race time models along with triple combinations of the predictor variables.

Table 4.4. *RMSE* for race time models along with triple combinations of the predictor variables

Models	*RMSE*					
	OPGRNN	**GRNN**	**SVM**	**MLP**	**SDT**	**RBFNN**
Model 160	11.04	13.32	13.67	14.10	13.26	18.00
Model 161	11.17	13.52	13.63	13.93	13.53	17.28
Model 45	11.77	13.42	13.35	13.87	13.26	16.03
Model 1	11.88	13.58	13.82	14.41	13.95	15.18
Model 23	11.88	13.59	13.92	14.01	13.95	15.54
Model 99	11.91	13.32	13.99	14.12	13.79	16.57
Model 101	11.91	13.42	13.56	14.00	13.97	16.31
Model 17	11.91	13.58	13.94	14.13	13.95	16.27
Model 96	11.92	13.66	13.96	14.29	14.05	16.13
Model 39	11.93	13.59	13.43	13.82	14.30	16.72

Table 4.5. *RMSE* for race time models along with triple combinations of the predictor variables

Models	*RMSE*					
	OPGRNN	**GRNN**	**SVM**	**MLP**	**SDT**	**RBFNN**
Model 29	11.96	13.57	13.91	13.98	13.99	15.58
Model 157	12.02	13.56	13.64	14.04	13.32	15.95
Model 102	12.03	13.34	13.44	13.78	13.69	19.51
Model 56	12.06	13.42	13.99	14.02	13.92	16.95
Model 149	12.07	13.46	13.88	13.83	14.20	17.04
Model 125	12.08	13.45	13.98	13.91	13.79	14.93
Model 156	12.08	13.64	13.43	14.00	13.53	24.31
Model 162	12.13	13.56	13.77	13.89	13.35	21.61
Model 41	12.14	13.60	13.27	13.99	13.95	16.18
Model 112	12.19	13.53	13.57	14.05	13.26	17.29

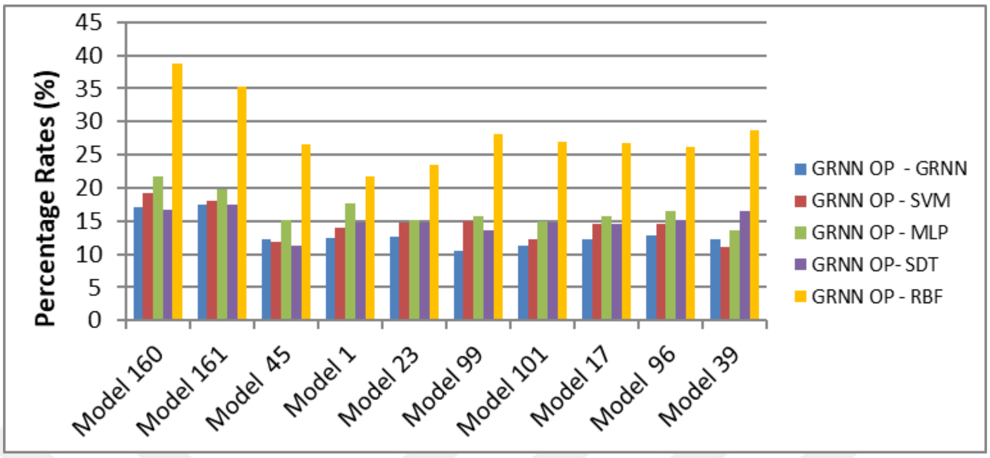

Figure 4.4. Percentage decrease rates in *RMSE* values of race time for OPGRNN-based models compared to *RMSE* values obtained by GRNN, SVM, MLP, SDT, and RBFNN-based models for triple combinations

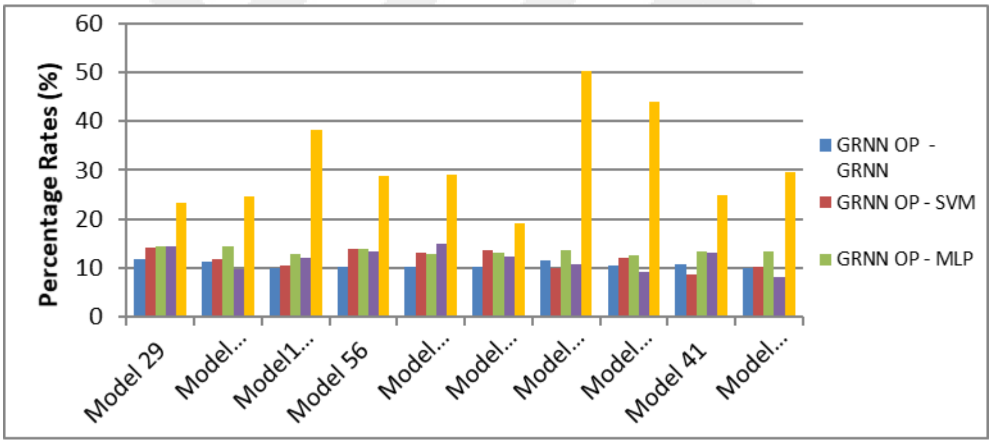

Figure 4.5. Percentage decrease rates in *RMSE* values of race time for OPGRNN-based models compared to *RMSE* values obtained by GRNN, SVM, MLP, SDT, and RBFNN-based models for triple combinations

4.6. Discussion for Prediction Models Using Triple Combinations of the Predictor Variables

- When the average of the method results for each model is taken, it is seen that the best model is Model-125 with 14.01 *RMSE* value and the worst model is Model-32 with 29.59 *RMSE* value.
- When the prediction models are analyzed, it is seen that the relationship between wave predictor variable and racing time has a high correlation.
- When the prediction models are analyzed, it is seen that the relationship between RaceComp prediction variable and racing time has a low correlation.
- When the average of the *RMSE* values of the methods based on models is taken, the best method is found to be GRNN with 13.72 *RMSE* value. It is observed that the worst method is RBFNN with 18.02 *RMSE* value.
- It is observed that SVM based prediction models produce 1.9% lower *RMSE* value on average compared to that of MLP based prediction models.
- It is observed that SVM based prediction models produce 1.08% higher *RMSE* value on average compared to that of GRNN based prediction models.
- It is observed that SVM based prediction models produce 23.02% lower *RMSE* value on average compared to that of RBFNN based prediction models.
- It is observed that SVM based prediction models produce 0.92% lower *RMSE* value on average compared to that of SDT based prediction models.

- It is observed that MLP based prediction models produce 2.97% higher *RMSE* value on average compared to that of GRNN based prediction models.
- It is observed that MLP based prediction models produce 21.53% lower *RMSE* value on average compared to that of RBFNN based prediction models.
- It is observed that MLP based prediction models produce 0.99% higher *RMSE* value on average compared to that of SDT based prediction models.
- It is observed that GRNN based prediction models produce 23.86% lower *RMSE* value on average compared to that of RBFNN based prediction models.
- It is observed that GRNN based prediction models produce 2% lower *RMSE* value on average compared to that of SDT based prediction models.
- It is observed that RBFNN based prediction models produce 22.30% higher *RMSE* value on average compared to that of SDT based prediction models.
- Average training times of SVM, GRNN, MLP, RBFNN and SDT based prediction models are 33.42, 20.66, 1.76, 22.39 and 0.17 seconds, respectively.
- An average of 11.85% improvement is observed in the *RMSE* values of the Optimized- GRNN based prediction models.
- It is observed that Optimized-GRNN based prediction models produce 13.13% lower *RMSE* value on average than that of SVM based prediction models.

- It is observed that Optimized-GRNN based prediction models produce 13.32% lower *RMSE* value on average than that of MLP based prediction models.
- It is observed that Optimized-GRNN based prediction models produce 30.65% lower *RMSE* value on average than that of RBFNN based prediction models.
- It is observed that Optimized-GRNN based prediction models produce 13.45% lower *RMSE* value on average than that of SDT based prediction models.
- The average training time of Optimized-GRNN based prediction models is 522.5 seconds.
- The average training time of Optimized-GRNN based prediction models is 96.04% higher than the average training time of GRNN based prediction models.

4.7. Results for Prediction Models Using Quadruple Combinations of the Predictor Variables

Table 4.6. and 4.7. show the *RMSE* values for race time models along with quadruple combinations of the predictor variables.

Table 4.6. *RMSE* for race time models along with quadruple combinations of the predictor variables

Models	*RMSE*					
	OPGRNN	GRNN	SVM	MLP	SDT	RBFNN
Model 328	10.80	13.10	13.59	13.83	13.26	60.91
Model 330	11.15	13.37	13.60	14.16	13.35	25.25
Model 314	11.62	13.36	13.74	13.99	13.69	20.62
Model 70	11.68	13.36	13.96	14.12	14.22	20.30
Model 257	11.70	13.37	13.81	14.11	13.86	18.82
Model 311	11.74	13.36	13.92	14.10	13.69	30.22
Model 210	11.76	13.38	14.21	13.90	13.71	16.79
Model 97	11.77	13.33	13.83	14.25	14.11	19.10
Model 154	11.79	13.38	14.03	14.08	14.05	17.53
Model 99	11.84	13.23	13.64	14.08	13.97	18.77

Table 4 7. *RMSE* for race time models along with quadruple combinations of the predictor variables

Models	*RMSE*					
	OPGRNN	GRNN	SVM	MLP	SDT	RBFNN
Model 274	11.85	13.29	13.76	14.02	13.97	17.17
Model 272	11.90	13.36	13.85	14.05	13.80	17.57
Model 100	11.91	13.37	13.76	14.00	13.69	17.75
Model 310	11.94	13.34	13.99	13.82	13.97	20.37
Model 184	12	13.36	13.42	14.14	13.74	18.21
Model 33	12.03	13.38	13.73	13.95	13.95	16.38
Model 240	12.05	13.35	13.80	13.94	13.69	16.39
Model 305	12.06	13.33	13.83	14.01	13.91	19.73
Model 107	12.06	13.34	13.64	13.93	14.30	17.37
Model 61	12.12	13.34	13.63	14.05	13.95	18.68

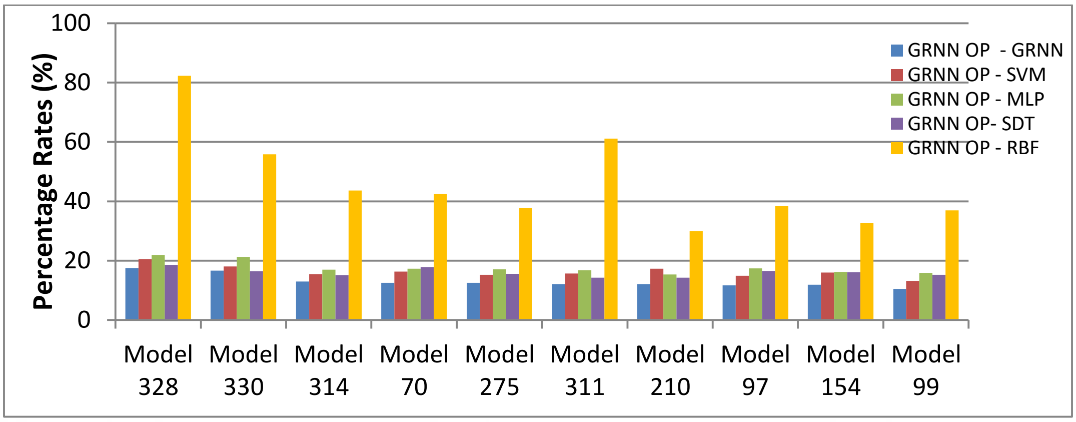

Figure 4.6. Percentage decrease rates in *RMSE* values of race time for OPGRNN-based models compared to *RMSE* values obtained by GRNN, SVM, MLP, SDT, and RBFNN-based models for quadruple combinations

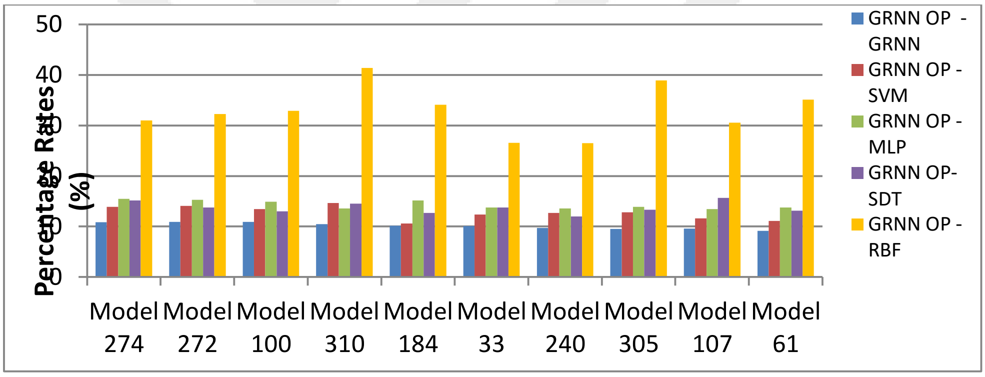

Figure 4.7. Percentage decrease rates in *RMSE* values of race time for OPGRNN-based models compared to *RMSE* values obtained by GRNN, SVM, MLP, SDT, and RBFNN-based models for quadruple combinations

4.8. Discussion for Prediction Models Using Quadruple Combinations of the Predictor Variables

- When the average of the method results for each model is taken, it is seen that the best model is Model-8 with 14.05 *RMSE* value and the worst model is Model-296 with 29.92 *RMSE* value.

- When the prediction models are analyzed, it is seen that the relationship between YRS10, BTM10 and Wave predictor variables and racing time has a high correlation.
- When the prediction models are analyzed, it is seen that the relationship between HrsSP and HrsXC prediction variables and racing time has a low correlation.
- When the average of the *RMSE* values of the methods based on models is taken, the best method is found to be SVM with 16.94 *RMSE* value. It is observed that the worst method is RBFNN with 24.98 *RMSE* value.
- It is observed that SVM based prediction models produce 4.02% lower *RMSE* value on average compared to that of MLP based prediction models.
- It is observed that SVM based prediction models produce 0.70% lower *RMSE* value on average compared to that of GRNN based prediction models.
- It is observed that SVM based prediction models produce 29.79% lower *RMSE* value on average compared to that of RBFNN based prediction models.
- It is observed that SVM based prediction models produce 10.65% lower *RMSE* value on average compared to that of SDT based prediction models.
- It is observed that MLP based prediction models produce 3.34% higher *RMSE* value on average compared to that of GRNN based prediction models.
- It is observed that MLP based prediction models produce 29.34% lower *RMSE* value on average compared to that of RBFNN based prediction models.

- It is observed that MLP based prediction models produce 6.90% lower *RMSE* value on average compared to that of SDT based prediction models.
- It is observed that GRNN based prediction models produce 31.70% lower *RMSE* value on average compared to that of RBFNN based prediction models.
- It is observed that GRNN based prediction models produce 10.02% lower *RMSE* value on average compared to that of SDT based prediction models.
- It is observed that RBFNN based prediction models produce 24.09% higher *RMSE* value on average compared to that of SDT based prediction models.
- Average training times of SVM, GRNN, MLP, RBFNN and SDT based prediction models are 31.45, 24.69, 1.67, 43.95 and 0.13 seconds, respectively.
- An average of 11.61% improvement is observed in the *RMSE* values of the Optimized- GRNN based prediction models.
- It is observed that Optimized-GRNN based prediction models produce 14.50% lower *RMSE* value on average than that of SVM based prediction models.
- It is observed that Optimized-GRNN based prediction models produce 15.96% lower *RMSE* value on average than that of MLP based prediction models.
- It is observed that Optimized-GRNN based prediction models produce 44.90% lower *RMSE* value on average than that of RBFNN based prediction models.

- It is observed that Optimized-GRNN based prediction models produce 14.81% lower *RMSE* value on average than that of SDT based prediction models.
- The average training time of Optimized-GRNN based prediction models is 1164.29 seconds.
- The average training time of Optimized-GRNN based prediction models is 97.87% higher than the average training time of GRNN based prediction models

4.9. Results for Prediction Models Using Quintuple Combinations of the Predictor Variables

Table 4.8. and 4.9. show the *RMSE* values for race time models along with quintuple combinations of the predictor variables.

Table 4.8. *RMSE* for race time models along with quintuple combinations of the predictor variables

Models	***RMSE***					
	OPGRNN	**GRNN**	**SVM**	**MLP**	**SDT**	**RBFNN**
Model 115	10.77	13.19	13.73	14.24	13.32	20.38
Model 382	10.79	13.13	13.70	14.11	13.35	25.28
Model 319	10.84	13.06	13.67	14.25	13.45	19.87
Model 389	10.84	13.29	13.57	13.94	13.45	19.07
Model 388	10.90	13.13	13.63	14.33	13.26	21.70
Model 346	11.05	13.11	13.74	13.77	13.48	19.09
Model 411	11.28	13.26	13.95	14.07	13.91	20.42
Model 241	11.38	13.05	13.72	13.87	13.26	25.14
Model 329	11.52	13.28	14.06	14.33	13.86	20.41
Model 448	11.53	13.31	13.75	13.96	13.69	21.03

Table 4.9. *RMSE* for race time models along with quintuple combinations of the predictor variables

Models	*RMSE*					
	OPGRNN	GRNN	SVM	MLP	SDT	RBFNN
Model 446	11.61	13.29	13.75	14.08	13.97	21.25
Model 396	11.61	13.31	13.89	14.10	13.97	20.72
Model 373	11.62	13.27	13.69	13.94	13.97	23.79
Model 442	11.75	13.24	13.52	13.95	13.77	40.04
Model 461	11.78	13.28	14.01	14.00	13.86	16.40
Model 318	11.98	13.02	13.60	13.93	13.26	22.07
Model 312	12.01	13.02	13.79	13.89	13.35	20.05
Model 395	12.03	13.31	14.04	14.15	13.97	20.68
Model 192	12.15	13.29	13.73	13.88	13.32	19.72
Model 315	12.16	13.28	13.80	14.14	13.53	18.71

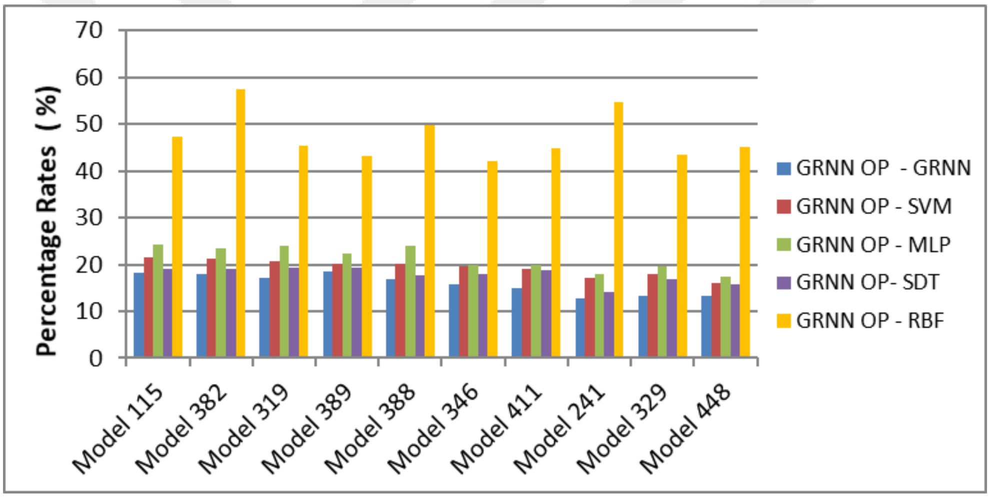

Figure 4.8. Percentage decrease rates in *RMSE* values of race time for OPGRNN-based models compared to *RMSE* values obtained by GRNN, SVM, MLP, SDT, and RBFNN-based models for quintuple combinations

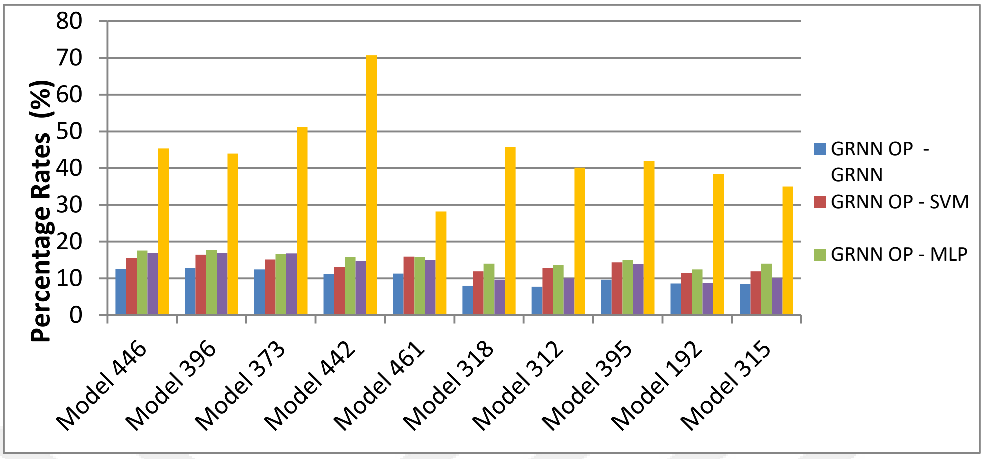

Figure 4.9. Percentage decrease rates in *RMSE* values of race time for OPGRNN-based models compared to *RMSE* values obtained by GRNN, SVM, MLP, SDT, and RBFNN-based models for quintuple combinations

4.10. Discussion for Prediction Models Using Quintuple Combinations of the Predictor Variables

- When the average of the method results for each model is taken, it is seen that the best model is Model-59 with 29.98 *RMSE* value and the worst model is Model-111 with 29.98 *RMSE* value.
- When the prediction models are analyzed, it is seen that the relationship between BMT5 and Wave predictor variables and racing time has a high correlation.
- When the prediction models are analyzed, it is seen that the relationship between HrsSP and RacePlnd predictior variables and racing time has a low correlation.
- When the average of the *RMSE* values of the methods based on models is taken, the best method is found to be GRNN with 16.40 *RMSE* value. It is observed that the worst method is RBFNN with 25.35 *RMSE* value.

- It is observed that SVM based prediction models produce 4.25% lower *RMSE* value on average compared to that of MLP based prediction models.
- It is observed that SVM based prediction models produce 0.12% higher *RMSE* value on average compared to that of GRNN based prediction models.
- It is observed that SVM based prediction models produce 35.22% lower *RMSE* value on average compared to that of RBFNN based prediction models.
- It is observed that SVM based prediction models produce 9.63% lower *RMSE* value on average compared to that of SDT based prediction models.
- It is observed that MLP based prediction models produce 4.37% higher *RMSE* value on average compared to that of GRNN based prediction models.
- It is observed that MLP based prediction models produce 32.34% lower *RMSE* value on average compared to that of RBFNN based prediction models.
- It is observed that MLP based prediction models produce 5.61% lower *RMSE* value on average compared to that of SDT based prediction models.
- It is observed that GRNN based prediction models produce 35.30% lower *RMSE* value on average compared to that of RBFNN based prediction models.
- It is observed that GRNN based prediction models produce 9.75% lower *RMSE* value on average compared to that of SDT based prediction models.

- It is observed that RBFNN based prediction models produce 28.32% lower *RMSE* value on average compared to that of SDT based prediction models.
- Average training times of SVM, GRNN, MLP, RBFNN and SDT based prediction models are 28.32, 28.15, 10.18, 38.63 and 0.15 seconds, respectively.
- An average of 13.09% improvement is observed in the *RMSE* values of the Optimized- GRNN based prediction models.
- It is observed that Optimized-GRNN based prediction models produce 16.63% lower *RMSE* value on average than that of SVM based prediction models.
- It is observed that Optimized-GRNN based prediction models produce 18.29% lower *RMSE* value on average than that of MLP based prediction models.
- It is observed that Optimized-GRNN based prediction models produce 47.31% lower *RMSE* value on average than that of RBFNN based prediction models.
- It is observed that Optimized-GRNN based prediction models produce 15.58% lower *RMSE* value on average than that of SDT based prediction models.
- The average training time of Optimized-GRNN based prediction models is 547.88 seconds.
- The average training time of Optimized-GRNN based prediction models is 94.86% higher than the average training time of GRNN based prediction models.

4.11. Results for Prediction Models Using Sextuple Combinations of the Predictor Variables

Table 4.10. and 4.11. show the *RMSE* values for race time models along with sextuple combinations of the predictor variables.

Table 4.10. *RMSE* for race time models along with sextuple combinations of the predictor variables

Models	RMSE					
	OPGRNN	GRNN	SVM	MLP	SDT	RBFNN
Model 231	10.79	13.06	13.86	13.85	13.53	27.26
Model 240	10.86	13.01	14.01	14.24	13.91	20.98
Model 434	10.92	13.18	13.73	13.83	13.35	19.89
Model 355	10.95	13.09	13.79	14.10	13.50	18.46
Model 458	10.96	13.22	13.74	13.92	13.53	20.80
Model 431	11.04	13.12	13.89	13.87	13.91	20.34
Model 377	11.04	13.26	13.78	13.81	13.48	24.59
Model 452	11.12	13.27	13.80	13.85	13.48	19.81
Model 192	11.13	13.27	13.84	14.16	13.66	24.46
Model 454	11.16	13.26	13.75	13.85	13.66	27.82

Table 4.11. *RMSE* for race time models along with sextuple combinations of the predictor variables

Models	RMSE					
	OPGRNN	GRNN	SVM	MLP	SDT	RBFNN
Model 124	11.20	13.28	13.76	14.10	13.32	23.05
Model 193	11.39	13.28	13.87	13.87	13.53	24.50
Model 215	11.47	13.05	13.75	14.22	13.86	18.97
Model 447	11.57	13.22	13.80	14.07	13.86	19.83
Model 211	11.58	13.24	14.14	13.98	13.97	20.68
Model 396	11.64	13.28	13.97	13.93	13.97	21.65
Model 461	11.78	13.25	13.64	14.06	13.77	19.61
Model 427	11.80	13.27	13.93	13.95	13.77	20.90
Model 160	11.95	13.07	13.84	13.83	13.45	19.78
Model 375	12.21	13.26	13.80	13.96	13.48	19.38

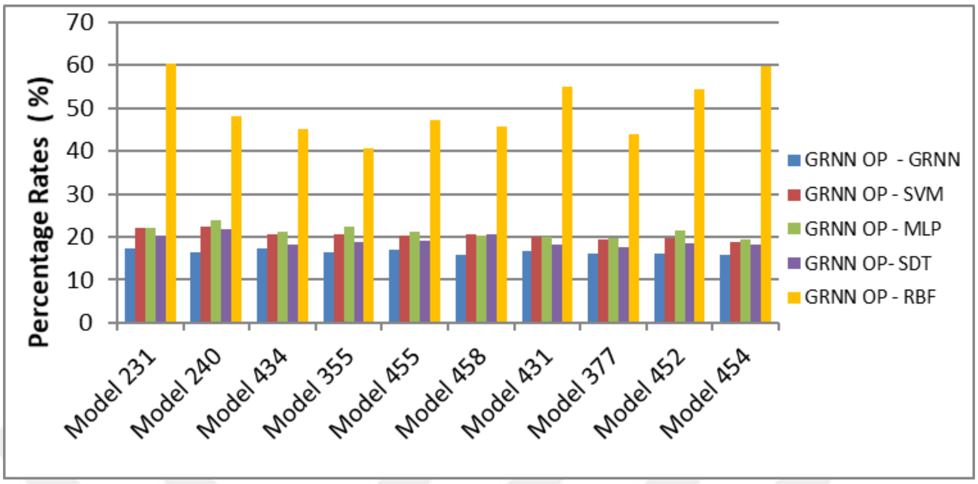

Figure 4.10. Percentage decrease rates in *RMSE* values of race time for OPGRNN-based models compared to *RMSE* values obtained by GRNN, SVM, MLP, SDT, and RBFNN-based models for sextuple combinations

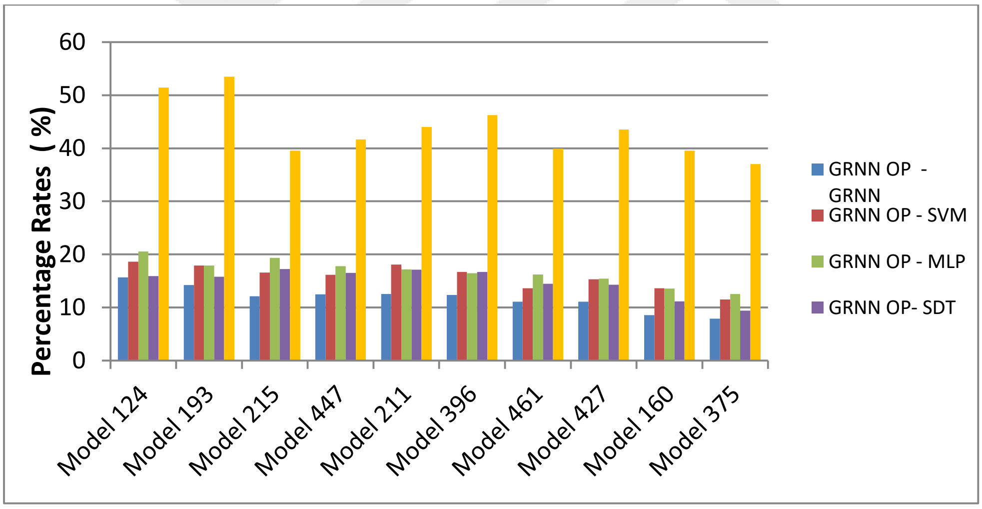

Figure 4.11. Percentage decrease rates in *RMSE* values of race time for OPGRNN-based models compared to *RMSE* values obtained by GRNN, SVM, MLP, SDT, and RBFNN-based models for sextuple combinations

4.12. Discussion for Prediction Models Using Sextuple Combinations of the Predictor Variables

- When the average of the method results for each model is taken, it is seen that the best model is Model-24 with 14.28 *RMSE* value and the worst model is Model-178 with 26.02 *RMSE* value.
- When the prediction models are analyzed, it is seen that the relationship between YRS10 and Wave predictor variables and racing time has a high correlation.
- When the prediction models are analyzed, it is seen that the relationship between HrsSP and RaceComp prediction variables and racing time has a low correlation.
- When the average of the *RMSE* values of the methods based on models is taken, the best method is found to be GRNN with 15.81 *RMSE* value. It is observed that the worst method is RBFNN with 24.55 *RMSE* value.
- It is observed that SVM based prediction models produce 3.15% lower *RMSE* value on average compared to that of MLP based prediction models.
- It is observed that SVM based prediction models produce 1.06% higher *RMSE* value on average compared to that of GRNN based prediction models.
- It is observed that SVM based prediction models produce 34.90% lower *RMSE* value on average compared to that of RBFNN based prediction models.
- It is observed that SVM based prediction models produce 8.21% lower *RMSE* value on average compared to that of SDT based prediction models.

- It is observed that MLP based prediction models produce 4.18% higher *RMSE* value on average compared to that of GRNN based prediction models.
- It is observed that MLP based prediction models produce 32.79% lower *RMSE* value on average compared to that of RBFNN based prediction models.
- It is observed that MLP based prediction models produce 5.22% lower *RMSE* value on average compared to that of SDT based prediction models.
- It is observed that GRNN based prediction models produce 35.60% lower *RMSE* value on average compared to that of RBFNN based prediction models.
- It is observed that GRNN based prediction models produce 9.19% lower *RMSE* value on average compared to that of SDT based prediction models.
- It is observed that RBFNN based prediction models produce 29.08% higher *RMSE* value on average compared to that of SDT based prediction models.
- Average training times of SVM, GRNN, MLP, RBFNN and SDT based prediction models are 28.79, 33.59, 1.553, 42.73 and 0.14 seconds, respectively.
- An average of 16.09% improvement is observed in the *RMSE* values of the Optimized- GRNN based prediction models.
- It is observed that Optimized-GRNN based prediction models produce 13.34% lower *RMSE* value on average than that of SVM based prediction models.

- It is observed that Optimized-GRNN based prediction models produce 16.55% lower *RMSE* value on average than that of MLP based prediction models.
- It is observed that Optimized-GRNN based prediction models produce 43.14% lower *RMSE* value on average than that of RBFNN based prediction models.
- It is observed that Optimized-GRNN based prediction models produce 27.15% lower *RMSE* value on average than that of SDT based prediction models.
- The average training time of Optimized-GRNN based prediction models is 404.38 seconds.
- The average training time of Optimized-GRNN based prediction models is 91.69% higher than the average training time of GRNN based prediction models.

4.13. Results for Prediction Models septuple combinations of the predictor variables

Table 4.12. and 4.13. show the *RMSE* values for race time models along with septuple combinations of the predictor variables.

Table 4.12. *RMSE* for race time models along with septuple combinations of the predictor variables

Models	*RMSE*					
	OPGRNN	GRNN	SVM	MLP	SDT	RBFNN
Model 315	10.96	13.17	13.96	13.89	13.53	20.47
Model 202	10.97	13.07	13.80	13.85	13.66	22.08
Model 312	10.97	13.13	13.88	14.17	13.66	20.57
Model 329	10.98	13.14	13.84	14.08	13.66	21.63
Model 294	11.06	13.13	13.78	13.98	13.48	20.76
Model 330	11.18	13.13	13.88	14.02	13.91	24.47
Model 68	11.23	13.01	13.96	13.92	13.32	22.60
Model 325	11.33	13.12	13.85	14.05	14.08	20.17
Model 191	11.37	12.99	14.00	14.13	14.08	19.88
Model 182	11.39	12.99	13.77	13.98	13.35	21.62

Table 4.13. *RMSE* for race time models along with septuple combinations of the predictor variables

Models	*RMSE*					
	OPGRNN	GRNN	SVM	MLP	SDT	RBFNN
Model 179	11.39	13.04	13.66	13.79	13.48	24.97
Model 159	11.40	13.09	13.87	14.21	13.45	21.07
Model 195	11.40	13.12	13.77	14.25	13.86	26.06
Model 89	11.44	13.06	13.90	14.09	13.91	21.22
Model 103	11.45	13.04	13.91	14.13	13.50	21.93
Model 203	11.48	13.10	13.81	14.06	13.53	25.19
Model 279	11.59	13.16	13.96	13.92	13.91	17.64
Model 209	11.82	12.99	13.85	14.12	13.77	20.18
Model 54	11.86	13.19	14.03	14.13	13.74	19.72
Model 105	11.94	13.04	13.97	14.28	13.53	17.26

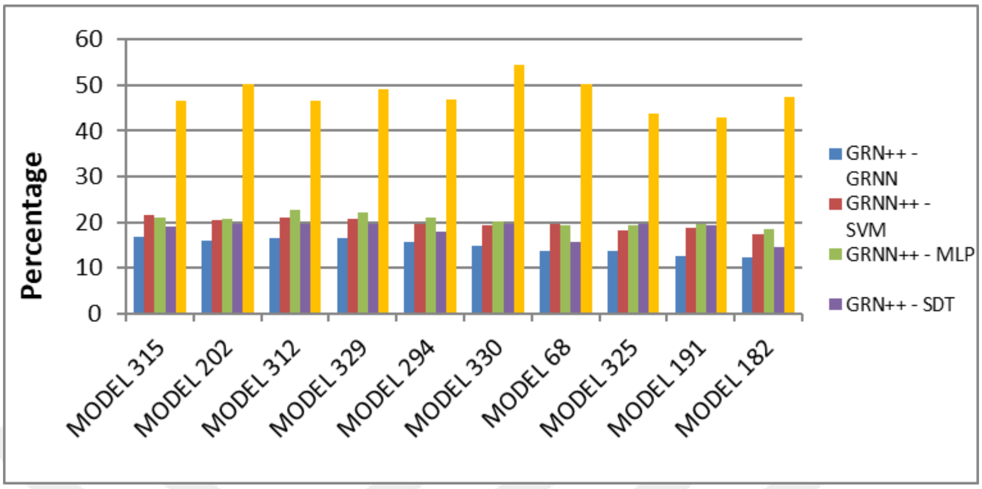

Figure 4.12. Percentage decrease rates in *RMSE* values of race time for OPGRNN-based models compared to *RMSE* values obtained by GRNN, SVM, MLP, SDT, and RBFNN-based models for septuple combinations

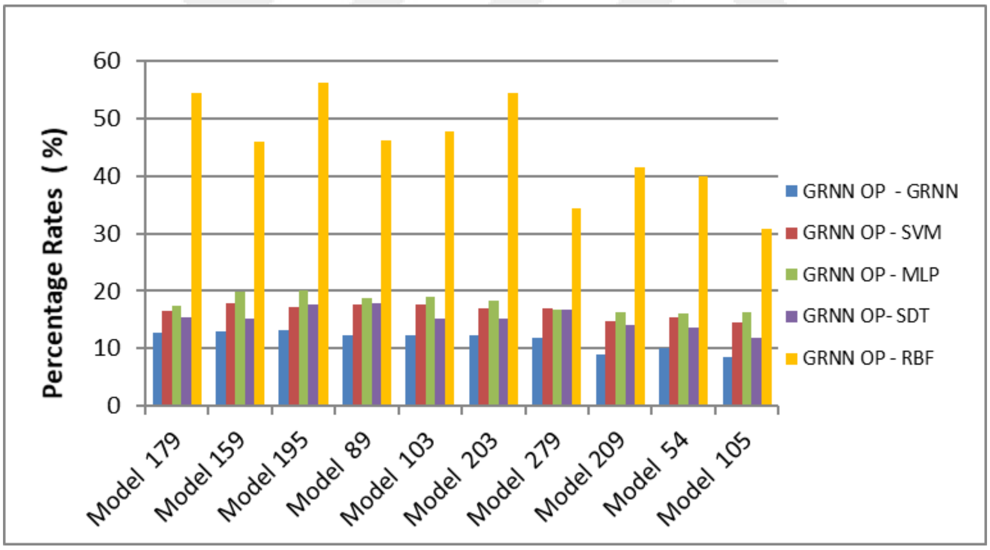

Figure 4.13. Percentage decrease rates in *RMSE* values of race time for OPGRNN-based models compared to *RMSE* values obtained by GRNN, SVM, MLP, SDT, and RBFNN-based models for septuple combinations

4.14. Discussion for Prediction Models Using Septuple Combinations of the Predictor Variables

- When the average of the method results for each model is taken, it is seen that the best model is Model-33 with 14.31 *RMSE* value and the worst model is Model-71 with 23.75 *RMSE* value.
- When the prediction models are analyzed, it is seen that the relationship between Wave predictor variable and racing time has a high correlation.
- When the prediction models are analyzed, it is seen that the relationship between HrsSP, RacePlnd and RaceComp prediction variables and racing time has a low correlation.
- When the average of the *RMSE* values of the methods based on models is taken, the best method is found to be GRNN with 15.25 *RMSE* value. It is observed that the worst method is RBFNN with 23.91 *RMSE* value.
- It is observed that SVM based prediction models produce 3.22% lower *RMSE* value on average compared to that of MLP based prediction models.
- It is observed that SVM based prediction models produce 2.11% higher *RMSE* value on average compared to that of GRNN based prediction models.
- It is observed that SVM based prediction models produce 34.83% lower *RMSE* value on average compared to that of RBFNN based prediction models.
- It is observed that SVM based prediction models produce 6.59% lower *RMSE* value on average compared to that of SDT based prediction models.

- It is observed that MLP based prediction models produce 5.27 % higher *RMSE* value on average compared to that of GRNN based prediction models.
- It is observed that MLP based prediction models produce 32.66% lower *RMSE* value on average compared to that of RBFNN based prediction models.
- It is observed that MLP based prediction models produce 3.47% lower *RMSE* value on average compared to that of SDT based prediction models.
- It is observed that GRNN based prediction models produce 36.21% lower *RMSE* value on average compared to that of RBFNN based prediction models.
- It is observed that GRNN based prediction models produce 8.57% lower *RMSE* value on average compared to that of SDT based prediction models.
- It is observed that RBFNN based prediction models produce 30.23% lower *RMSE* value on average compared to that of SDT based prediction models.
- Average training times of SVM, GRNN, MLP, RBFNN and SDT based prediction models are 30.54, 37.82, 1.63, 42.42 and 0.15 seconds, respectively.
- An average of 13.21% improvement is observed in the *RMSE* values of the Optimized- GRNN based prediction models.
- It is observed that Optimized-GRNN based prediction models produce 18.09% lower *RMSE* value on average than that of SVM based prediction models.

- It is observed that Optimized-GRNN based prediction models produce 19.04% lower *RMSE* value on average than that of MLP based prediction models.
- It is observed that Optimized-GRNN based prediction models produce 45.31% lower *RMSE* value on average than that of RBFNN based prediction models.
- It is observed that Optimized-GRNN based prediction models produce 16.89% lower *RMSE* value on average than that of SDT based prediction models.
- The average training time of Optimized-GRNN based prediction models is 1445.7 seconds.
- The average training time of Optimized-GRNN based prediction models is 97.38% higher than the average training time of GRNN based prediction models.

4.15. Results for Prediction Models Using Octuple Combinations of the Predictor Variables

Table 4.14. and 4.15. show the *RMSE* values for race time models along with octuple combinations of the predictor variables.

Table 4.14. *RMSE* for race time models along with octuple combinations of the predictor variables

Models	*RMSE*					
	OPGRNN	**GRNN**	**SVM**	**MLP**	**SDT**	**RBFNN**
Model 108	10.82	13.05	13.82	14.05	13.91	20.86
Model 120	10.88	13.05	13.86	14.12	13.91	21.18
Model 155	11.01	13.13	13.95	14.18	13.66	23.85
Model 80	11.15	12.95	14.08	14.29	13.91	24.29
Model 164	11.15	13.12	13.84	13.94	13.91	20.36
Model 76	11.19	13.11	13.89	14.08	13.66	23.22
Model 110	11.19	13.20	13.83	13.98	13.91	26.91
Model 165	11.20	13.15	13.94	14.21	14.08	24.33
Model 129	11.20	13.22	14.04	13.98	14.08	21.20
Model 93	11.25	13.17	13.86	13.89	14.08	23.33

Table 4.15. *RMSE* for race time models along with octuple combinations of the predictor variables

Models	*RMSE*					
	OPGRNN	**GRNN**	**SVM**	**MLP**	**SDT**	**RBFNN**
Model159	11.34	13.15	13.96	14.23	14.08	22.56
Model 115	11.41	13.06	13.96	14.31	14.08	21.28
Model 77	11.42	13.04	14.05	14.28	13.53	23.09
Model 33	11.43	13.22	14.03	14.35	13.50	26.74
Model 112	11.44	13.05	13.68	13.93	13.48	20.14
Model 156	11.48	13.13	14.09	14.34	13.91	22.45
Model 144	11.52	13.20	14.04	13.88	13.91	22.17
Model 65	11.78	13.22	14.09	14.08	14.08	20.72
Model 111	11.83	13.18	13.84	14.18	13.77	27.47
Model 56	12.16	13.00	13.89	13.86	13.35	22.66

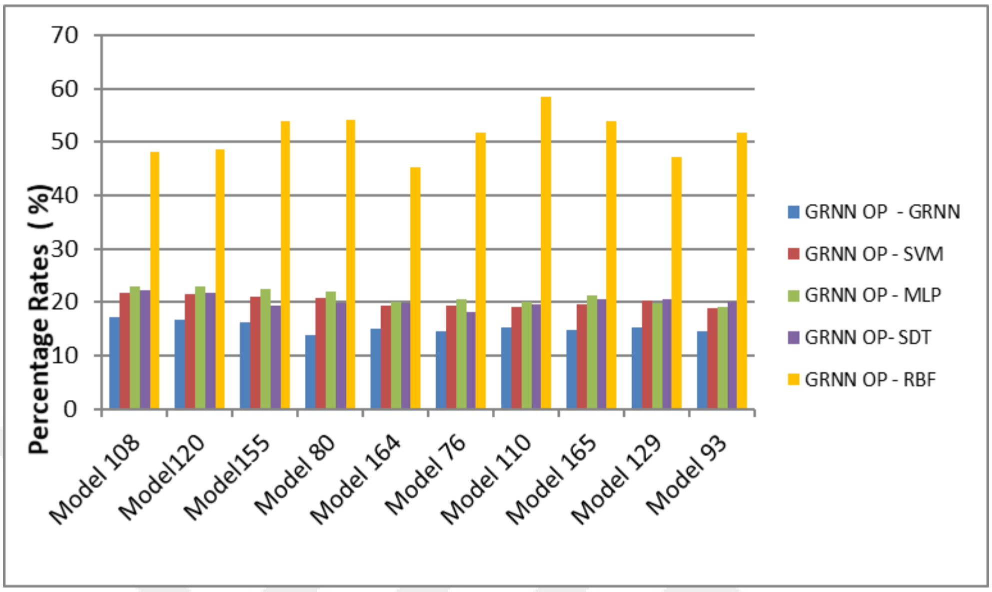

Figure 4.14. Percentage decrease rates in *RMSE* values of race time for OPGRNN-based models compared to *RMSE* values obtained by GRNN, SVM, MLP, SDT, and RBFNN-based models for octuple combinations

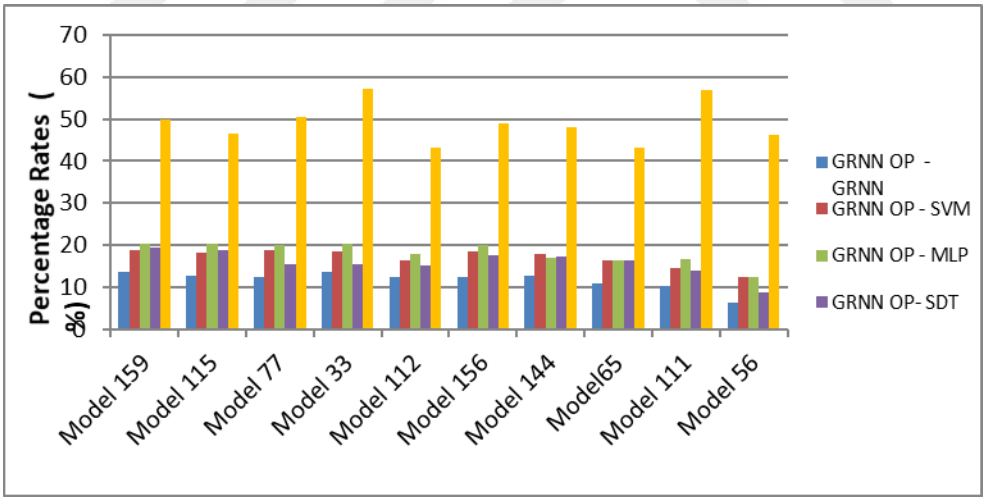

Figure 4.15. Percentage decrease rates in *RMSE* values of race time for OPGRNN-based models compared to *RMSE* values obtained by GRNN, SVM, MLP, SDT, and RBFNN-based models for octuple combinations

4.16. Discussion for Prediction Models Using Octuple Combinations of the Predictor Variables

- When the average of the method results for each model is taken, it is seen that the best model is Model-71 with 14.69 *RMSE* value and the worst model is Model-7 with 24.27 *RMSE* value.
- When the prediction models are analyzed, it is seen that the relationship between YRS10 and Wave predictor variables and racing time has a high correlation.
- When the prediction models are analyzed, it is seen that the relationship between HrsOther and Raceplnd predictor variables and racing time has a low correlation.
- When the average of the *RMSE* values of the methods based on models is taken, the best method is found to be GRNN with 14.72 *RMSE* value. It is observed that the worst method is RBFNN with 24.60 *RMSE* value.
- It is observed that SVM based prediction models produce 2.31% lower *RMSE* value on average compared to that of MLP based prediction models.
- It is observed that SVM based prediction models produce 3.15% higher *RMSE* value on average compared to that of GRNN based prediction models.
- It is observed that SVM based prediction models produce 38.21% lower *RMSE* value on average compared to that of RBFNN based prediction models.
- It is observed that SVM based prediction models produce 4.88% lower *RMSE* value on average compared to that of SDT based prediction models.

- It is observed that MLP based prediction models produce 5.39% higher *RMSE* value on average compared to that of GRNN based prediction models.
- It is observed that MLP based prediction models produce 36.74% lower *RMSE* value on average compared to that of RBFNN based prediction models.
- It is observed that MLP based prediction models produce 2.62% lower *RMSE* value on average compared to that of SDT based prediction models.
- It is observed that GRNN based prediction models produce 40.16% lower *RMSE* value on average compared to that of RBFNN based prediction models.
- It is observed that GRNN based prediction models produce 7.88% lower *RMSE* value on average compared to that of SDT based prediction models.
- It is observed that RBFNN based prediction models produce 35.04% higher *RMSE* value on average compared to that of SDT based prediction models.
- Average training times of SVM, GRNN, MLP, RBFNN and SDT based prediction models are 32.01, 44.04, 1.78, 52.29 and 0.16 seconds, respectively.
- An average of 16.40% improvement is observed in the *RMSE* values of the Optimized- GRNN based prediction models.
- It is observed that Optimized-GRNN based prediction models produce 15.58% lower *RMSE* value on average than that of SVM based prediction models.

- It is observed that Optimized-GRNN based prediction models produce 20.34% lower *RMSE* value on average than that of MLP based prediction models.
- It is observed that Optimized-GRNN based prediction models produce 48.49% lower *RMSE* value on average than that of RBFNN based prediction models.
- It is observed that Optimized-GRNN based prediction models produce 28.25% lower *RMSE* value on average than that of SDT based prediction models.
- The average training time of Optimized-GRNN based prediction models is 973.45 seconds.
- The average training time of Optimized-GRNN based prediction models is 95.47% higher than the average training time of GRNN based prediction models

4.17. Results for Prediction Models Using Nonuple Combinations of the Predictor Variables

Table 4.16. and 4.17. show the *RMSE* values for race time models along with nonuple combinations of the predictor variables.

Table 4.16. *RMSE* for race time models along with nonuple combinations of the predictor variables

Models	RMSE					
	OPGRNN	GRNN	SVM	MLP	SDT	RBFNN
Model 44	10.87	13.25	14.08	13.86	13.91	24.04
Model 54	11.13	13.34	14.02	14.05	14.08	23.44
Model 45	11.16	13.29	14.09	14.17	14.08	20.84
Model 52	11.18	13.15	14.02	13.83	13.66	20.21
Model 24	11.22	13.26	14.15	14.25	13.91	21.42
Model 28	11.28	13.04	14.04	14.14	13.48	23.22
Model 8	11.29	13.33	14.21	14.15	13.97	19.44
Model 38	11.30	13.34	14.10	14.45	13.97	22.38
Model 9	11.31	13.10	14.15	14.09	14.08	19.59
Model 35	11.32	13.30	14.01	14.03	13.66	21.12

Table 4.17. *RMSE* for race time models along with nonuple combinations of the predictor variables

Models	RMSE					
	OPGRNN	GRNN	SVM	MLP	SDT	RBFNN
Model 39	11.33	13.18	14.15	14.48	14.08	23.90
Model 50	11.41	13.31	14.08	14.14	14.08	19.70
Model 13	11.44	13.25	14.04	14.34	13.91	20.78
Model 43	11.47	13.30	13.97	14.14	13.66	19.70
Model 15	11.51	13.32	14.03	14.26	13.95	17.68
Model 31	11.52	13.31	14.08	14.21	14.08	21.46
Model 47	11.57	13.35	14.14	14.06	13.97	21.52
Model 14	11.66	13.34	14.29	14.25	13.95	22.35
Model 27	11.82	13.35	14.14	14.21	13.77	22.73
Model 21	12.10	13.25	14.19	13.94	13.53	21.75

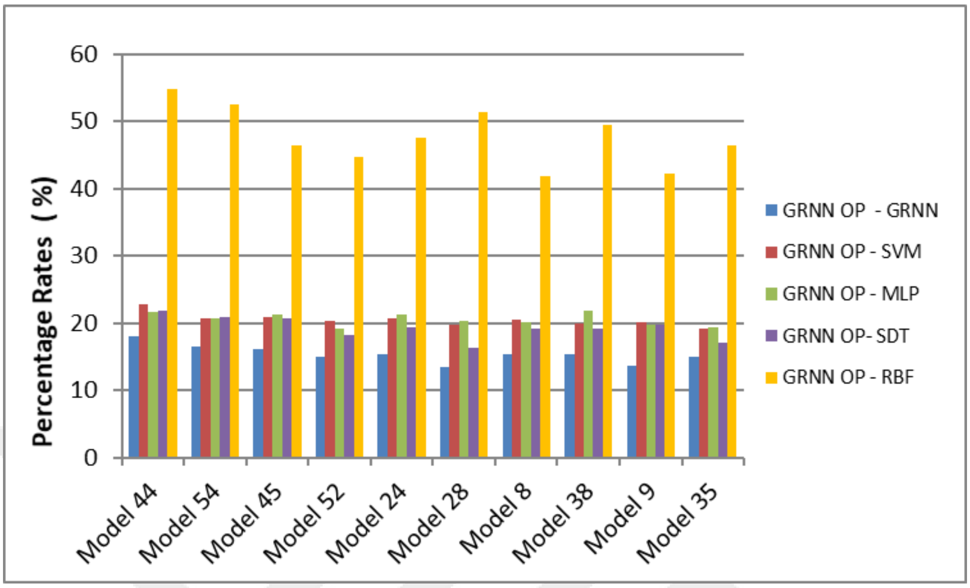

Figure 4.16. Percentage decrease rates in *RMSE* values of race time for OPGRNN-based models compared to *RMSE* values obtained by GRNN, SVM, MLP, SDT, and RBFNN-based models for nonuple combinations

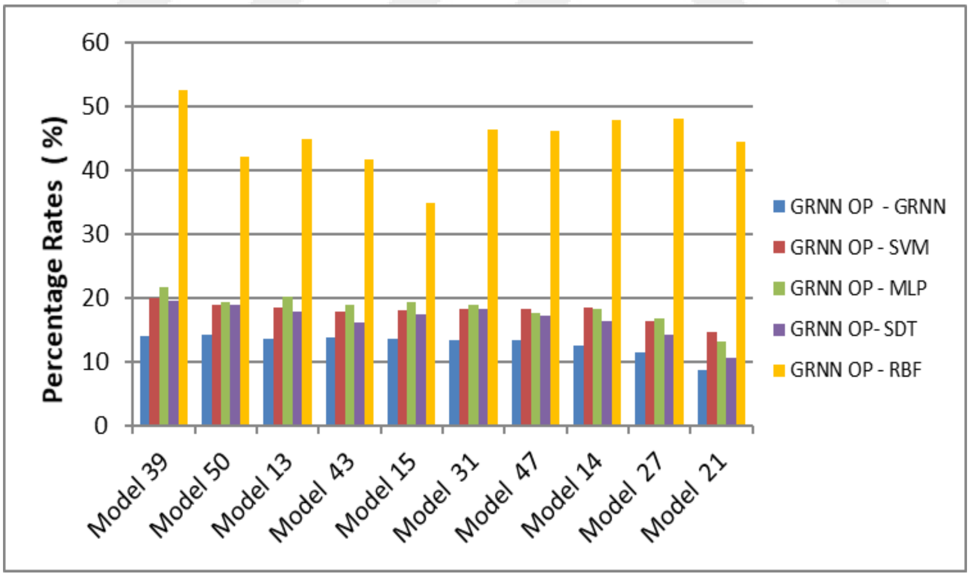

Figure 4.17. Percentage decrease rates in RMSE values of race time for OPGRNN-based models compared to RMSE values obtained by GRNN, SVM, MLP, SDT, and RBFNN-based models for nonuple combinations

4.18. Discussion for Prediction Models Using Nonuple Combinations of the Predictor Variables

- When the average of the method results for each model is taken, it is seen that the best model is Model-15 with 14.65 *RMSE* value and the worst model is Model-46 with 22.75 *RMSE* value.
- When the prediction models are analyzed, it is seen that the relationship between Wave, BMT5 ve BMT10 predictor variables and racing time has a high correlation.
- When the prediction models are analyzed, it is seen that the relationship between HrsSP and RacePlnd prediction variables and racing time has a low correlation.
- When the average of the *RMSE* values of the methods based on models is taken, the best method is found to be GRNN with 14.27 *RMSE* value. It is observed that the worst method is RBFNN with 23.60 *RMSE* value.
- It is observed that SVM based prediction models 1.52% lower *RMSE* value on average compared to that of MLP based prediction models.
- It is observed that SVM based prediction models produce 3.92% higher *RMSE* value on average compared to that of GRNN based prediction models.
- It is observed that SVM based prediction models produce 37.03% lower *RMSE* value on average compared to that of RBFNN based prediction models.
- It is observed that SVM based prediction models produce 3% lower *RMSE* value on average compared to that of SDT based prediction models.

- It is observed that MLP based prediction models produce 5.43% higher *RMSE* value on average compared to that of GRNN based prediction models.
- It is observed that MLP based prediction models produce 36.05% lower *RMSE* value on average compared to that of RBFNN based prediction models.
- It is observed that MLP based prediction models produce 1.50% lower *RMSE* value on average compared to that of SDT based prediction models.
- It is observed that GRNN based prediction models produce 39.53% lower *RMSE* value on average compared to that of RBFNN based prediction models.
- It is observed that GRNN based prediction models produce 6.85% lower *RMSE* value on average compared to that of SDT based prediction models.
- It is observed that RBFNN based prediction models produce 35.08% higher *RMSE* value on average compared to that of SDT based prediction models.
- Average training times of SVM, GRNN, MLP, RBFNN and SDT based prediction models are 35.03, 32.24, 1.74, 40.41 and 0.16 seconds, respectively.
- An average of 14.16% improvement is observed in the *RMSE* values of the Optimized- GRNN based prediction models.
- It is observed that Optimized-GRNN based prediction models produce 19.21% lower *RMSE* value on average than that of SVM based prediction models.

- It is observed that Optimized-GRNN based prediction models produce 19.50% lower *RMSE* value on average than that of MLP based prediction models.
- It is observed that Optimized-GRNN based prediction models produce 46.81% lower *RMSE* value on average than that of RBFNN based prediction models.
- It is observed that Optimized-GRNN based prediction models produce 17.09% lower *RMSE* value on average than that of SDT based prediction models.
- The average training time of Optimized-GRNN based prediction models is 1135.55 seconds.
- The average training time of Optimized-GRNN based prediction models is 97.16% higher than the average training time of GRNN based prediction models.

4.19. Results for Prediction Models Using Decuple Combinations of the Predictor Variables

Table 4.18. shows the *RMSE* values for race time models along with nonuple combinations of the predictor variables.

Table 4.18. *RMSE* for race time models along with decuple combinations of the predictor variables

Models	***RMSE***					
	OPGRNN	**GRNN**	**SVM**	**MLP**	**SDT**	**RBFNN**
Model 8	10.90	13.75	14.19	14.16	13.91	20.61
Model 10	11.12	13.41	14.11	13.95	14.08	20.52
Model 11	11.14	13.15	14.10	14.17	14.08	20.80
Model 5	11.31	13.47	14.20	13.97	14.08	21.46
Model 3	11.45	13.06	14.22	13.94	14.08	20.04
Model 7	11.46	13.65	14.12	14.18	13.66	21.18
Model 6	11.48	13.36	14.21	14.17	13.95	22.72
Model 9	11.50	13.45	14.08	14.03	14.08	23.42
Model 4	11.72	13.56	14.36	14.22	14.88	23.14
Model 2	11.77	13.45	14.26	14.11	13.97	20.66
Model 1	15.01	17.90	17.97	19.27	21.66	28.04

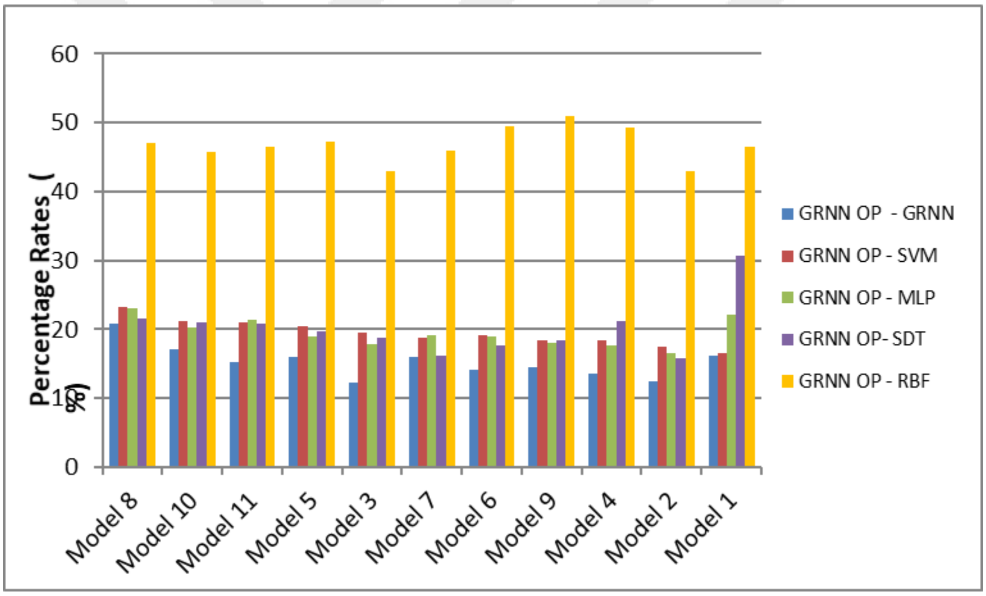

Figure 4.18. Percentage decrease rates in *RMSE* values of race time for OPGRNN-based models compared to *RMSE* values obtained by GRNN, SVM, MLP, SDT, and RBFNN-based models for decuple combinations

4.20. Discussion for Prediction Models Using Decuple Combinations of the Predictor Variables

- When the average of the method results for each model is taken, it is seen that the best model is Model-3 with 15.07 *RMSE* value and the worst model is Model-1 with 20.97 *RMSE* value.
- When the prediction models are analyzed, it is seen that the relationship between Wave predictor variable and racing time has a high correlation.
- When the prediction models are analyzed, it is seen that the relationship between RaceComp prediction variable and racing time has a low correlation.
- When the average of the *RMSE* values of the methods based on models is taken, the best method is found to be GRNN with 13.84 *RMSE* value. It is observed that the worst method is RBFNN with 22.05 *RMSE* value.
- It is observed that SVM based prediction models 0.20% lower *RMSE* value on average compared to that of MLP based prediction models.
- It is observed that SVM based prediction models produce 4.74% higher *RMSE* value on average compared to that of GRNN based prediction models.
- It is observed that SVM based prediction models produce 34.10% lower *RMSE* value on average compared to that of RBFNN based prediction models.
- It is observed that SVM based prediction models produce 1.62% lower *RMSE* value on average compared to that of SDT based prediction models.

- It is observed that MLP based prediction models produce 4.94% higher *RMSE* value on average compared to that of GRNN based prediction models.
- It is observed that MLP based prediction models produce 33.96% lower *RMSE* value on average compared to that of RBFNN based prediction models.
- It is observed that MLP based prediction models produce 1.42% lower *RMSE* value on average compared to that of SDT based prediction models.
- It is observed that GRNN based prediction models produce 37.23% lower *RMSE* value on average compared to that of RBFNN based prediction models.
- It is observed that GRNN based prediction models produce 6.29% lower *RMSE* value on average compared to that of SDT based prediction models.
- It is observed that RBFNN based prediction models produce 33.01% higher *RMSE* value on average compared to that of SDT based prediction models.
- Average training times of SVM, GRNN, MLP, RBFNN and SDT based prediction models are 35.56, 33.76, 1.86, 40.26 and 0.16 seconds, respectively.
- An average of 14.81% improvement is observed in the *RMSE* values of the Optimized- GRNN based prediction models.
- It is observed that Optimized-GRNN based prediction models produce 18.85% lower *RMSE* value on average than that of SVM based prediction models.

- It is observed that Optimized-GRNN based prediction models produce 19.02% lower *RMSE* value on average than that of MLP based prediction models.
- It is observed that Optimized-GRNN based prediction models produce 46.53% lower *RMSE* value on average than that of RBFNN based prediction models.
- It is observed that Optimized-GRNN based prediction models produce 20.17% lower *RMSE* value on average than that of SDT based prediction models.
- The average training time of Optimized-GRNN based prediction models is 565.7 seconds.
- The average training time of Optimized-GRNN based prediction models is 94.3% higher than the average training time of GRNN based prediction models.

4.21. Results for Prediction Models Using Undecuple Combinations of the Predictor Variables

Table 4.19. shows the *RMSE* values for race time models along with undecuple combinations of the predictor variables.

Table 4.19. *RMSE* for race time models along with undecuple combinations of the predictor variables

Models	***RMSE***					
	OPGRNN	**GRNN**	**SVM**	**MLP**	**SDT**	**RBFNN**
Model 1	11.14	13.50	14.21	14.15	14.08	21.62

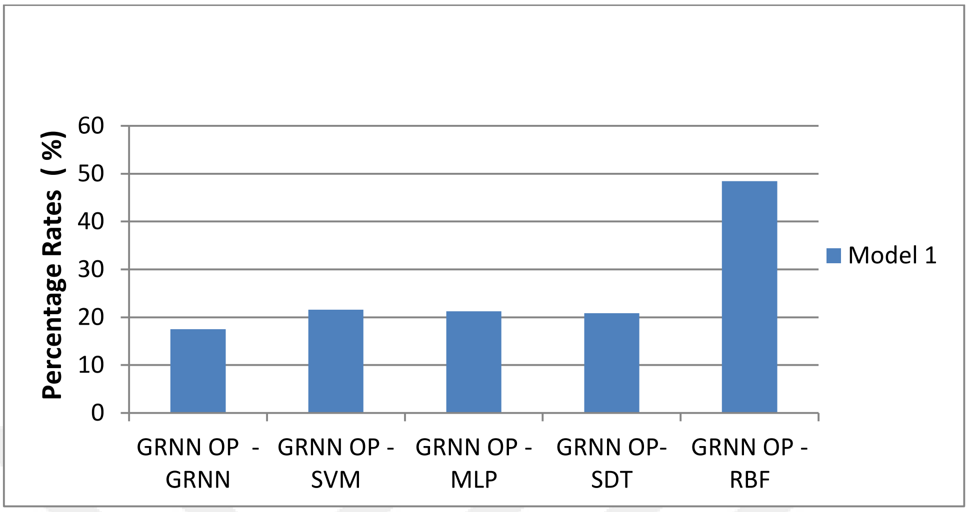

Figure 4.19. Percentage decrease rates in *RMSE* values of race time for OPGRNN-based models compared to *RMSE* values obtained by GRNN, SVM, MLP, SDT, and RBFNN-based models for undecuple combinations

4.22. Discussion for Prediction Models Using Undecuple Combinations of the Predictor Variables

- The best method is found to be GRNN with 13.50 *RMSE* value. It is observed that the worst method is RBFNN with 21.62 *RMSE* value.
- It is observed that SVM based prediction model produces 0.55% lower *RMSE* value compared to that of MLP based prediction model.
- It is observed that SVM based prediction model produces 4.99% higher *RMSE* value compared to that of GRNN based prediction model.
- It is observed that SVM based prediction model produces 34.27% lower *RMSE* value compared to that of RBFNN based prediction model.
- It is observed that SVM based prediction model produces 0.91% lower *RMSE* value compared to that of SDT based prediction model.

- It is observed that MLP based prediction model produces 4.59% higher *RMSE* value compared to that of GRNN based prediction model.
- It is observed that MLP based prediction model produces 34.55% lower *RMSE* value compared to that of RBFNN based prediction model.
- It is observed that MLP based prediction model produces 0.49% higher *RMSE* value compared to that of SDT based prediction model.
- It is observed that GRNN based prediction model produces 37.55% lower *RMSE* value compared to that of RBFNN based prediction model.
- It is observed that GRNN based prediction model produces 4.11% lower *RMSE* value compared to that of SDT based prediction model.
- It is observed that RBFNN based prediction model produces 34.78% higher *RMSE* value compared to that of SDT based prediction model.
- Training times of SVM, GRNN, MLP, RBFNN and SDT based prediction models are 31.58, 65.75, 1.91, 267.37 and 0.15 seconds, respectively.
- 17.48% improvement is observed in the *RMSE* value of the Optimized-GRNN based prediction models.
- It is observed that Optimized-GRNN based prediction model produces 21.06% lower *RMSE* value than that of SVM based prediction model.
- It is observed that Optimized-GRNN based prediction model produces 21.27% lower *RMSE* value than that of MLP based prediction model.
- It is observed that Optimized-GRNN based prediction model produces 48.47% lower *RMSE* value than that of RBFNN based prediction model.

- It is observed that Optimized-GRNN based prediction model produces 20.88% lower *RMSE* value than that of SDT based prediction model.
- Training time of Optimized-GRNN based prediction model is 1153.04 seconds.
- Training time of Optimized-GRNN based prediction model is 94.29% higher than the training time of GRNN based prediction model.

4.23. General Discussion

- For racing times prediction, Optimized-GRNN shows superior performance and RBFNN exhibits the poorest prediction performance.
- There is no strict order between SVM-based and MLP-based prediction models, but the RMSEs related to SVM-based and MLP-based prediction models are always higher than those of GRNN-based prediction models, and lower than those of RBFNN-based prediction models.
- In general, inclusion of RaceComp, RacePlnd and Wave in place of combinations of the predictor variables models give lower error rates for the prediction of racing times regardless of which regression methods have been used.
- When the wave variable is not included in the datasets, the predictor variable is assigned with the highest rank for racing-time
- Among the predictor variables, the wave attribute has the strongest effect on the performance of racing time prediction.
- GRNN-based Model 80 that is made up of the predictor variables BMT5, BMT10, HrsXC, HrsSP, HrsOther, HrsTot, RacePlnd, Wave for 8 combinations of the predictor variables with GRNN yields the lowest *RMSE* with 12.95 min among all GRNN-based models.

- SVM -based Model 41 that is made up of the predictor variables BMT5, HrsTot, Wave for 3 combinations of the predictor variables with SVM yields the lowest *RMSE* with 13.27 min among all SVM based models.
- MLP-based Model 102 that is made up of the predictor variables, HrsXC, RacePlnd, Wave for 3 combinations of the predictor variables with MLP yields the lowest *RMSE* with 13.78 min among all MLP based models.

4.24. Results for Feature Selection Based Prediction Models

Table 4.20 and Table 4.21 present the results for all prediction models developed for prediction of the racing time of cross-country skiers using OPGRNN, GRNN, SVM, MLP, SDT, and RBFNN on racing-time-set-(1) and racing-time-set-(2), respectively. In addition, Figure 4.20 and Figure 4.21 represent the percentage decrease rates (PDRs) in *RMSE*s of racing time prediction models for OPGRNN compared to *RMSE*s achieved by GRNN, SVM, MLP, SDT, and RBFNN methods using racing-time-set-(1) and racing-time-set-(2), respectively.

Table 4.20. Averages of 10-fold validation results on racing-time-set-(1)

Models	***RMSE***					
	OPGRNN	**GRNN**	**SVM**	**MLP**	**SDT**	**RBFNN**
Model 1	15.31	17.54	17.98	19.00	21.76	31.04
Model 2	15.18	17.29	18.85	19.45	21.93	27.66
Model 3	15.42	17.19	18.75	19.06	21.63	27.73
Model 4	15.50	17.57	17.65	19.07	21.63	24.19
Model 5	16.32	18.14	19.06	19.01	22.79	25.67
Model 6	15.98	18.25	20.64	19.89	22.28	26.24
Model 7	17.05	20.21	20.79	20.50	22.74	30.44
Model 8	16.88	20.04	20.45	20.55	22.61	25.74
Model 9	17.68	20.77	20.92	21.05	22.91	28.86
Model 10	19.74	21.99	22.17	21.87	23.57	24.70
Model 11	19.61	21.79	21.85	22.01	23.66	26.04
Model 12	20.99	23.17	23.24	23.43	24.02	54.41
Model 13	21.04	22.31	23.14	23.25	23.92	24.09
Model 14	22.23	23.37	23.46	23.50	23.82	23.89

Table 4.21. Averages of 10-fold validation results on racing-time-set-(2)

Models	*RMSE*					
	OPGRNN	**GRNN**	**SVM**	**MLP**	**SDT**	**RBFNN**
Model 15	11.48	13.52	14.01	14.08	14.11	24.46
Model 16	11.36	13.08	14.05	14.18	14.14	21.84
Model 17	10.97	13.50	14.02	14.08	14.08	23.63
Model 18	11.27	13.14	14.00	13.84	14.08	21.78
Model 19	11.12	13.12	13.87	13.06	14.91	19.58
Model 20	11.73	13.52	13.99	13.84	14.14	23.22
Model 21	11.65	13.76	14.00	13.95	14.02	18.91
Model 22	11.73	13.69	13.72	13.72	14.02	19.03
Model 23	12.00	13.71	13.75	13.84	13.95	15.51
Model 24	12.07	13.01	13.70	13.83	14.95	17.72
Model 25	12.58	13.81	14.20	13.44	13.95	17.22
Model 26	12.57	13.79	14.23	13.61	13.95	16.79
Model 27	12.57	13.79	13.96	13.16	13.95	19.05
Model 28	13.17	13.89	13.96	13.94	13.95	14.62
Model 29	14.44	14.60	14.64	14.66	14.68	14.81

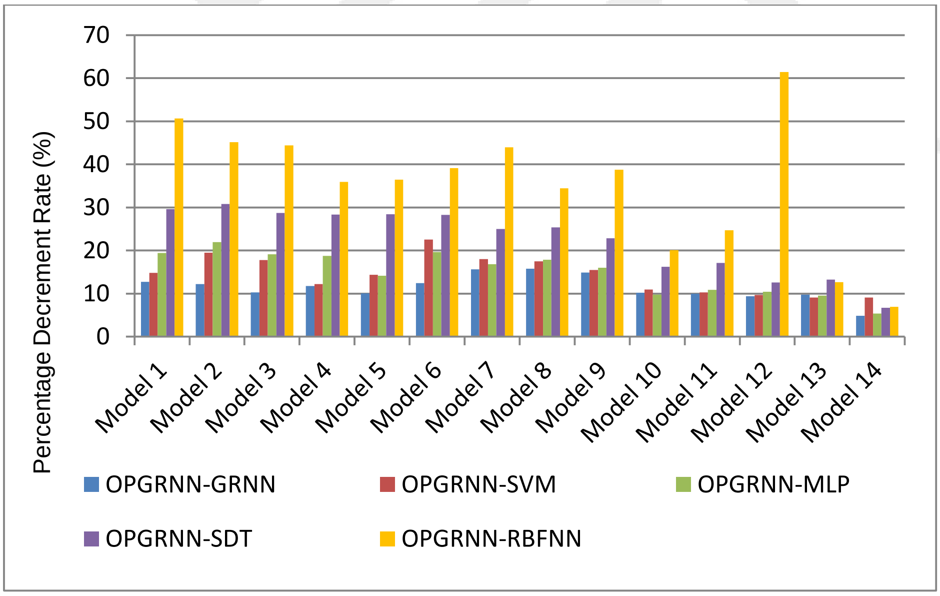

Figure 4.20. Percentage decrement rates in RMSEs of racing time prediction models for OPGRNN compared to RMSEs obtained by GRNN, SVM, MLP,SDT, and RBFNN methods using racing-time-set-(1)

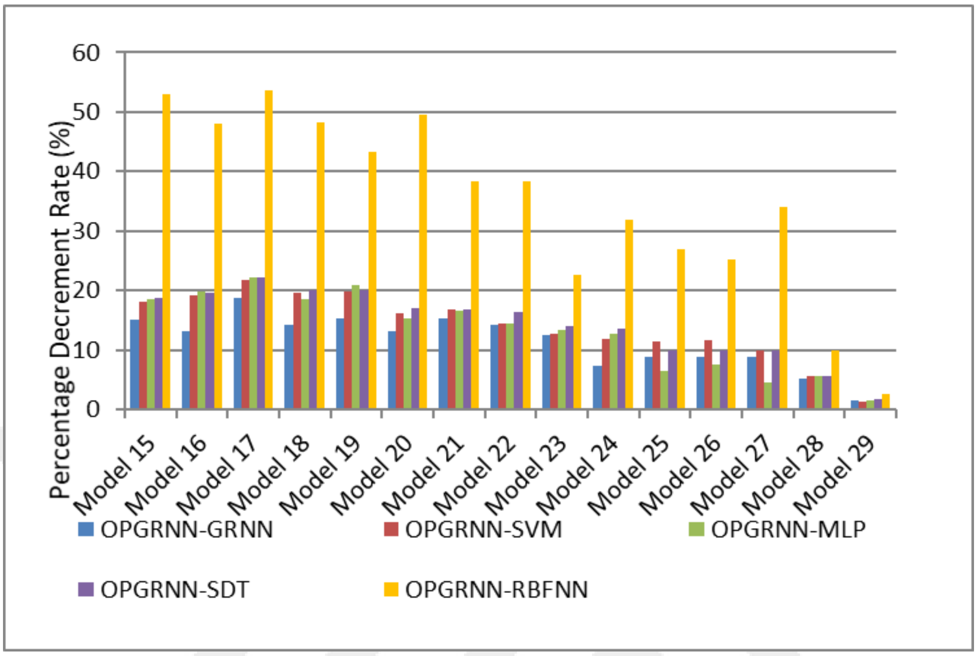

Figure 4.21. Percentage decrement rates in *RMSE*s of racing time prediction models for OPGRNN compared to *RMSE*s obtained by GRNN, SVM, MLP, SDT, and RBFNN methods using racing-time-set-(2)

4.25. Discussion for Feature Selection Based Prediction Models

The results reported by the Relief-F feature selector suggest that the variables age and assigned starting wave of cross-country skiers, in general, have been observed to be the most relevant predictors of racing time. In more detail, as is seen in Table 2, when the wave variable is not included in the data sets, the predictor variable age is assigned with the highest rank for racing-time-set-(1). In the other case, the predictor variable wave is assigned with the highest rank for racing-time-set-(2), while age is assigned with the second highest rank for prediction of racing time. For both data sets, the variables RaceComp, BMT5, and BMT10 have been ranked with the last 3 orders for prediction of racing time.

Generally, the results illustrate that OPGRNN-based models show superior performance, and RBFNN-based models exhibit the poorest performance for prediction of racing time. The GRNN-based models occupy the second rank in terms of performane. There is no strict order between SVM-based and MLP-based models, but the RMSEs related to SVM-based and MLP-based prediction models are always higher than those of GRNN-based prediction models, and lower than those of RBFNN-based prediction models. Particularly, as compared to the RMSEs produced by GRNN, SVM, MLP, SDT, and RBFNN, the PDRs in RMSEs achieved by OPGRNN are in average 11.42%, 14.37%, 14.73%, 22.37%, and 37.65% for racing-time-set-(1), and 11.48%, 14.10%, 14.47%, 14.33%, and 37.24% for racing-time-set-(2), respectively.

No prediction model always produces the lowest estimation errors for all considered machine learning methods. Stated in other words, the best performing racing time prediction model varies according to the machine learning method being used. Particularly, building the Model 17 including the predictor variables wave, age, weight, HrsSP, height, sex, HrsTot, HrsOther, YRS10, HrsXC, RacePlnd, YRSALL, and BMT5 with OPGRNN yields the lowest *RMSE* with 10.97 min among all OPGRNN-based models. Simiarly, building the Model 24 including the predictor variables wave, age, weight, HrsSP, height, sex with GRNN produces the lowest *RMSE* with 10.97 min among all GRNN-based models. Similarly, the SVM-based Model 24 that is made up of the predictor variables wave, age, weight, HrsSP, height, and sex gives the lowest RMSE with 13.70 min among all SVM-based models. Developing the Model 22 including the predictor variables wave, age, weight, HrsSP, height, sex, HrsTot, and HrsOther with MLP produces the lowest *RMSE* with 13.72 min among all MLP-based models. Finally, forming the Model 20 including the predictor variable wave with RBFNN gives the lowest *RMSE* with 14.60 min among all RBFNN-based models. In contrast, except from RBFNN, models including only a single predictor variable (i.e. age or wave) have the highest *RMSE*s, independent of whether they are built with GRNN, SVM, or MLP.

Among the predictor variables, the performance of racing time prediction has strongly been affected by the wave attribute. The average *RMSE*s of all prediction models including the wave variable are 12.05 min, 13.60 min, 14.02 min, 14.09 min, 22.83 min, and 19.20 min for OPGRNN, GRNN, SVM, MLP, SDT, and RBFNN, respectively. The average *RMSE*s of all prediction models not including the wave variables are 17.78 min, 20.05 min, 20.02 min, 20.85 min, 22.83 min and 28.52 min for GRNN, SVM, MLP, and RBFNN, respectively. Particularly, compared to the average *RMSE*s of models not including the wave variable; the average *RMSE*s of prediction models including the wave variable have been found to be 29.86%, 32.22%, 29.97%, 32.42%, 38.41%, and 32.68% lower for GRNN, SVM, MLP, and RBFNN, respectively.

5. CONCLUSION AND FUTURE WORK

The application of machine learning methods in sports science has long been an active research area. Although machine learning methods have been applied on different problems in various sports branches, some of the problems require further investigation. One such sports field is cross-country skiing. The purpose of this thesis is to develop new regular and feature selection-based models for predicting the racing times of cross-country skiers by using machine learning and feature selection methods. Particularly, six popular machine learning methods including Optimized-General Regression Neural Network (OPGRNN), General Regression Neural Network (GRNN), Support Vector Machine (SVM), Multilayer Perceptron (MLP), Radial Basis Function Neural Network (RBFNN), and Single Decision Tree (SDT) have been used, whereas Relief-F has been employed as the feature selector. A dataset containing physiological and survey-based information belonging to 370 cross-country skiers with heterogeneous properties was created.

The results reveal that among the evaluated machine learning methods, Optimized GRNN (OPGRNN) exhibits the best prediction performance and can be considered as a feasible tool to predict the racing time of cross-country skiers from survey-based data with acceptable RMSEs. The GRNN-based models yield the second lowest RMSEs. There is no strict order between SVM-based and MLP-based prediction models, but the RMSEs related to SVM-based and MLP-based prediction models are always higher than those of GRNN-based prediction models, and lower than those of RBFNN-based prediction models. The age and wave variables have been found to be the most relevant attributes in predicting the racing time of cross-country skiers. Among the set of all prediction models built by using various machine learning methods, it is seen that the OPGRNN-based model including age, height, weight, gender, BMT5, BMT10, HrsXC, HrsSP, RaceComp, RacePlnd, and wave comparatively gives the lowest RMSE value 10.77 min for prediction of racing time of cross-country skiers.

As future work, two important research directions deserve further investigation. First, the models are trained off-line, but the models can be used as the basis to provide web or mobile applications for enabling the users the possibility to produce real-time predictions regarding new data. Second, it would be of interest to predict the racing time using other promising machine learning methods such as deep learning combined with other popular feature selectors.

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APPENDIX

A.1. Prediction Models Created Using Unique Combinations

By using the unique combinations of the predictor variables, a total of 11 prediction models have been formed, respectively

Table A.3.8. Overview of race time models along with unique predictor variables

Models	Predictor Variables
Model 1	Age, Gender, Height, Weight, BMT5
Model 2	Age, Gender, Height, Weight, BMT10
Model 3	Age, Gender, Height, Weight, YRS10
Model 4	Age, Gender, Height, Weight, YRSALL
Model 5	Age, Gender, Height, Weight, HrsXC
Model 6	Age, Gender, Height, Weight, HrsSP
Model 7	Age, Gender, Height, Weight, HrsOther
Model 8	Age, Gender, Height, Weight, HrsTot
Model 9	Age, Gender, Height, Weight, RaceComp
Model 10	Age, Gender, Height, Weight, RacePlnd
Model 11	Age, Gender, Height, Weight, Wave

A.2. Prediction Models Created Using Double Combinations

By using double combinations of the predictor variables, a total of 55 prediction models have been formed, respectively

Table A.3.9. Overview of race time models along with double combinations of the predictor variables.

Models	Predictor Variables
Model 1	Age, Height, Weight, Gender, BMT5, BMT10
Model 2	Age, Height, Weight, Gender, BMT5, YRS10
Model 3	Age, Height, Weight, Gender, BMT5, YRSALL
Model 4	Age, Height, Weight, Gender, BMT5, HrsXC
Model 5	Age, Height, Weight, Gender, BMT5, HrsSP
Model 6	Age, Height, Weight, Gender,BMT5, HrsOther
Model 7	Age, Height, Weight, Gender, BMT5, HrsTot
Model 8	Age, Height, Weight, Gender, BMT5, RaceComp
Model 9	Age, Height, Weight, Gender, BMT5, RacePlnd
Model 10	Age, Height, Weight, Gender, BMT5, Wave
Model 11	Age, Height, Weight, Gender, BMT10, YRS10

Table A.3.10. Overview of race time models along with double combinations of the predictor variables

Models	**Predictor Variables**
Model 12	Age, Height, Weight, Gender, BMT10, YRSALL
Model 13	Age, Height, Weight, Gender, BMT10, HrsXC
Model 14	Age, Height, Weight, Gender, BMT10, HrsSP
Model 15	Age, Height, Weight, Gender,BMT10, HrsOther
Model 16	Age, Height, Weight, Gender, BMT10, HrsTot
Model 17	Age, Height, Weight, Gender, BMT10, RaceComp
Model 18	Age, Height, Weight, Gender, BMT10, RacePlnd
Model 19	Age, Height, Weight, Gender, BMT10, Wave
Model 20	Age, Height, Weight Gender,YRS10, YRSALL
Model 21	Age, Height, Weight, Gender, YRS10, HrsXC
Model 22	Age, Height, Weight, Gender, YRS10, HrsSP

Table A.3.11. Overview of race time models along with double combinations of the predictor variables

Models	**Predictor Variables**
Model 23	Age, Height, Weight, Gender, YRS10, HrsOther
Model 24	Age, Height, Weight, Gender, YRS10, HrsTot
Model 25	Age, Height, Weight, Gender, YRS10, RaceComp
Model 26	Age, Height, Weight, Gender, YRS10, RacePlnd
Model 27	Age, Height, Weight, Gender, YRS10, Wave
Model 28	Age, Height, Weight, Gender, YRSALL, HrsXC
Model 29	Age, Height, Weight, Gender, YRSALL, HrsSP
Model 30	Age, Height, Weight, Gender, YRSALL, HrsOther
Model 31	Age, Height, Weight, Gender, YRSALL, HrsTot
Model 32	Age, Height, Weight, Gender, YRSALL, RaceComp
Model 33	Age, Height, Weight, Gender, YRSALL, RacePlnd

Table A.3.12. Overview of race time models along with double combinations of the predictor variables

Models	Predictor Variables
Model 34	Age, Height, Weight, Gender, YRSALL, Wave
Model 35	Age, Height, Weight, Gender, HrsXC, HrsSP
Model 36	Age, Height, Weight, Gender, HrsXC, HrsOther
Model 37	Age, Height, Weight, Gender, HrsXC, HrsTot
Model 38	Age, Height, Weight, Gender, HrsXC, RaceComp
Model 39	Age, Height, Weight, Gender, HrsXC, RacePlnd
Model 40	Age, Height, Weight, Gender, HrsXC, Wave
Model 41	Age, Height, Weight, Gender, HrsSP, HrsOther
Model 42	Age, Height, Weight, Gender, HrsSP, HrsTot
Model 43	Age, Height, Weight, Gender, HrsSP, RaceComp
Model 44	Age, Height, Weight, Gender, HrsSP, RacePlnd

Table A.3.13. Overview of race time models along with double combinations of the predictor variables

Models	Predictor Variables
Model 45	Age, Height, Weight, Gender, HrsSP, Wave
Model 46	Age, Height, Weight, Gender,HrsOther, HrsTot
Model 47	Age, Height, Weight, Gender, HrsOther, RaceComp
Model 48	Age, Height, Weight, Gender, HrsOther, RacePlnd
Model 49	Age, Height, Weight, Gender,HrsOther, Wave
Model 50	Age, Height, Weight, Gender, HrsTot, RaceComp
Model 51	Age, Height, Weight, Gender,HrsTot, RacePlnd
Model 52	Age, Height, Weight, Gender, HrsTot, Wave
Model 53	Age, Height, Weight, Gender, RaceComp, RacePlnd
Model 54	Age, Height, Weight, Gender,RaceComp, Wave
Model 55	Age, Height, Weight, Gender,RacePlnd, Wave

A.3. Prediction Models Created Using Triple Combinations

By using triple combinations of the predictor variables, a total of 165 prediction models have been formed, respectively

Table A.3.14. Overview of race time models along with triple combinations of the predictor variables.

Models	Predictor Variables
Model 1	Age, Height, Weight, Gender, BMT5, BMT10, Wave
Model 2	Age, Height, Weight, Gender, BMT5, BMT10, YRSALL
Model 3	Age, Height, Weight, Gender, BMT5, BMT10, HrsXC
Model 4	Age, Height, Weight, Gender, BMT5, BMT10, HrsSP
Model 5	Age, Height, Weight, Gender, BMT5, BMT10, HrsOther
Model 6	Age, Height, Weight, Gender, BMT5, BMT10, HrsTot
Model 7	Age, Height, Weight, Gender, BMT5, BMT10, RaceComp
Model 8	Age, Height, Weight, Gender, BMT5, BMT10, RacePlnd
Model 9	Age, Height, Weight, Gender, BMT5, BMT10, YRS10
Model 10	Age, Height, Weight, Gender, BMT5, YRS10, YRSALL
Model 11	Age, Height, Weight, Gender, BMT5, YRS10, HrsXC

Table A.3.15. Overview of race time models along with triple combinations of the predictor variables.

Models	Predictor Variables
Model 12	Age, Height, Weight, Gender, BMT5, YRS10, HrsSP
Model 13	Age, Height, Weight, Gender, BMT5, YRS10, HrsOther
Model 14	Age, Height, Weight, Gender, BMT5, YRS10, HrsTot
Model 15	Age, Height, Weight, Gender, BMT5, YRS10, RaceComp
Model 16	Age, Height, Weight, Gender, BMT5, YRS10, RacePlnd
Model 17	Age, Height, Weight, Gender, BMT5, YRS10, Wave
Model 18	Age, Height, Weight, Gender, BMT5, YRSALL, HrsSP
Model 19	Age, Height, Weight, Gender, BMT5, YRSALL, HrsOther
Model 20	Age, Height, Weight, Gender, BMT5, YRSALL, HrsTot
Model 21	Age, Height, Weight, Gender, BMT5, YRSALL, RaceComp
Model 22	Age, Height, Weight, Gender, BMT5, YRSALL, RacePlnd

Table A.3.16. Overview of race time models along with triple combinations of the predictor variables.

Models	Predictor Variables
Model 23	Age, Height, Weight, Gender, BMT5, YRSALL, Wave
Model 24	Age, Height, Weight, Gender, BMT5, YRSALL, HrsXC
Model 25	Age, Height, Weight, Gender, BMT5, HrsXC, HrsOther
Model 26	Age, Height, Weight, Gender, BMT5, HrsXC, HrsTot
Model 27	Age, Height, Weight, Gender, BMT5, HrsXC, RaceComp
Model 28	Age, Height, Weight, Gender, BMT5, HrsXC, RacePlnd
Model 29	Age, Height, Weight, Gender, BMT5, HrsXC, Wave
Model 30	Age, Height, Weight, Gender, BMT5, HrsXC, HrsSP
Model 31	Age, Height, Weight, Gender, BMT5, HrsSP, HrsTot
Model 32	Age, Height, Weight, Gender, BMT5, HrsSP, RaceComp
Model 33	Age, Height, Weight, Gender, BMT5, HrsSP, RacePlnd

Table A.3.17. Overview of race time models along with triple combinations of the predictor variables.

Models	Predictor Variables
Model 34	Age, Height, Weight, Gender, BMT5, HrsSP, Wave
Model 35	Age, Height, Weight, Gender, BMT5, HrsSP, HrsOther
Model 36	Age, Height, Weight, Gender, BMT5, HrsOther, HrsTot
Model 37	Age, Height, Weight, Gender, BMT5, HrsOther, RaceComp
Model 38	Age, Height, Weight, Gender, BMT5, HrsOther, RacePlnd
Model 39	Age, Height, Weight, Gender, BMT5, HrsOther, Wave
Model 40	Age, Height, Weight, Gender, BMT5, HrsTot, RacePlnd
Model 41	Age, Height, Weight, Gender, BMT5, HrsTot, Wave
Model 42	Age, Height, Weight, Gender, BMT5, HrsTot, RaceComp
Model 43	Age, Height, Weight, Gender, BMT5, RaceComp, Wave
Model 44	Age, Height, Weight, Gender, BMT5, RaceComp, RacePlnd

Table A.3.18. Overview of race time models along with triple combinations of the predictor variables.

Models	Predictor Variables
Model 45	Age, Height, Weight, Gender, BMT5, RacePlnd, Wave
Model 46	Age, Height, Weight, Gender, YRSALL, BMT10, HrsSP
Model 47	Age Height, Weight, Gender, YRSALL, BMT10, HrsOther
Model 48	Age Height, Weight, Gender, YRSALL, BMT10, HrsTot
Model 49	Age, Height, Weight, Gender, YRSALL, BMT10, RaceComp
Model 50	Age, Height, Weight, Gender, YRSALL, BMT10, RacePlnd
Model 51	Age, Height, Weight, Gender, YRSALL, HrsXC, HrsSP
Model 52	Age, Height, Weight, Gender, YRSALL, HrsXC, HrsOther
Model 53	Age, Height, Weight, Gender, YRSALL, HrsXC, HrsTot
Model 54	Age Height, Weight, Gender, YRSALL, HrsXC, RaceComp
Model 55	Age, Height, Weight, Gender, YRSALL, HrsXC, RacePlnd

Table A.3.19. Overview of race time models along with triple combinations of the predictor variables.

Models	Predictor Variables
Model 56	Age, Height, Weight, Gender, YRSALL,HrsXC, Wave
Model 57	Age, Height, Weight, Gender , YRSALL,HrsSP, HrsOther
Model 58	Age, Height, Weight, Gender, YRSALL,HrsSP, HrsTot
Model 59	Age, Height, Weight, Gender, YRSALL,HrsSP, RaceComp
Model 60	Age, Height, Weight, Gender, YRSALL,HrsSP, RacePlnd
Model 61	Age, Height, Weight, Gender, YRSALL, HrsSP, Wave
Model 62	Age, Height, Weight, Gender, YRSALL,HrsOther, HrsTot
Model 63	Age, Height, Weight, Gender, YRSALL, HrsOther, RaceComp
Model 64	Age Height, Weight, Gender, YRSALL, HrsOther, RacePlnd
Model 65	Age, Height, Weight, Gender, YRSALL, HrsOther, Wave
Model 66	Age, Height, Weight, Gender, YRSALL, HrsTot, RaceComp

Table A.3.20. Overview of race time models along with triple combinations of the predictor variables.

Models	**Predictor Variables**
Model 67	Age, Height, Weight, Gender, YRSALL,HrsTot, RacePlnd
Model 68	Age, Height, Weight, Gender, YRSALL, HrsTot, Wave
Model 69	Age, Height, Weight, Gender, YRSALL, RaceComp, RacePlnd
Model 70	Age, Height, Weight, Gender, YRSALL,RaceComp, Wave
Model 71	Age, Height, Weight, Gender, YRSALL,RacePlnd, Wave
Model 72	Age, Height, Weight, Gender, HrsSP, BMT10, YRS10
Model 73	Age, Height, Weight, Gender, HrsSP, BMT10, RacePlnd
Model 74	Age, Height, Weight, Gender, HrsSP, BMT10, Wave
Model 75	Age, Height, Weight, Gender, HrsSP, HrsTot, RaceComp
Model 76	Age, Height, Weight, Gender, HrsSP, HrsTot, RacePlnd
Model 77	Age, Height, Weight, Gender, HrsSP, HrsTot, Wave

Table A.3.21. Overview of race time models along with triple combinations of the predictor variables.

Models	**Predictor Variables**
Model 78	Age, Height, Weight, Gender, HrsSP, HrsOther, HrsTot
Model 79	Age, Height, Weight, Gender, HrsSP, HrsOther, RaceComp
Model 80	Age, Height, Weight, Gender, HrsSP, HrsOther, RacePlnd
Model 81	Age, Height, Weight, Gender, HrsSP, HrsOther, Wave
Model 82	Age, Height, Weight, Gender, HrsSP, RaceComp, RacePlnd
Model 83	Age, Height, Weight, Gender, HrsSP, RaceComp, Wave
Model 84	Age, Height, Weight, Gender, HrsSP,RacePlnd, Wave
Model 85	Age, Height, Weight, Gender, HrsXC, BMT10, YRS10
Model 86	Age, Height, Weight, Gender, HrsXC,BMT10, HrsTot
Model 87	Age, Height, Weight, Gender, HrsXC, BMT10, RaceComp
Model 88	Age, Height, Weight, Gender, HrsXC, BMT10, RacePlnd

Table A.3.22. Overview of race time models along with triple combinations of the predictor variables.

Models	**Predictor Variables**
Model 89	Age, Height, Weight, Gender, HrsXC,HrsSP, HrsOther
Model 90	Age, Height, Weight, Gender, HrsXC,HrsSP, HrsTot
Model 91	Age, Height, Weight, Gender, HrsXC,HrsSP, RaceComp
Model 92	Age, Height, Weight, Gender, HrsXC,HrsSP, RacePlnd
Model 93	Age, Height, Weight, Gender, HrsXC, HrsSP, Wave
Model 94	Age, Height, Weight, Gender, HrsXC, HrsTot, RaceComp
Model 95	Age, Height, Weight, Gender, HrsXC,HrsTot, RacePlnd
Model 96	Age, Height, Weight, Gender, HrsXC, HrsTot, Wave
Model 97	Age, Height, Weight, Gender, HrsXC, HrsOther, HrsTot
Model 98	Age, Height, Weight, Gender, HrsXC, HrsOther, RacePlnd
Model 99	Age, Height, Weight, Gender, HrsXC, HrsOther, Wave

Table A.3.23. Overview of race time models along with triple combinations of the predictor variables.

Models	**Predictor Variables**
Model 100	Age, Height, Weight, Gender, HrsXC, RaceComp, RacePlnd
Model 101	Age, Height, Weight, Gender, HrsXC, RaceComp, Wave
Model 102	Age, Height, Weight, Gender, HrsXC,RacePlnd, Wave
Model 103	Age, Height, Weight, Gender, HrsOther, BMT10, YRS10
Model 104	Age, Height, Weight, Gender, HrsOther, BMT10, HrsXC
Model 105	Age, Height, Weight, Gender, HrsOther, BMT10, Wave
Model 106	Age, Height, Weight, Gender, HrsOther, HrsTot, RaceComp
Model 107	Age, Height, Weight, Gender, HrsOther, HrsTot, RacePlnd
Model 108	Age, Height, Weight, Gender, HrsOther, HrsTot, Wave
Model 109	Age, Height, Weight, Gender, HrsOther, YRS10, RaceComp
Model 110	Age, Height, Weight, Gender, HrsOther, RaceComp, RacePlnd

Table A.3.24. Overview of race time models along with triple combinations of the predictor variables.

Models	**Predictor Variables**
Model 111	Age, Height, Weight, Gender, HrsOther, RaceComp, Wave
Model 112	Age, Height, Weight, Gender, HrsOther, RacePlnd, Wave
Model 113	Age, Height, Weight, Gender, YRS10, YRSALL, HrsXC
Model 114	Age, Height, Weight, Gender, YRS10, YRSALL, HrsSP
Model 115	Age, Height, Weight, Gender, YRS10, YRSALL, HrsOther
Model 116	Age, Height, Weight, Gender, YRS10, YRSALL, HrsTot
Model 117	Age, Height, Weight, Gender, YRS10, YRSALL, RaceComp
Model 118	Age, Height, Weight, Gender, YRS10, YRSALL, RacePlnd
Model 119	Age, Height, Weight, Gender, YRS10, YRSALL, Wave
Model 120	Age, Height, Weight, Gender, YRS10, HrsXC, HrsSP
Model 121	Age, Height, Weight, Gender, YRS10, HrsXC, HrsOther

Table A.3.25. Overview of race time models along with triple combinations of the predictor variables.

Models	**Predictor Variables**
Model 122	Age, Height, Weight, Gender, YRS10, HrsXC, HrsTot
Model 123	Age, Height, Weight, Gender, YRS10, HrsXC, RaceComp
Model 124	Age, Height, Weight, Gender, YRS10, HrsXC, RacePlnd
Model 125	Age, Height, Weight, Gender, YRS10, HrsXC, Wave
Model 126	Age, Height, Weight, Gender, YRS10, HrsSP, HrsOther
Model 127	Age, Height, Weight, Gender, YRS10, HrsSP, HrsTot
Model 128	Age, Height, Weight, Gender, YRS10, HrsSP, RaceComp
Model 129	Age, Height, Weight, Gender, YRS10, HrsSP, RacePlnd
Model 130	Age, Height, Weight, Gender, YRS10, HrsSP, Wave
Model 131	Age, Height, Weight, Gender, YRS10, HrsTot, RaceComp
Model 132	Age, Height, Weight, Gender, YRS10, HrsTot, RacePlnd

Table A.3.26. Overview of race time models along with triple combinations of the predictor variables.

Models	**Predictor Variables**
Model 133	Age, Height, Weight, Gender, YRS10, HrsTot, Wave
Model 134	Age, Height, Weight, Gender, YRS10, HrsOther, HrsTot
Model 135	Age, Height, Weight, Gender, YRS10, HrsOther, RacePlnd
Model 136	Age, Height, Weight, Gender, YRS10, HrsOther, Wave
Model 137	Age, Height, Weight, Gender, YRS10, RaceComp, RacePlnd
Model 138	Age, Height, Weight, Gender, YRS10, RacePlnd, Wave
Model 139	Age, Height, Weight, Gender, YRS10, RaceComp, Wave
Model 140	Age, Height, Weight, Gender, YRS10, BMT10, HrsTot
Model 141	Age, Height, Weight, Gender, BMT10, YRS10, YRSALL
Model 142	Age, Height, Weight, Gender, BMT10, YRS10, Wave
Model 143	Age, Height, Weight, Gender, BMT10, YRS10, RacePlnd

Table A.3.27. Overview of race time models along with triple combinations of the predictor variables.

Models	**Predictor Variables**
Model 144	Age, Height, Weight, Gender, BMT10, YRSALL, HrsXC
Model 145	Age, Height, Weight, Gender, BMT10, YRSALL, Wave
Model 146	Age, Height, Weight, Gender, BMT10, HrsSP, HrsOther
Model 147	Age, Height, Weight, Gender, BMT10, HrsSP, HrsTot
Model 148	Age, Height, Weight, Gender, BMT10, HrsXC, HrsSP
Model 149	Age, Height, Weight, Gender, BMT10, HrsXC, Wave
Model 150	Age, Height, Weight, Gender, BMT10, HrsTot, RaceComp
Model 151	Age, Height, Weight, Gender, BMT10, HrsTot, Wave
Model 152	Age, Height, Weight, Gender, BMT10, HrsOther, HrsTot
Model 153	Age, Height, Weight, Gender, BMT10, HrsOther, RaceComp
Model 154	Age, Height, Weight, Gender, BMT10, HrsOther, RacePlnd

Table A.3.28. Overview of race time models along with triple combinations of the predictor variables.

Models	**Predictor Variables**
Model 155	Age, Height, Weight, Gender, BMT10, RaceComp, RacePlnd
Model 156	Age, Height, Weight, Gender, BMT10, RaceComp, Wave
Model 157	Age, Height, Weight, Gender, BMT10, RacePlnd, Wave
Model 158	Age, Height, Weight, Gender, BMT10, RacePlnd, HrsTot
Model 159	Age, Height, Weight, Gender, HrsTot, RaceComp, RacePlnd
Model 160	Age, Height, Weight, Gender, HrsTot, RacePlnd, Wave
Model 161	Age, Height, Weight, Gender, HrsTot, RaceComp, Wave
Model 162	Age, Height, Weight, Gender, RaceComp, RacePlnd, Wave
Model 163	Age, Height, Weight, Gender, RaceComp, HrsXC, HrsOther
Model 164	Age, Height, Weight, Gender, RaceComp, BMT10, YRS10
Model 165	Age, Height, Weight, Gender, RaceComp, BMT10, HrsSP

A.4. Prediction Models Created Using Quadruple Combinations

By using quadruple combinations of the predictor variables, a total of 330 prediction models have been formed, respectively

Table A.3.29. Overview of race time models along with quadruple combinations of the predictor variables

Models	Predictor Variables
Model 1	Age, Height, Weight, Gender, BMT5, BMT10, YRS10, YRSALL
Model 2	Age, Height, Weight, Gender, BMT5, BMT10, YRS10, HrsXC
Model 3	Age, Height, Weight, Gender, BMT5, BMT10, YRS10, HrsSP
Model 4	Age, Height, Weight, Gender, BMT5, BMT10, YRS10, HrsOther
Model 5	Age, Height, Weight, Gender, BMT5, BMT10, YRS10, HrsTot
Model 6	Age, Height, Weight, Gender, BMT5, BMT10, YRS10, RaceComp
Model 7	Age, Height, Weight, Gender, BMT5, BMT10, YRS10, RacePlnd
Model 8	Age, Height, Weight, Gender, BMT5, BMT10, YRS10, Wave
Model 9	Age, Height, Weight, Gender, BMT5, BMT10, YRSALL, HrsXC
Model 10	Age, Height, Weight, Gender, BMT5, BMT10, YRSALL, HrsSP
Model 11	Age, Height, Weight, Gender, BMT5, BMT10, YRSALL, HrsOther

Table A.3.30. Overview of race time models along with quadruple combinations of the predictor variables

Models	Predictor Variables
Model 12	Age, Height, Weight, Gender, BMT5, BMT10, YRSALL, HrsTot
Model 13	Age, Height, Weight, Gender, BMT5, BMT10, YRSALL, RaceComp
Model 14	Age, Height, Weight, Gender, BMT5, BMT10, YRSALL, RacePlnd
Model 15	Age, Height, Weight, Gender, BMT5, BMT10, YRSALL, Wave
Model 16	Age, Height, Weight , Gender, BMT5, BMT10, HrsXC, HrsSP
Model 17	Age, Height, Weight, Gender, BMT5, BMT10 , HrsXC, HrsOther
Model 18	Age, Height, Weight, Gender, BMT5, BMT10, HrsXC, HrsTot
Model 19	Age, Height, Weight, Gender, BMT5, BMT10, HrsXC, RaceComp
Model 20	Age, Height, Weight, Gender, BMT5, BMT10, HrsXC, RacePlnd
Model 21	Age, Height, Weight, Gender, BMT5, BMT10, HrsXC, Wave
Model 22	Age, Height, Weight, Gender, BMT5, BMT10, HrsSP, HrsOther

Table 3.31. Overview of race time models along with quadruple combinations of the predictor variables

Models	Predictor Variables
Model 23	Age, Height, Weight, Gender, BMT5, BMT10, HrsSP, HrsTot
Model 24	Age, Height, Weight, Gender, BMT5, BMT10, HrsSP, RaceComp
Model 25	Age, Height, Weight, Gender, BMT5, BMT10, HrsSP, RacePlnd
Model 26	Age, Height, Weight, Gender, BMT5, BMT10, HrsSP, Wave
Model 27	Age, Height, Weight, Gender, BMT5, BMT10, HrsOther, HrsTot
Model 28	Age, Height, Weight, Gender, BMT5, BMT10, HrsOther, RaceComp
Model 29	Age, Height, Weight, Gender, BMT5, BMT10, HrsOther, RacePlnd
Model 30	Age, Height, Weight, Gender, BMT5, BMT10, HrsOther, Wave
Model 31	Age, Height, Weight, Gender, BMT5, BMT10, HrsTot, RaceComp
Model 32	Age, Height, Weight, Gender, BMT5, BMT10, HrsTot, RacePlnd
Model 33	Age, Height, Weight, Gender, BMT5, BMT10, HrsTot, Wave

Table A.3.32. Overview of race time models along with quadruple combinations of the predictor variables

Models	Predictor Variables
Model 34	Age, Height, Weight, Gender, BMT5, BMT10, RaceComp, RacePlnd
Model 35	Age, Height, Weight, Gender, BMT5, BMT10, RaceComp, Wave
Model 36	Age, Height, Weight, Gender, BMT5, BMT10, RacePlnd, Wave
Model 37	Age, Height, Weight, Gender, BMT5, YRS10, YRSALL, HrsXC
Model 38	Age, Height, Weight, Gender, BMT5, YRS10, YRSALL, HrsSP
Model 39	Age, Height, Weight, Gender, BMT5, YRS10, YRSALL, HrsOther
Model 40	Age, Height, Weight, Gender, BMT5, YRS10, YRSALL, HrsTot
Model 41	Age, Height, Weight, Gender, BMT5, YRS10, YRSALL, RaceComp
Model 42	Age, Height, Weight, Gender, BMT5, YRS10, YRSALL, RacePlnd
Model 43	Age, Height, Weight, Gender, BMT5, YRS10, YRSALL, Wave
Model 44	Age, Height, Weight, Gender, BMT5, YRS10, HrsXC, HrsSP

Table A.3.33. Overview of race time models along with quadruple combinations of the predictor variables

Models	**Predictor Variables**
Model 45	Age, Height, Weight, Gender, BMT5, YRS10, HrsXC, HrsOther
Model 46	Age, Height, Weight, Gender, BMT5, YRS10, HrsXC, HrsTot
Model 47	Age, Height, Weight, Gender, BMT5, YRS10, HrsXC, RaceComp
Model 48	Age, Height, Weight, Gender, BMT5, YRS10, HrsXC, RacePlnd
Model 49	Age, Height, Weight, Gender, BMT5, YRS10, HrsXC, Wave
Model 50	Age, Height, Weight, Gender, BMT5, YRS10, HrsSP, HrsOther
Model 51	Age, Height, Weight, Gender, BMT5, YRS10, HrsSP, HrsTot
Model 52	Age, Height, Weight, Gender, BMT5, YRS10, HrsSP, RaceComp
Model 53	Age, Height, Weight, Gender, BMT5, YRS10, HrsSP, RacePlnd
Model 54	Age, Height, Weight, Gender, BMT5, YRS10, HrsSP, Wave
Model 55	Age, Height, Weight, Gender, BMT5, YRS10, HrsOther, HrsTot

Table A.3.34. Overview of race time models along with quadruple combinations of the predictor variables

Models	**Predictor Variables**
Model 56	Age, Height, Weight, Gender, BMT5, YRS10, HrsOther, RaceComp
Model 57	Age, Height, Weight, Gender, BMT5, YRS10, HrsOther, RacePlnd
Model 58	Age, Height, Weight, Gender, BMT5, YRS10, HrsOther, Wave
Model 59	Age, Height, Weight, Gender, BMT5, YRS10, HrsTot, RaceComp
Model 60	Age, Height, Weight, Gender, BMT5, YRS10, HrsTot, RacePlnd
Model 61	Age, Height, Weight, Gender, BMT5, YRS10, HrsTot, Wave
Model 62	Age, Height, Weight, Gender, BMT5, YRS10, RaceComp, RacePlnd
Model 63	Age, Height, Weight, Gender, BMT5, YRS10, RaceComp, Wave
Model 64	Age, Height, Weight, Gender, BMT5, YRS10, RacePlnd, Wave
Model 65	Age, Height, Weight, Gender, BMT5, YRSALL, HrsXC, HrsSP
Model 66	Age, Height, Weight, Gender, BMT5, YRSALL, HrsXC, HrsOther

Table A.3.35. Overview of race time models along with quadruple combinations of the predictor variables

Models	Predictor Variables
Model 67	Age, Height, Weight, Gender, BMT5, YRSALL, HrsXC, HrsTot
Model 68	Age, Height, Weight, Gender, BMT5, YRSALL, HrsXC, RaceComp
Model 69	Age, Height, Weight, Gender, BMT5, YRSALL, HrsXC, RacePlnd
Model 70	Age, Height, Weight, Gender, BMT5, YRSALL, HrsXC, Wave
Model 71	Age, Height, Weight, Gender, BMT5, YRSALL, HrsSP, HrsOther
Model 72	Age, Height, Weight, Gender, BMT5, YRSALL, HrsSP, HrsTot
Model 73	Age, Height, Weight, Gender, BMT5, YRSALL, HrsSP, RaceComp
Model 74	Age, Height, Weight, Gender, BMT5, YRSALL, HrsSP, RacePlnd
Model 75	Age, Height, Weight, Gender, BMT5, YRSALL, HrsSP, Wave
Model 76	Age, Height, Weight, Gender, BMT5, YRSALL, HrsOther, HrsTot
Model 77	Age, Height, Weight, Gender, BMT5, YRSALL, HrsOther, RaceComp

Table A.3.36. Overview of race time models along with quadruple combinations of the predictor variables

Models	Predictor Variables
Model 78	Age, Height, Weight, Gender, BMT5, YRSALL, HrsOther , RacePlnd
Model 79	Age, Height, Weight, Gender, BMT5, YRSALL, HrsOther, Wave
Model 80	Age, Height, Weight, Gender, BMT5, YRSALL, HrsTot, RaceComp
Model 81	Age, Height, Weight, Gender, BMT5, YRSALL, HrsTot, RacePlnd
Model 82	Age, Height, Weight, Gender, BMT5, YRSALL, HrsTot, Wave
Model 83	Age, Height, Weight, Gender, BMT5, YRSALL, RaceComp, RacePlnd
Model 84	Age, Height, Weight, Gender, BMT5, YRSALL, RaceComp, Wave
Model 85	Age, Height, Weight, Gender, BMT5, YRSALL, RacePlnd, Wave
Model 86	Age, Height, Weight, Gender, BMT5, HrsXC, HrsSP, HrsOther
Model 87	Age, Height, Weight, Gender, BMT5, HrsXC, HrsSP, HrsTot
Model 88	Age, Height, Weight, Gender, BMT5, HrsXC, HrsSP, RaceComp

Table A.3.37. Overview of race time models along with quadruple combinations of the predictor variables

Models	Predictor Variables
Model 89	Age, Height, Weight, Gender, BMT5, HrsXC, HrsSP, RacePlnd
Model 90	Age, Height, Weight, Gender, BMT5, HrsXC, HrsSP, Wave
Model 91	Age, Height, Weight, Gender, BMT5, HrsXC, HrsOther, HrsTot
Model 92	Age, Height, Weight, Gender, BMT5, HrsXC, HrsOther, RaceComp
Model 93	Age, Height, Weight, Gender, BMT5, HrsXC, HrsOther, RacePlnd
Model 94	Age, Height, Weight, Gender, BMT5, HrsXC, HrsOther, Wave
Model 95	Age, Height, Weight, Gender, BMT5, HrsXC, HrsTot, RaceComp
Model 96	Age, Height, Weight, Gender, BMT5, HrsXC, HrsTot, RacePlnd
Model 97	Age, Height, Weight, Gender, BMT5, HrsXC, HrsTot, Wave
Model 98	Age, Height, Weight, Gender, BMT5, HrsXC, RaceComp, RacePlnd
Model 99	Age, Height, Weight, Gender, BMT5, HrsXC, RaceComp, Wave

Table A.3.38. Overview of race time models along with quadruple combinations of the predictor variables

Models	Predictor Variables
Model 100	Age, Height, Weight, Gender, BMT5, HrsXC,RacePlnd, Wave
Model 101	Age, Height, Weight, Gender, BMT5, HrsSP, HrsOther, HrsTot
Model 102	Age, Height, Weight, Gender, BMT5, HrsSP, HrsOther, RaceComp
Model 103	Age, Height, Weight, Gender, BMT5, HrsSP, HrsOther, RacePlnd
Model 104	Age, Height, Weight, Gender, BMT5, HrsSP, HrsOther, Wave
Model 105	Age, Height, Weight, Gender, BMT5, HrsSP, HrsTot, RaceComp
Model 106	Age, Height, Weight, Gender, BMT5, HrsSP,HrsTot, RacePlnd
Model 107	Age, Height, Weight, Gender, BMT5, HrsSP, HrsTot, Wave
Model 108	Age, Height, Weight, Gender, BMT5, HrsSP, RaceComp, RacePlnd
Model 109	Age, Height, Weight, Gender, BMT5, HrsSP, RaceComp, Wave
Model 110	Age, Height, Weight, Gender, BMT5, HrsSP,RacePlnd, Wave

Table A.3.39. Overview of race time models along with quadruple combinations of the predictor variables

Models	Predictor Variables
Model 111	Age, Height, Weight, Gender, BMT5, HrsOther, HrsTot, RaceComp
Model 112	Age, Height, Weight, Gender, BMT5, HrsOther, HrsTot, RacePlnd
Model 113	Age, Height, Weight, Gender, BMT5, HrsOther, HrsTot, Wave
Model 114	Age, Height, Weight, Gender, BMT5, HrsOther, RaceComp, RacePlnd
Model 115	Age, Height, Weight, Gender, BMT5, HrsOther, RaceComp, Wave
Model 116	Age, Height, Weight, Gender, BMT5, HrsOther, RacePlnd, Wave
Model 117	Age, Height, Weight, Gender, BMT5, HrsTot, RaceComp, RacePlnd
Model 118	Age, Height, Weight, Gender, BMT5, HrsTot, RaceComp, Wave
Model 119	Age, Height, Weight, Gender, BMT5, HrsTot, RacePlnd, Wave
Model 120	Age, Height, Weight, Gender, BMT5, RaceComp, RacePlnd, Wave
Model 121	Age, Height, Weight, Gender, BMT10, YRS10, YRSALL, HrsXC

Table A.3.40. Overview of race time models along with quadruple combinations of the predictor variables

Models	Predictor Variables
Model 122	Age, Height, Weight, Gender, BMT10, YRS10, YRSALL, HrsSP
Model 123	Age, Height, Weight, Gender, BMT10, YRS10, YRSALL, HrsOther
Model 124	Age, Height, Weight, Gender, BMT10, YRS10, YRSALL, HrsTot
Model 125	Age, Height, Weight, Gender, BMT10, YRS10, YRSALL, RaceComp
Model 126	Age, Height, Weight, Gender, BMT10, YRS10, YRSALL, RacePlnd
Model 127	Age, Height, Weight, Gender, BMT10, YRS10, YRSALL, Wave
Model 128	Age, Height, Weight, Gender, BMT10, YRS10, HrsXC , HrsSP
Model 129	Age, Height, Weight, Gender, BMT10, YRS10, HrsXC , HrsOther
Model 130	Age, Height, Weight, Gender, BMT10, YRS10, HrsXC , HrsTot
Model 131	Age, Height, Weight, Gender, BMT10, YRS10, HrsXC , RaceComp
Model 132	Age, Height, Weight, Gender, BMT10, YRS10, HrsXC , RacePlnd

Table A.3.41. Overview of race time models along with quadruple combinations of the predictor variables

Models	Predictor Variables
Model 133	Age, Height, Weight, Gender, BMT10, YRS10, HrsXC , Wave
Model 134	Age, Height, Weight, Gender, BMT10, YRS10, HrsSP, HrsOther
Model 135	Age, Height, Weight, Gender, BMT10, YRS10, HrsSP, HrsTot
Model 136	Age, Height, Weight, Gender, BMT10, YRS10, HrsSP, RaceComp
Model 137	Age, Height, Weight, Gender, BMT10, YRS10, HrsSP, RacePlnd
Model 138	Age Height, Weight, Gender, BMT10, YRS10, HrsSP, Wave
Model 139	Age, Height, Weight, Gender, BMT10, YRS10, HrsOther, HrsTot
Model 140	Age, Height, Weight, Gender, BMT10, YRS10, HrsOther, RaceComp
Model 141	Age, Height, Weight, Gender, BMT10, YRS10, HrsOther, RacePlnd
Model 142	Age, Height, Weight, Gender, BMT10, YRS10, HrsOther, Wave
Model 143	Age, Height, Weight, Gender, BMT10, YRS10 , HrsTot, RaceComp

Table A.3.42. Overview of race time models along with quadruple combinations of the predictor variables

Models	Predictor Variables
Model 144	Age, Height, Weight, Gender, BMT10, YRS10, HrsTot, RacePlnd
Model 145	Age, Height, Weight, Gender, BMT10, YRS10, HrsTot, Wave
Model 146	Age, Height, Weight, Gender, BMT10, YRS10, RaceComp, RacePlnd
Model 147	Age, Height, Weight, Gender, BMT10, YRS10, RaceComp, Wave
Model 148	Age, Height, Weight, Gender, BMT10, YRS10, RacePlnd, Wave
Model 149	Age, Height, Weight, Gender, BMT10, YRSALL, HrsXC , HrsSP
Model 150	Age, Height, Weight, Gender, BMT10, YRSALL, HrsXC , HrsOther
Model 151	Age, Height, Weight, Gender, BMT10 , YRSALL, HrsXC , HrsTot
Model 152	Age, Height, Weight, Gender, BMT10, YRSALL, HrsXC , RaceComp
Model 153	Age, Height, Weight, Gender, BMT10, YRSALL, HrsXC , RacePlnd
Model 154	Age, Height, Weight, Gender, BMT10, YRSALL, HrsXC , Wave

Table A.3.43. Overview of race time models along with quadruple combinations of the predictor variables

Models	Predictor Variables
Model 155	Age, Height, Weight, Gender, BMT10, YRSALL, HrsSP, HrsOther
Model 156	Age, Height, Weight, Gender, BMT10, YRSALL, HrsSP, HrsTot
Model 157	Age, Height, Weight, Gender, BMT10, YRSALL, HrsSP, RaceComp
Model 158	Age, Height, Weight, Gender, BMT10, YRSALL , HrsSP, RacePlnd
Model 159	Age, Height, Weight, Gender, BMT10, YRSALL, HrsSP, Wave
Model 160	Age, Height, Weight, Gender, BMT10, YRSALL, HrsOther, HrsTot
Model 161	Age, Height, Weight, Gender, BMT10, YRSALL, HrsOther, RaceComp
Model 162	Age, Height, Weight, Gender, BMT10, YRSALL, HrsOther, RacePlnd
Model 163	Age, Height, Weight, Gender, BMT10, YRSALL, HrsOther, Wave
Model 164	Age, Height, Weight, Gender, BMT10, YRSALL, HrsTot, RaceComp
Model 165	Age, Height, Weight, Gender, BMT10, YRSALL, HrsTot, RacePlnd

Table A.3.44. Overview of race time models along with quadruple combinations of the predictor variables

Models	Predictor Variables
Model 166	Age, Height, Weight, Gender, BMT10, YRSALL, HrsTot, Wave
Model 167	Age, Height, Weight, Gender, BMT10, YRSALL, RaceComp, RacePlnd
Model 168	Age, Height, Weight, Gender, BMT10, YRSALL, RaceComp, Wave
Model 169	Age, Height, Weight, Gender, BMT10 , YRSALL, RacePlnd, Wave
Model 170	Age, Height, Weight, Gender, BMT10, HrsXC, HrsSP, HrsOther
Model 171	Age, Height, Weight, Gender, BMT10, HrsXC, HrsSP, HrsTot
Model 172	Age, Height, Weight, Gender, BMT10, HrsXC, HrsSP, RaceComp
Model 173	Age, Height, Weight, Gender, BMT10, HrsXC, HrsSP, RacePlnd
Model 174	Age, Height, Weight, Gender, BMT10, HrsXC, HrsSP, Wave
Model 175	Age, Height, Weight, Gender, BMT10, HrsXC, HrsOther, HrsTot
Model 176	Age, Height, Weight, Gender, BMT10, HrsXC, HrsOther, RaceComp

Table A.3.45. Overview of race time models along with quadruple combinations of the predictor variables

Models	Predictor Variables
Model 177	Age, Height, Weight, Gender, BMT10, HrsXC, HrsOther, RacePlnd
Model 178	Age, Height, Weight, Gender, BMT10, HrsXC, HrsOther, Wave
Model 179	Age, Height, Weight, Gender, BMT10, HrsXC, HrsTot, RaceComp
Model 180	Age, Height, Weight, Gender, BMT10, HrsXC, HrsTot, RacePlnd
Model 181	Age, Height, Weight, Gender, BMT10, HrsXC, HrsTot, Wave
Model 182	Age, Height, Weight, Gender BMT10, HrsXC, RaceComp, RacePlnd
Model 183	Age, Height, Weight, Gender, BMT10, HrsXC, RaceComp, Wave
Model 184	Age, Height, Weight, Gender, BMT10, HrsXC, RacePlnd, Wave
Model 185	Age, Height, Weight, Gender, BMT10, HrsSP, HrsOther, HrsTot
Model 186	Age, Height, Weight, Gender, BMT10, HrsSP, HrsOther, RaceComp
Model 187	Age, Height, Weight, Gender, BMT10, HrsSP, HrsOther, RacePlnd

Table A.3.46. Overview of race time models along with quadruple combinations of the predictor variables

Models	**Predictor Variables**
Model 188	Age, Height, Weight, Gender, BMT10, HrsSP, HrsOther, Wave
Model 189	Age, Height, Weight, Gender, BMT10, HrsSP, HrsTot, RaceComp
Model 190	Age, Height, Weight, Gender, BMT10, HrsSP, HrsTot, RacePlnd
Model 191	Age, Height, Weight, Gender, BMT10, HrsSP, HrsTot, Wave
Model 192	Age, Height, Weight, Gender, BMT10, HrsSP, RaceComp, RacePlnd
Model 193	Age, Height, Weight, Gender, BMT10, HrsSP, RaceComp, Wave
Model 194	Age, Height, Weight, Gender, BMT10, HrsSP, RacePlnd, Wave
Model 195	Age, Height, Weight, Gender, BMT10, HrsOther, HrsTot, RaceComp
Model 196	Age, Height, Weight, Gender, BMT10, HrsOther, HrsTot, RacePlnd
Model 197	Age, Height, Weight, Gender, BMT10, HrsOther, HrsTot, Wave
Model 198	Age, Height, Weight, Gender, BMT10, HrsOther, RaceComp, RacePlnd

Table A.3.47. Overview of race time models along with quadruple combinations of the predictor variables

Models	**Predictor Variables**
Model 199	Age, Height, Weight, Gender, BMT10, HrsOther, RaceComp, Wave
Model 200	Age, Height, Weight, Gender, BMT10, HrsOther, RacePlnd, Wave
Model 201	Age, Height, Weight, Gender, BMT10, HrsTot, RaceComp, RacePlnd
Model 202	Age Height, Weight, Gender, BMT10, HrsTot, RaceComp, Wave
Model 203	Age, Height, Weight, Gender, BMT10, HrsTot, RacePlnd, Wave
Model 204	Age, Height, Weight, Gender, BMT10, RaceComp, RacePlnd, Wave
Model 205	Age, Height, Weight, Gender, YRS10, YRSALL, HrsXC, HrsSP
Model 206	Age, Height, Weight, Gender, YRS10, YRSALL, HrsXC, HrsOther
Model 207	Age Height, Weight, Gender, YRS10, YRSALL, HrsXC, HrsTot
Model 208	Age, Height, Weight, Gender, YRS10, YRSALL, HrsXC, RaceComp
Model 209	Age, Height, Weight, Gender, YRS10, YRSALL, HrsXC, RacePlnd

Table A.3.48. Overview of race time models along with quadruple combinations of the predictor variables

Models	Predictor Variables
Model 210	Age, Height, Weight, Gender, YRS10, YRSALL, HrsXC, Wave
Model 211	Age, Height, Weight, Gender, YRS10, YRSALL, HrsSP, HrsOther
Model 212	Age, Height, Weight, Gender, YRS10, YRSALL, HrsSP, HrsTot
Model 213	Age, Height, Weight, Gender, YRS10, YRSALL, HrsSP, RaceComp
Model 214	Age, Height, Weight, Gender, YRS10, YRSALL, HrsSP, RacePlnd
Model 215	Age, Height, Weight, Gender, YRS10, YRSALL, HrsSP, Wave
Model 216	Age Height, Weight, Gender, YRS10, YRSALL, HrsOther, HrsTot
Model 217	Age, Height, Weight, Gender, YRS10, YRSALL, HrsOther, RaceComp
Model 218	Age, Height, Weight, Gender, YRS10, YRSALL, HrsOther, RacePlnd
Model 219	Age, Height, Weight, Gender, YRS10, YRSALL, HrsOther, Wave
Model 220	Age, Height, Weight, Gender, YRS10, YRSALL, HrsTot, RaceComp

Table A.3.49. Overview of race time models along with quadruple combinations of the predictor variables

Models	Predictor Variables
Model 221	Age, Height, Weight, Gender, YRS10, YRSALL, HrsTot, RacePlnd
Model 222	Age, Height, Weight, Gender, YRS10, YRSALL, HrsTot, Wave
Model 223	Age, Height, Weight, Gender, YRS10, YRSALL, RaceComp, RacePlnd
Model 224	Age, Height, Weight, Gender, YRS10, YRSALL, RaceComp, Wave
Model 225	Age, Height, Weight, Gender, YRS10, YRSALL, RacePlnd, Wave
Model 226	Age, Height, Weight, Gender, YRS10, HrsXC, HrsSP, HrsOther
Model 227	Age, Height, Weight, Gender, YRS10, HrsXC, HrsSP, HrsTot
Model 228	Age, Height, Weight, Gender, YRS10, HrsXC, HrsSP, RaceComp
Model 229	Age, Height, Weight, Gender, YRS10, HrsXC, HrsSP, RacePlnd
Model 230	Age, Height, Weight, Gender, YRS10, HrsXC, HrsSP, Wave
Model 231	Age, Height, Weight, Gender, YRS10, HrsXC, HrsOther, HrsTot

Table A.3.50. Overview of race time models along with quadruple combinations of the predictor variables

Models	Predictor Variables
Model 232	Age, Height, Weight, Gender, YRS10, HrsXC, HrsOther, RaceComp
Model 233	Age, Height, Weight, Gender, YRS10, HrsXC, HrsOther, RacePlnd
Model 234	Age, Height, Weight, Gender, YRS10, HrsXC, HrsOther, Wave
Model 235	Age, Height, Weight, Gender, YRS10, HrsXC, HrsTot, RaceComp
Model 236	Age Height, Weight, Gender, YRS10, HrsXC, HrsTot, RacePlnd
Model 237	Age, Height, Weight, Gender, YRS10, HrsXC, HrsTot, Wave
Model 238	Age, Height, Weight, Gender, YRS10, HrsXC, RaceComp, RacePlnd
Model 239	Age, Height, Weight, Gender, YRS10, HrsXC, RaceComp, Wave
Model 240	Age, Height, Weight, Gender, YRS10, HrsXC, RacePlnd, Wave
Model 241	Age, Height, Weight, Gender, YRS10, HrsSP, HrsOther, HrsTot
Model 242	Age, Height, Weight, Gender, YRS10, HrsSP, HrsOther, RaceComp

Table A.3.51. Overview of race time models along with quadruple combinations of the predictor variables

Models	Predictor Variables
Model 243	Age, Height, Weight, Gender, YRS10, HrsSP, HrsOther, RacePlnd
Model 244	Age, Height, Weight, Gender, YRS10, HrsSP, HrsOther, Wave
Model 245	Age, Height, Weight, Gender, YRS10, HrsSP, HrsTot, RaceComp
Model 246	Age, Height, Weight, Gender, YRS10, HrsSP, HrsTot, RacePlnd
Model 247	Age, Height, Weight, Gender, YRS10, HrsSP, HrsTot, Wave
Model 248	Age, Height, Weight, Gender, YRS10, HrsSP, RaceComp, RacePlnd
Model 249	Age, Height, Weight, Gender, YRS10, HrsSP, RaceComp, Wave
Model 250	Age, Height, Weight, Gender, YRS10, HrsSP, RacePlnd, Wave
Model 251	Age, Height, Weight, Gender, YRS10, HrsOther, HrsTot, RaceComp
Model 252	Age, Height, Weight, Gender, YRS10, HrsOther, HrsTot, RacePlnd
Model 253	Age ,Height, Weight, Gender, YRS10, HrsOther, HrsTot, Wave

Table A.3.52. Overview of race time models along with quadruple combinations of the predictor variables

Models	Predictor Variables
Model 254	Age, Height, Weight, Gender, YRS10, HrsOther, RaceComp, RacePlnd
Model 255	Age, Height, Weight, Gender, YRS10, HrsOther, RaceComp, Wave
Model 256	Age, Height, Weight, Gender, YRS10, HrsOther, RacePlnd, Wave
Model 257	Age, Height, Weight, Gender, YRS10, HrsTot, RaceComp, RacePlnd
Model 258	Age, Height, Weight, Gender, YRS10, HrsTot, RaceComp, Wave
Model 259	Age, Height, Weight, Gender, YRS10, HrsTot, RacePlnd, Wave
Model 260	Age, Height, Weight, Gender, YRS10, RaceComp, RacePlnd, Wave
Model 261	Age, Height, Weight, Gender, YRSALL, HrsXC, HrsSP, HrsOther
Model 262	Age, Height, Weight, Gender, YRSALL, HrsXC, HrsSP, HrsTot
Model 263	Age, Height, Weight, Gender, YRSALL, HrsXC, HrsSP, RaceComp
Model 264	Age, Height, Weight, Gender, YRSALL, HrsXC, HrsSP, RacePlnd

Table A.3.53. Overview of race time models along with quadruple combinations of the predictor variables

Models	Predictor Variables
Model 265	Age, Height, Weight, Gender, YRSALL, HrsXC, HrsSP, Wave
Model 266	Age, Height, Weight, Gender, YRSALL, HrsXC, HrsOther, HrsTot
Model 267	Age, Height, Weight, Gender, YRSALL, HrsXC, HrsOther, RaceComp
Model 268	Age, Height, Weight, Gender, YRSALL, HrsXC, HrsOther, RacePlnd
Model 269	Age, Height, Weight, Gender, YRSALL, HrsXC, HrsOther, Wave
Model 270	Age, Height, Weight, Gender, YRSALL, HrsXC, HrsTot, RaceComp
Model 271	Age, Height, Weight, Gender, YRSALL, HrsXC, HrsTot, RacePlnd
Model 272	Age, Height, Weight, Gender, YRSALL, HrsXC, HrsTot, Wave
Model 273	Age, Height, Weight, Gender, YRSALL, HrsXC, RaceComp, RacePlnd
Model 274	Age, Height, Weight, Gender, YRSALL, HrsXC, RaceComp, Wave
Model 275	Age, Height, Weight, Gender, YRSALL, HrsXC, RacePlnd, Wave
Model 276	Age, Height, Weight, Gender, YRSALL, HrsSP, HrsOther, HrsTot
Model 277	Age, Height, Weight, Gender, YRSALL, HrsSP, HrsOther, RaceComp

Table A.3.54. Overview of race time models along with quadruple combinations of the predictor variables

Models	Predictor Variables
Model 278	Age, Height, Weight, Gender, YRSALL, HrsSP, HrsOther, RacePlnd
Model 279	Age, Height, Weight, Gender, YRSALL, HrsSP, HrsOther, Wave
Model 280	Age, Height, Weight, Gender, YRSALL, HrsSP, HrsTot, RaceComp
Model 281	Age, Height, Weight, Gender, YRSALL, HrsSP, HrsTot, RacePlnd
Model 282	Age, Height, Weight, Gender, YRSALL, HrsSP, HrsTot, Wave
Model 283	Age, Height, Weight, Gender, YRSALL, HrsSP, RaceComp, RacePlnd
Model 284	Age, Height, Weight, Gender, YRSALL, HrsSP, RaceComp, Wave
Model 285	Age, Height, Weight, Gender, YRSALL, HrsSP, RacePlnd, Wave
Model 286	Age, Height, Weight, Gender, YRSALL, HrsOther, HrsTot, RaceComp
Model 287	Age, Height, Weight, Gender, YRSALL, HrsOther, HrsTot, RacePlnd
Model 288	Age, Height, Weight, Gender, YRSALL, HrsOther, HrsTot, Wave

Table A.3.55. Overview of race time models along with quadruple combinations of the predictor variables

Models	Predictor Variables
Model 289	Age, Height, Weight, Gender, YRSALL, HrsOther, RaceComp, RacePlnd
Model 290	Age, Height, Weight, Gender, YRSALL, HrsOther, RaceComp, Wave
Model 291	Age, Height, Weight, Gender, YRSALL, HrsOther, RacePlnd, Wave
Model 292	Age, Height, Weight, Gender, YRSALL, HrsTot, RaceComp, RacePlnd
Model 293	Age, Height, Weight, Gender, YRSALL, HrsTot, RaceComp, Wave
Model 294	Age, Height, Weight, Gender, YRSALL, HrsTot, RacePlnd, Wave
Model 295	Age, Height, Weight, Gender, YRSALL, RaceComp, RacePlnd, Wave
Model 296	Age, Height, Weight, Gender, HrsXC, HrsSP, HrsOther, HrsTot
Model 297	Age, Height, Weight, Gender, HrsXC, HrsSP, HrsOther, RaceComp
Model 298	Age, Height, Weight, Gender, HrsXC, HrsSP, HrsOther, RacePlnd
Model 299	Age, Height, Weight, Gender, HrsXC, HrsSP, HrsOther, Wave

Table A.3.56. Overview of race time models along with quadruple combinations of the predictor variables

Models	Predictor Variables
Model 300	Age, Height, Weight, Gender, HrsXC, HrsSP, HrsTot, RaceComp
Model 301	Age, Height, Weight, Gender, HrsXC, HrsSP, HrsTot, RacePlnd
Model 302	Age, Height, Weight, Gender, HrsXC, HrsSP, HrsTot, Wave
Model 303	Age, Height, Weight, Gender, HrsXC, HrsSP, RaceComp, RacePlnd
Model 304	Age, Height, Weight, Gender, HrsXC, HrsSP, RaceComp, Wave
Model 305	Age, Height, Weight, Gender, HrsXC, HrsSP, RacePlnd, Wave
Model 306	Age, Height, Weight, Gender, HrsXC, HrsOther, HrsTot, RaceComp
Model 307	Age, Height, Weight, Gender, HrsXC, HrsOther, HrsTot, RacePlnd
Model 308	Age, Height, Weight, Gender, HrsXC, HrsOther, HrsTot, Wave
Model 309	Age, Height, Weight, Gender, HrsXC, HrsOther, RaceComp, RacePlnd
Model 310	Age, Height, Weight, Gender, HrsXC, HrsOther, RaceComp, Wave

Table A.3.57. Overview of race time models along with quadruple combinations of the predictor variables

Models	Predictor Variables
Model 311	Age, Height, Weight, Gender, HrsXC, HrsOther,RacePlnd, Wave
Model 312	Age, Height, Weight, Gender, HrsXC, HrsTot, RaceComp, RacePlnd
Model 313	Age, Height, Weight, Gender, HrsXC, HrsTot,RaceComp, Wave
Model 314	Age, Height, Weight, Gender, HrsXC, HrsTot,RacePlnd, Wave
Model 315	Age, Height, Weight, Gender, HrsXC, RaceComp,RacePlnd, Wave
Model 316	Age, Height, Weight, Gender, HrsSP, HrsOther, HrsTot, RaceComp
Model 317	Age, Height, Weight, Gender, HrsSP, HrsOther, HrsTot, RacePlnd
Model 318	Age, Height, Weight, Gender, HrsSP, HrsOther, HrsTot, Wave
Model 319	Age, Height, Weight, Gender, HrsSP, HrsOther, RaceComp, RacePlnd
Model 320	Age, Height, Weight, Gender, HrsSP, HrsOther,RaceComp, Wave
Model 321	Age, Height, Weight, Gender, HrsSP, HrsOther,RacePlnd, Wave

Table A.3.58. Overview of race time models along with quadruple combinations of the predictor variables

Models	**Predictor Variables**
Model 322	Age, Height, Weight, Gender, HrsSP, HrsTot, RaceComp, RacePlnd
Model 323	Age, Height, Weight, Gender, HrsSP, HrsTot, RaceComp, Wave
Model 324	Age, Height, Weight, Gender, HrsSP, HrsTot, RacePlnd, Wave
Model 325	Age, Height, Weight, Gender, HrsSP, RaceComp, RacePlnd, Wave
Model 326	Age, Height, Weight, Gender, HrsOther, HrsTot, RaceComp,R acePlnd
Model 327	Age, Height, Weight, Gender, HrsOther, HrsTot, RaceComp, Wave
Model 328	Age, Height, Weight, Gender, HrsOther, HrsTot, RacePlnd, Wave
Model 329	Age, Height, Weight, Gender, HrsOther, RaceComp, RacePlnd, Wave
Model 330	Age, Height, Weight, Gender, HrsTot, RaceComp, RacePlnd, Wave

A.5. Prediction Models Created Using Quintuple Combinations

By quintuple double combinations of the predictor variables, a total of 462 prediction models have been formed, respectively

Table A.3.59. Overview of race time models along with quintuple combinations of the predictor variables

Models	Predictor Variables
Model 1	Age, Height, Weight, Gender, BMT10, BMT5, HrsOther, HrsSP, HrsTot
Model 2	Age, Height, Weight, Gender, BMT10, BMT5, HrsOther, HrsSP, HrsXC
Model 3	Age, Height, Weight, Gender, BMT10, BMT5, HrsOther, HrsSP, RaceComp
Model 4	Age, Height, Weight, Gender, BMT10, BMT5, HrsOther, HrsSP, RacePlnd
Model 5	Age, Height, Weight, Gender, BMT10, BMT5, HrsOther, HrsSP, Wave
Model 6	Age, Height, Weight, Gender, BMT10, BMT5, HrsOther, HrsSP, YRS10
Model 7	Age, Height, Weight, Gender, BMT10, BMT5, HrsOther, HrsSP, YRSALL
Model 8	Age, Height, Weight, Gender, BMT10, BMT5, HrsOther, HrsTot, HrsXC
Model 9	Age, Height, Weight, Gender, BMT10, BMT5, HrsOther, HrsTot, RaceComp
Model 10	Age, Height, Weight, Gender, BMT10, BMT5, HrsOther, HrsTot, RacePlnd
Model 11	Age, Height, Weight, Gender, BMT10, BMT5, HrsOther, HrsTot, Wave

Table A.3.60. Overview of race time models along with quintuple combinations of the predictor variables

Models	Predictor Variables
Model 12	Age, Height, Weight, Gender, BMT10, BMT5, HrsOther, HrsTot, YRS10
Model 13	Age, Height, Weight, Gender, BMT10, BMT5, HrsOther, HrsTot, YRSALL
Model 14	Age, Height, Weight, Gender, BMT10, BMT5, HrsOther, HrsXC, RaceComp
Model 15	Age, Height, Weight, Gender, BMT10, BMT5, HrsOther, HrsXC, RacePlnd
Model 16	Age, Height, Weight, Gender, BMT10, BMT5, HrsOther, HrsXC, Wave
Model 17	Age, Height, Weight, Gender, BMT10, BMT5, HrsOther, HrsXC, YRS10
Model 18	Age, Height, Weight, Gender, BMT10, BMT5, HrsOther, HrsXC, YRSALL
Model 19	Age, Height, Weight, Gender, BMT10, BMT5, HrsOther, RaceComp, RacePlnd
Model 20	Age, Height, Weight, Gender, BMT10, BMT5, HrsOther, RaceComp, Wave
Model 21	Age, Height, Weight, Gender, BMT10, BMT5, HrsOther, RaceComp, YRS10
Model 22	Age, Height, Weight, Gender, BMT10, BMT5, HrsOther, RaceComp, YRSALL

Table A.3.61. Overview of race time models along with quintuple combinations of the predictor variables

Models	Predictor Variables
Model 23	Age, Height, Weight, Gender, BMT10, BMT5, HrsOther, RacePlnd, Wave
Model 24	Age, Height, Weight, Gender, BMT10, BMT5, HrsOther, RacePlnd, YRS10
Model 25	Age, Height, Weight, Gender, BMT10, BMT5, HrsOther, RacePlnd, YRSALL
Model 26	Age, Height, Weight, Gender, BMT10, BMT5, HrsOther, Wave, YRS10
Model 27	Age, Height, Weight, Gender, BMT10, BMT5, HrsOther, Wave, YRSALL
Model 28	Age, Height, Weight, Gender, BMT10, BMT5, HrsOther, YRS10, YRSALL
Model 29,	Age, Height, Weight, Gender, BMT10, BMT5, HrsSP, HrsTot, HrsXC
Model 30,	Age, Height, Weight, Gender, BMT10, BMT5, HrsSP, HrsTot, RaceComp
Model 31,	Age, Height, Weight, Gender, BMT10, BMT5, HrsSP, HrsTot, RacePlnd
Model 32,	Age, Height, Weight, Gender, BMT10, BMT5, HrsSP, HrsTot, Wave
Model 33,	Age, Height, Weight, Gender, BMT10, BMT5, HrsSP, HrsTot, YRS10

Table A.3.62. Overview of race time models along with quintuple combinations of the predictor variables

Models	Predictor Variables
Model 34	Age, Height, Weight, Gender, BMT10, BMT5, HrsSP, HrsTot, YRSALL
Model 35	Age, Height, Weight, Gender, BMT10, BMT5, HrsSP, HrsXC, RaceComp
Model 36	Age, Height, Weight, Gender, BMT10, BMT5, HrsSP, HrsXC, RacePlnd
Model 37	Age, Height, Weight, Gender, BMT10, BMT5, HrsSP, HrsXC, Wave
Model 38	Age, Height, Weight, Gender, BMT10, BMT5, HrsSP, HrsXC, YRS10
Model 39	Age, Height, Weight, Gender , BMT10, BMT5, HrsSP, HrsXC, YRSALL
Model 40	Age, Height, Weight, Gender, BMT10, BMT5, HrsSP, RaceComp, RacePlnd
Model 41	Age, Height, Weight, Gender, BMT10, BMT5, HrsSP, RaceComp, Wave
Model 42	Age, Height, Weight, Gender, BMT10, BMT5, HrsSP, RaceComp, YRS10
Model 43	Age, Height, Weight, Gender, BMT10, BMT5, HrsSP, RaceComp, YRSALL
Model 44	Age, Height, Weight, Gender, BMT10, BMT5, HrsSP, RacePlnd, Wave

Table A.3.63. Overview of race time models along with quintuple combinations of the predictor variables

Models	**Predictor Variables**
Model 45	Age, Height, Weight, Gender, BMT10, BMT5, HrsSP, RacePlnd, YRS10
Model 46	Age Height, Weight, Gender, BMT10, BMT5, HrsSP, RacePlnd, YRSALL
Model 47	Age, Height, Weight, Gender, BMT10, BMT5, HrsSP, Wave, YRS10
Model 48	Age, Height, Weight, Gender, BMT10, BMT5, HrsSP, Wave, YRSALL
Model 49	Age, Height, Weight, Gender, BMT10, BMT5, HrsSP, YRS10, YRSALL
Model 50	Age, Height, Weight, Gender, BMT10, BMT5, HrsTot, HrsXC, RaceComp
Model 51,	Age, Height, Weight, Gender, BMT10, BMT5, HrsTot, HrsXC, RacePlnd
Model 52,	Age, Height, Weight, Gender, BMT10, BMT5, HrsTot, HrsXC, Wave
Model 53,	Age, Height, Weight, Gender, BMT10, BMT5, HrsTot, HrsXC, YRS10
Model 54,	Age, Height, Weight, Gender, BMT10, BMT5, HrsTot, HrsXC, YRSALL
Model 55,	Age, Height, Weight, Gender, BMT10, BMT5, HrsTot, RaceComp, RacePlnd

Table A.3.64. Overview of race time models along with quadruple combinations of the predictor variables

Models	**Predictor Variables**
Model 56	Age, Height, Weight, Gender, BMT10, BMT5, HrsTot, RaceComp, Wave
Model 57	Age, Height, Weight, Gender, BMT10, BMT5, HrsTot, RaceComp, YRS10
Model 58	Age, Height, Weight, Gender, BMT10, BMT5, HrsTot, RaceComp, YRSALL
Model 59	Age, Height, Weight, Gender, BMT10, BMT5, HrsTot, RacePlnd, Wave
Model 60	Age, Height, Weight, Gender, BMT10, BMT5, HrsTot, RacePlnd, YRS10
Model 61	Age, Height, Weight, Gender, BMT10, BMT5, HrsTot, RacePlnd, YRSALL
Model 62	Age, Height, Weight, Gender, BMT10, BMT5, HrsTot, Wave, YRS10
Model 63	Age, Height, Weight, Gender, BMT10, BMT5, HrsTot, Wave, YRSALL
Model 64	Age, Height, Weight, Gender, BMT10, BMT5, HrsTot, YRS10, YRSALL
Model 65	Age, Height, Weight, Gender, BMT10, BMT5, HrsXC, RaceComp, RacePlnd
Model 66	Age, Height, Weight, Gender, BMT10, BMT5, HrsXC, RaceComp, Wave

Table A.3.65. Overview of race time models along with quintuple combinations of the predictor variables

Models	Predictor Variables
Model 67	Age, Height, Weight, Gender, BMT10, BMT5, HrsXC, RaceComp, YRS10
Model 68	Age, Height, Weight, Gender, BMT10, BMT5, HrsXC, RaceComp, YRSALL
Model 69	Age, Height, Weight, Gender, BMT10, BMT5, HrsXC, RacePlnd, Wave
Model 70	Age, Height, Weight, Gender, BMT10, BMT5, HrsXC, RacePlnd, YRS10
Model 71	Age, Height, Weight, Gender, BMT10, BMT5, HrsXC, RacePlnd, YRSALL
Model 72	Age, Height, Weight, Gender, BMT10, BMT5, HrsXC, Wave, YRS10
Model 73	Age, Height, Weight, Gender, BMT10, BMT5, HrsXC, Wave, YRSALL
Model 74	Age, Height, Weight, Gender, BMT10, BMT5, HrsXC, YRS10, YRSALL
Model 75	Age, Height, Weight, Gender, BMT10, BMT5, RaceComp, RacePlnd, Wave
Model 76	Age, Height, Weight, Gender, BMT10, BMT5, RaceComp, RacePlnd, YRS10

Table A.3.66. Overview of race time models along with quintuple combinations of the predictor variables

Models	Predictor Variables
Model 77	Age, Height, Weight, Gender, BMT10, BMT5 , RaceComp, RacePlnd, YRSALL
Model 78	Age, Height, Weight, Gender , BMT10, BMT5, RaceComp, Wave, YRS10
Model 79	Age, Height, Weight, Gender, BMT10, BMT5, RaceComp, Wave, YRSALL
Model 80	Age, Height, Weight, Gender, BMT10, BMT5, RaceComp, YRS10, YRSALL
Model 81	Age, Height, Weight, Gender, BMT10, BMT5, RacePlnd, Wave, YRS10
Model 82	Age, Height, Weight, Gender, BMT10, BMT5, RacePlnd, Wave, YRSALL
Model 83	Age, Height, Weight, Gender, BMT10, BMT5, RacePlnd, YRS10, YRSALL
Model 84	Age, Height, Weight, Gender, BMT10, BMT5, Wave, YRS10, YRSALL
Model 85	Age, Height, Weight, Gender, BMT10, HrsOther, HrsSP, HrsTot, HrsXC
Model 86	Age, Height, Weight, Gender, BMT10, HrsOther, HrsSP, HrsTot, RaceComp
Model 87	Age, Height, Weight, Gender, BMT10, HrsOther, HrsSP, HrsTot, RacePlnd

Table A.3.67. Overview of race time models along with quintuple combinations of the predictor variables

Models	Predictor Variables
Model 88	Age, Height, Weight, Gender, BMT10, HrsOther, HrsSP, HrsTot, Wave
Model 89	Age, Height, Weight, Gender, BMT10, HrsOther, HrsSP, HrsTot, YRS10
Model 90	Age, Height, Weight, Gender, BMT10, HrsOther, HrsSP, HrsTot, YRSALL
Model 91	Age, Height, Weight, Gender, BMT10, HrsOther, HrsSP, HrsXC, RaceComp
Model 92	Age, Height, Weight, Gender, BMT10, HrsOther, HrsSP, HrsXC, RacePlnd
Model 93	Age, Height, Weight, Gender, BMT10, HrsOther, HrsSP, HrsXC, Wave
Model 94	Age, Height, Weight, Gender, BMT10, HrsOther, HrsSP, HrsXC, YRS10
Model 95	Age, Height, Weight, Gender, BMT10, HrsOther, HrsSP, HrsXC, YRSALL
Model 96	Age, Height, Weight, Gender, BMT10, HrsOther, HrsSP, RaceComp, RacePlnd
Model 97	Age, Height, Weight, Gender, BMT10, HrsOther, HrsSP, RaceComp, Wave
Model 98	Age, Height, Weight, Gender, BMT10, HrsOther, HrsSP, RaceComp, YRS10

Table A.3.68. Overview of race time models along with quintuple combinations of the predictor variables

Models	Predictor Variables
Model 99	Age, Height, Weight, Gender, BMT10, HrsOther, HrsSP, RaceComp, YRSALL
Model 100	Age, Height, Weight, Gender, BMT10, HrsOther, HrsSP, RacePlnd, Wave
Model 101	Age, Height, Weight, Gender, BMT10, HrsOther, HrsSP, RacePlnd, YRS10
Model 102	Age, Height, Weight, Gender, BMT10, HrsOther, HrsSP, RacePlnd, YRSALL
Model 103	Age, Height, Weight, Gender, BMT10, HrsOther, HrsSP,Wave, YRS10
Model 104	Age, Height, Weight, Gender, BMT10, HrsOther, HrsSP, Wave, YRSALL
Model 105	Age, Height, Weight, Gender, BMT10, HrsOther, HrsSP,YRS10, YRSALL
Model 106	Age, Height, Weight, Gender, BMT10, HrsOther, HrsTot, HrsXC, RaceComp
Model 107	Age, Height, Weight, Gender, BMT10, HrsOther, HrsTot, HrsXC, RacePlnd
Model 108	Age, Height, Weight, Gender,BMT10, HrsOther,HrsTot, HrsXC, Wave
Model 109	Age, Height, Weight, Gender,BMT10, HrsOther,HrsTot, HrsXC, YRS10

Table A.3.69. Overview of race time models along with quintuple combinations of the predictor variables

Models	Predictor Variables
Model 110	Age, Height, Weight, Gender,BMT10, HrsOther,HrsTot, HrsXC, YRSALL
Model 111	Age, Height, Weight, Gender, BMT10, HrsOther, HrsTot, RaceComp, RacePlnd
Model 112	Age, Height, Weight, Gender, BMT10, HrsOther, HrsTot, RaceComp, Wave
Model 113	Age, Height, Weight, Gender, BMT10, HrsOther, HrsTot, RaceComp, YRS10
Model 114	Age, Height, Weight, Gender, BMT10, HrsOther, HrsTot, RaceComp, YRSALL
Model 115	Age, Height, Weight, Gender, BMT10, HrsOther, HrsTot, RacePlnd, Wave
Model 116	Age, Height, Weight, Gender, BMT10, HrsOther, HrsTot, RacePlnd, YRS10
Model 117	Age, Height, Weight, Gender, BMT10, HrsOther, HrsTot, RacePlnd, YRSALL
Model 118	Age, Height, Weight, Gender, BMT10, HrsOther, HrsTot, Wave, YRS10
Model 119	Age, Height, Weight, Gender, BMT10, HrsOther, HrsTot, Wave, YRSALL
Model 120	Age, Height, Weight, Gender, BMT10, HrsOther, HrsTot, YRS10, YRSALL

Table A.3.70. Overview of race time models along with quintuple combinations of the predictor variables

Models	Predictor Variables
Model 121	Age, Height, Weight, Gender, BMT10, HrsOther, HrsXC, RaceComp, RacePlnd
Model 122	Age, Height, Weight, Gender, BMT10, HrsOther, HrsXC, RaceComp, Wave
Model 123	Age, Height, Weight, Gender, BMT10, HrsOther, HrsXC, RaceComp, YRS10
Model 124	Age, Height, Weight, Gender, BMT10, HrsOther, HrsXC, RaceComp, YRSALL
Model 125	Age, Height, Weight, Gender, BMT10, HrsOther, HrsXC, RacePlnd, Wave
Model 126	Age, Height, Weight, Gender, BMT10, HrsOther, HrsXC, RacePlnd, YRS10
Model 127	Age, Height, Weight, Gender, BMT10, HrsOther, HrsXC, RacePlnd, YRSALL
Model 128	Age, Height, Weight, Gender, BMT10, HrsOther, HrsXC,Wave, YRS10
Model 129	Age, Height, Weight, Gender, BMT10, HrsOther, HrsXC, Wave, YRSALL
Model 130	Age, Height, Weight, Gender, BMT10, HrsOther, HrsXC, YRS10, YRSALL
Model 131	Age, Height, Weight, Gender, BMT10, HrsOther, RaceComp, RacePlnd, Wave

Table A.3.71. Overview of race time models along with quintuple combinations of the predictor variables

Models	**Predictor Variables**
Model 132	Age, Height, Weight, Gender, BMT10, HrsOther, RaceComp, RacePlnd, YRS10
Model 133	Age, Height, Weight, Gender, BMT10, HrsOther, RaceComp, RacePlnd, YRSALL
Model 134	Age, Height, Weight, Gender, BMT10, HrsOther, RaceComp, Wave, YRS10
Model 135	Age, Height, Weight, Gender, BMT10, HrsOther, RaceComp, Wave, YRSALL
Model 136	Age, Height, Weight, Gender, BMT10, HrsOther, RaceComp, YRS10, YRSALL
Model 137	Age, Height, Weight, Gender, BMT10, HrsOther,RacePlnd, Wave, YRS10
Model 138	Age, Height, Weight, Gender, BMT10, HrsOther, RacePlnd, Wave, YRSALL
Model 139	Age, Height, Weight, Gender, BMT10, HrsOther, RacePlnd, YRS10, YRSALL
Model 140	Age, Height, Weight, Gender, BMT10, HrsOther, Wave, YRS10, YRSALL
Model 141	Age, Height, Weight, Gender, BMT10, HrsSP, HrsTot, HrsXC, RaceComp
Model 142	Age, Height, Weight, Gender, BMT10, HrsSP, HrsTot, HrsXC, RacePlnd

Table A.3.72. Overview of race time models along with quintuple combinations of the predictor variables

Models	Predictor Variables
Model 143	Age, Height, Weight, Gender, BMT10, HrsSP, HrsTot, HrsXC, Wave
Model 144	Age, Height, Weight, Gender, BMT10, HrsSP, HrsTot, HrsXC, YRS10
Model 145	Age, Height, Weight, Gender, BMT10, HrsSP, HrsTot, HrsXC, YRSALL
Model 146	Age, Height, Weight, Gender, BMT10, HrsSP, HrsTot, RaceComp, RacePlnd
Model 147	Age, Height, Weight, Gender, BMT10, HrsSP, HrsTot,RaceComp, Wave
Model 148	Age, Height, Weight, Gender, BMT10, HrsSP, HrsTot, RaceComp, YRS10
Model 149	Age, Height, Weight, Gender, BMT10, HrsSP, HrsTot, RaceComp, YRSALL
Model 150	Age, Height, Weight, Gender, BMT10, HrsSP, HrsTot, RacePlnd, Wave
Model 151	Age, Height, Weight, Gender, BMT10, HrsSP, HrsTot, RacePlnd, YRS10
Model 152	Age, Height, Weight, Gender, BMT10, HrsSP, HrsTot, RacePlnd, YRSALL
Model 153	Age, Height, Weight, Gender, BMT10, HrsSP, HrsTot,Wave, YRS10

Table A.3.73. Overview of race time models along with quintuple combinations of the predictor variables

Models	Predictor Variables
Model 154	Age, Height, Weight, Gender, BMT10, HrsSP, HrsTot, Wave, YRSALL
Model 155	Age, Height, Weight, Gender, BMT10, HrsSP, HrsTot, YRS10, YRSALL
Model 156	Age, Height, Weight, Gender, BMT10, HrsSP, HrsXC, RaceComp, RacePlnd
Model 157	Age, Height, Weight, Gender, BMT10, HrsSP, HrsXC, RaceComp, Wave
Model 158	Age, Height, Weight, Gender, BMT10, HrsSP, HrsXC, RaceComp, YRS10
Model 159	Age, Height, Weight, Gender, BMT10, HrsSP, HrsXC, RaceComp, YRSALL
Model 160	Age, Height, Weight, Gender, BMT10, HrsSP, HrsXC,RacePlnd, Wave
Model 161	Age, Height, Weight, Gender, BMT10, HrsSP, HrsXC, RacePlnd, YRS10
Model 162	Age, Height, Weight, Gender, BMT10, HrsSP, HrsXC, RacePlnd, YRSALL
Model 163	Age, Height, Weight, Gender, BMT10, HrsSP, HrsXC, Wave, YRS10
Model 164	Age, Height, Weight, Gender, BMT10, HrsSP, HrsXC, Wave, YRSALL

Table A.3.74. Overview of race time models along with quintuple combinations of the predictor variables

Models	**Predictor Variables**
Model 165	Age, Height, Weight, Gender, BMT10, HrsSP, HrsXC,YRS10, YRSALL
Model 166	Age, Height, Weight, Gender, BMT10, HrsSP, RaceComp, RacePlnd, Wave
Model 167	Age, Height, Weight, Gender, BMT10, HrsSP, RaceComp, RacePlnd, YRS10
Model 168	Age, Height, Weight, Gender, BMT10, HrsSP, RaceComp, RacePlnd, YRSALL
Model 169	Age, Height, Weight, Gender, BMT10, HrsSP, RaceComp,Wave, YRS10
Model 170	Age, Height, Weight, Gender, BMT10, HrsSP, RaceComp, Wave, YRSALL
Model 171	Age, Height, Weight, Gender, BMT10, HrsSP, RaceComp, YRS10, YRSALL
Model 172	Age, Height, Weight, Gender, BMT10, HrsSP, RacePlnd, Wave, YRS10
Model 173	Age, Height, Weight, Gender, BMT10, HrsSP, RacePlnd, Wave, YRSALL
Model 174	Age, Height, Weight, Gender, BMT10, HrsSP, RacePlnd, YRS10, YRSALL
Model 175	Age, Height, Weight, Gender, BMT10, HrsSP, Wave,YRS10, YRSALL

Table A.3.75. Overview of race time models along with quintuple combinations of the predictor variables

Models	Predictor Variables
Model 176	Age, Height, Weight, Gender, BMT10, HrsTot, HrsXC, RaceComp, RacePlnd
Model 177	Age, Height, Weight, Gender, BMT10, HrsTot, HrsXC, RaceComp, Wave
Model 178	Age, Height, Weight, Gender, BMT10, HrsTot, HrsXC, RaceComp, YRS10
Model 179	Age, Height, Weight, Gender, BMT10, HrsTot, HrsXC, RaceComp, YRSALL
Model 180	Age, Height, Weight, Gender, BMT10, HrsTot, HrsXC,RacePlnd, Wave
Model 181	Age, Height, Weight, Gender, BMT10, HrsTot, HrsXC, RacePlnd, YRS10
Model 182	Age, Height, Weight, Gender, BMT10, HrsTot, HrsXC, RacePlnd, YRSALL
Model 183	Age, Height, Weight, Gender, BMT10, HrsTot, HrsXC,Wave, YRS10
Model 184	Age, Height, Weight, Gender, BMT10, HrsTot, HrsXC, Wave, YRSALL
Model 185	Age, Height, Weight, Gender, BMT10, HrsTot, HrsXC,YRS10, YRSALL
Model 186	Age, Height, Weight, Gender, BMT10, HrsTot, RaceComp, RacePlnd, Wave
Model 187	Age, Height, Weight, Gender, BMT10, HrsTot, RaceComp, RacePlnd, YRS10

Table A.3.76. Overview of race time models along with quintuple combinations of the predictor variables

Models	Predictor Variables
Model 188	Age, Height, Weight, Gender, BMT10, HrsTot, RaceComp, RacePlnd, YRSALL
Model 189	Age, Height, Weight, Gender, BMT10, HrsTot, RaceComp, Wave, YRS10
Model 190	Age, Height, Weight, Gender, BMT10, HrsTot, RaceComp, Wave, YRSALL
Model 191	Age, Height, Weight, Gender, BMT10, HrsTot, RaceComp, YRS10, YRSALL
Model 192	Age, Height, Weight, Gender, BMT10, HrsTot, RacePlnd, Wave, YRS10
Model 193	Age, Height, Weight, Gender, BMT10, HrsTot, RacePlnd, Wave, YRSALL
Model 194	Age, Height, Weight, Gender, BMT10, HrsTot, RacePlnd, YRS10, YRSALL
Model 195	Age, Height, Weight, Gender, BMT10, HrsTot, Wave, YRS10, YRSALL
Model 196	Age, Height, Weight, Gender, BMT10, HrsXC, RaceComp, RacePlnd, Wave
Model 197	Age, Height, Weight, Gender, BMT10, HrsXC, RaceComp, RacePlnd, YRS10
Model 198	Age, Height, Weight, Gender, BMT10, HrsXC, RaceComp, RacePlnd, YRSALL

Table A.3.77. Overview of race time models along with quintuple combinations of the predictor variables

Models	**Predictor Variables**
Model 199	Age, Height, Weight, Gender, BMT10, HrsXC, RaceComp,Wave, YRS10
Model 200	Age, Height, Weight, Gender, BMT10, HrsXC, RaceComp, Wave, YRSALL
Model 201	Age, Height, Weight, Gender, BMT10, HrsXC, RaceComp, YRS10, YRSALL
Model 202	Age, Height, Weight, Gender, BMT10, HrsXC, RacePlnd, Wave, YRS10
Model 203	Age, Height, Weight, Gender, BMT10, HrsXC, RacePlnd, Wave, YRSALL
Model 204	Age, Height, Weight, Gender, BMT10, HrsXC, RacePlnd, YRS10, YRSALL
Model 205	Age, Height, Weight, Gender, BMT10, HrsXC, Wave,YRS10, YRSALL
Model 206	Age, Height, Weight, Gender, BMT10, RaceComp, RacePlnd, Wave, YRS10
Model 207	Age, Height, Weight, Gender, BMT10, RaceComp, RacePlnd, Wave, YRSALL
Model 208	Age, Height, Weight, Gender, BMT10, RaceComp, RacePlnd, YRS10, YRSALL
Model 209	Age, Height, Weight, Gender, BMT10, RaceComp, Wave, YRS10, YRSALL

Table A.3.78. Overview of race time models along with quintuple combinations of the predictor variables

Models	Predictor Variables
Model 210	Age, Height, Weight, Gender, BMT10, RacePlnd, Wave, YRS10, YRSALL
Model 211	Age, Height, Weight, Gender, BMT5, HrsOther, HrsSP, HrsTot, HrsXC
Model 212	Age, Height, Weight, Gender, BMT5, HrsOther, HrsSP, HrsTot, RaceComp
Model 213	Age, Height, Weight, Gender, BMT5, HrsOther, HrsSP, HrsTot, RacePlnd
Model 214	Age, Height, Weight, Gender, BMT5, HrsOther, HrsSP, HrsTot, Wave
Model 215	Age, Height, Weight, Gender, BMT5, HrsOther, HrsSP, HrsTot, YRS10
Model 216	Age, Height, Weight, Gender, BMT5, HrsOther, HrsSP, HrsTot, YRSALL
Model 217	Age, Height, Weight, Gender, BMT5, HrsOther, HrsSP, HrsXC, RaceComp
Model 218	Age, Height, Weight, Gender, BMT5, HrsOther, HrsSP, HrsXC, RacePlnd
Model 219	Age, Height, Weight, Gender, BMT5, HrsOther, HrsSP, HrsXC, Wave
Model 220	Age, Height, Weight, Gender, BMT5, HrsOther, HrsSP, HrsXC, YRS10

Table A.3.79. Overview of race time models along with quintuple combinations of the predictor variables

Models	Predictor Variables
Model 221	Age, Height, Weight, Gender, BMT5, HrsOther, HrsSP, HrsXC, YRSALL
Model 222	Age, Height, Weight, Gender, BMT5, HrsOther, HrsSP, RaceComp, RacePlnd
Model 223	Age, Height, Weight, Gender, BMT5, HrsOther, HrsSP, RaceComp, Wave
Model 224	Age, Height, Weight, Gender, BMT5, HrsOther, HrsSP, RaceComp, YRS10
Model 225	Age, Height, Weight, Gender, BMT5, HrsOther, HrsSP, RaceComp, YRSALL
Model 226	Age, Height, Weight, Gender, BMT5, HrsOther, HrsSP, RacePlnd, Wave
Model 227	Age, Height, Weight, Gender, BMT5, HrsOther, HrsSP, RacePlnd, YRS10
Model 228	Age, Height, Weight, Gender, BMT5, HrsOther, HrsSP, RacePlnd, YRSALL
Model 229	Age, Height, Weight, Gender, BMT5, HrsOther, HrsSP, Wave, YRS10
Model 230	Age, Height, Weight, Gender, BMT5, HrsOther, HrsSP, Wave, YRSALL
Model 231	Age, Height, Weight, Gender, BMT5, HrsOther, HrsSP, YRS10, YRSALL

Table A.3.80. Overview of race time models along with quintuple combinations of the predictor variables

Models	**Predictor Variables**
Model 232	Age, Height, Weight, Gender, BMT5, HrsOther, HrsTot, HrsXC, RaceComp
Model 233	Age, Height, Weight, Gender, BMT5, HrsOther, HrsTot, HrsXC, RacePlnd
Model 234	Age, Height, Weight, Gender, BMT5, HrsOther, HrsTot, HrsXC, Wave
Model 235	Age, Height, Weight, Gender, BMT5, HrsOther, HrsTot, HrsXC, YRS10
Model 236	Age, Height, Weight, Gender, BMT5, HrsOther, HrsTot, HrsXC, YRSALL
Model 237	Age, Height, Weight, Gender, BMT5, HrsOther, HrsTot, RaceComp, RacePlnd
Model 238	Age, Height, Weight, Gender, BMT5, HrsOther, HrsTot, RaceComp, Wave
Model 239	Age, Height, Weight, Gender, BMT5, HrsOther, HrsTot, RaceComp, YRS10
Model 240	Age, Height, Weight, Gender, BMT5, HrsOther, HrsTot, RaceComp, YRSALL
Model 241	Age, Height, Weight, Gender, BMT5, HrsOther, HrsTot, RacePlnd, Wave
Model 242	Age, Height, Weight, Gender, BMT5, HrsOther, HrsTot, RacePlnd, YRS10

Table A.3.81. Overview of race time models along with quintuple combinations of the predictor variables

Models	**Predictor Variables**
Model 243	Age, Height, Weight, Gender, BMT5, HrsOther, HrsTot, RacePlnd, YRSALL
Model 244	Age, Height, Weight, Gender, BMT5, HrsOther, HrsTot,Wave, YRS10
Model 245	Age, Height, Weight, Gender, BMT5, HrsOther, HrsTot, Wave, YRSALL
Model 246	Age, Height, Weight, Gender, BMT5, HrsOther, HrsTot, YRS10, YRSALL
Model 247	Age, Height, Weight, Gender, BMT5, HrsOther, HrsXC, RaceComp, RacePlnd
Model 248	Age, Height, Weight, Gender, BMT5, HrsOther, HrsXC, RaceComp, Wave
Model 249	Age Height, Weight, Gender, BMT5, HrsOther, HrsXC, RaceComp, YRS10
Model 250	Age, Height, Weight, Gender, BMT5, HrsOther, HrsXC, RaceComp, YRSALL
Model 251	Age, Height, Weight, Gender, BMT5, HrsOther, HrsXC,RacePlnd, Wave
Model 252	Age, Height, Weight, Gender, BMT5, HrsOther, HrsXC, RacePlnd, YRS10
Model 253	Age, Height, Weight, Gender, BMT5, HrsOther , HrsXC, RacePlnd, YRSALL

Table A.3.82. Overview of race time models along with quintuple combinations of the predictor variables

Models	Predictor Variables
Model 254	Age, Height, Weight, Gender, BMT5,HrsOther, HrsXC,Wave, YRS10
Model 255	Age, Height, Weight, Gender, BMT5,HrsOther, HrsXC, Wave, YRSALL
Model 256	Age, Height, Weight, Gender, BMT5, HrsOther, HrsXC, YRS10, YRSALL
Model 257	Age, Height, Weight, Gender, BMT5, HrsOther, RaceComp, RacePlnd, Wave
Model 258	Age, Height, Weight, Gender, BMT5, HrsOther, RaceComp, RacePlnd, YRS10
Model 259	Age, Height, Weight, Gender, BMT5, HrsOther, RaceComp, RacePlnd, YRSALL
Model 260	Age, Height, Weight, Gender, BMT5, HrsOther, RaceComp,Wave, YRS10
Model 261	Age, Height, Weight, Gender, BMT5, HrsOther, RaceComp, Wave, YRSALL
Model 262	Age, Height, Weight, Gender, BMT5, HrsOther, RaceComp, YRS10, YRSALL
Model 263	Age, Height, Weight, Gender, BMT5, HrsOther, RacePlnd, Wave, YRS10
Model 264	Age, Height, Weight, Gender, BMT5, HrsOther, RacePlnd, Wave, YRSALL

Table A.3.83. Overview of race time models along with quintuple combinations of the predictor variables

Models	Predictor Variables
Model 265	Age, Height, Weight, Gender, BMT5, HrsOther, RacePlnd, YRS10, YRSALL
Model 266	Age, Height, Weight, Gender, BMT5, HrsOther, Wave,YRS10, YRSALL
Model 267	Age, Height, Weight, Gender, BMT5, HrsSP, HrsTot, HrsXC, RaceComp
Model 268	Age, Height, Weight, Gender, BMT5, HrsSP, HrsTot, HrsXC, RacePlnd
Model 269	Age, Height, Weight, Gender, BMT5, HrsSP, HrsTot, HrsXC, Wave
Model 270	Age, Height, Weight, Gender, BMT5, HrsSP, HrsTot, HrsXC, YRS10
Model 271	Age, Height, Weight, Gender, BMT5, HrsSP, HrsTot, HrsXC, YRSALL
Model 272	Age, Height, Weight, Gender, BMT5, HrsSP, HrsTot, RaceComp , RacePlnd
Model 273	Age, Height, Weight, Gender, BMT5, HrsSP, HrsTot,RaceComp, Wave
Model 274	Age, Height, Weight, Gender, BMT5, HrsSP, HrsTot, RaceComp, YRS10
Model 275	Age, Height, Weight, Gender, BMT5, HrsSP, HrsTot, RaceComp, YRSALL

Table A.3.84. Overview of race time models along with quintuple combinations of the predictor variables

Models	Predictor Variables
Model 276	Age, Height, Weight, Gender, BMT5,HrsSP, HrsTot,RacePlnd, Wave
Model 277	Age, Height, Weight, Gender, BMT5, HrsSP, HrsTot, RacePlnd, YRS10
Model 278	Age, Height, Weight, Gender, BMT5, HrsSP, HrsTot, RacePlnd, YRSALL
Model 279	Age, Height, Weight, Gender, BMT5,HrsSP, HrsTot,Wave, YRS10
Model 280	Age, Height, Weight, Gender, BMT5,HrsSP, HrsTot, Wave, YRSALL
Model 281	Age, Height, Weight, Gender, BMT5,HrsSP, HrsTot,YRS10, YRSALL
Model 282	Age, Height, Weight, Gender, BMT5, HrsSP, HrsXC, RaceComp, RacePlnd
Model 283	Age, Height, Weight, Gender, BMT5, HrsSP, HrsXC, RaceComp, Wave
Model 284	Age, Height, Weight, Gender, BMT5, HrsSP, HrsXC, RaceComp, YRS10
Model 285	Age, Height, Weight, Gender, BMT5, HrsSP, HrsXC, RaceComp, YRSALL
Model 286	Age, Height, Weight, Gender, BMT5, HrsSP, HrsXC,RacePlnd, Wave

Table A.3.85. Overview of race time models along with quintuple combinations of the predictor variables

Models	Predictor Variables
Model 287	Age, Height, Weight, Gender, BMT5, HrsSP,HrsXC, RacePlnd, YRS10
Model 288	Age, Height, Weight, Gender, BMT5, HrsSP,HrsXC, RacePlnd, YRSALL
Model 289	Age, Height, Weight, Gender, BMT5, HrsSP, HrsXC,Wave, YRS10
Model 290	Age, Height, Weight, Gender, BMT5, HrsSP, HrsXC, Wave, YRSALL
Model 291	Age, Height, Weight, Gender, BMT5, HrsSP, HrsXC,YRS10, YRSALL
Model 292,	Age, Height, Weight, Gender, BMT5, HrsSP, RaceComp,RacePlnd, Wave
Model 293	Age, Height, Weight, Gender, BMT5, HrsSP, RaceComp, RacePlnd, YRS10
Model 294	Age, Height, Weight, Gender, BMT5, HrsSP, RaceComp, RacePlnd, YRSALL
Model 295	Age, Height, Weight, Gender, BMT5, HrsSP, RaceComp, Wave, YRS10
Model 296	Age, Height, Weight, Gender, BMT5, HrsSP, RaceComp, Wave, YRSALL
Model 297	Age, Height, Weight, Gender, BMT5, HrsSP, RaceComp,YRS10, YRSALL

Table A.3.86. Overview of race time models along with quintuple combinations of the predictor variables

Models	Predictor Variables
Model 298	Age, Height, Weight, Gender, BMT5, HrsSP,RacePlnd, Wave, YRS10
Model 299	Age, Height, Weight, Gender, BMT5, HrsSP,RacePlnd, Wave, YRSALL
Model 300	Age, Height, Weight, Gender, BMT5, HrsSP, RacePlnd,YRS10, YRSALL
Model 301	Age, Height, Weight, Gender, BMT5, HrsSP, Wave,YRS10, YRSALL
Model 302	Age, Height, Weight, Gender, BMT5, HrsTot, HrsXC, RaceComp, RacePlnd
Model 303	Age, Height, Weight, Gender, BMT5, HrsTot, HrsXC, RaceComp, Wave
Model 304	Age, Height, Weight, Gender, BMT5, HrsTot, HrsXC, RaceComp, YRS10
Model 305	Age, Height, Weight, Gender, BMT5, HrsTot, HrsXC, RaceComp, YRSALL
Model 306	Age, Height, Weight, Gender, BMT5, HrsTot, HrsXC,RacePlnd, Wave
Model 307	Age, Height, Weight, Gender, BMT5, HrsTot, HrsXC, RacePlnd, YRS10
Model 308	Age, Height, Weight, Gender, BMT5, HrsTot, HrsXC, RacePlnd, YRSALL

Table A.3.87. Overview of race time models along with quintuple combinations of the predictor variables

Models	**Predictor Variables**
Model 309	Age, Height, Weight, Gender, BMT5, HrsTot, HrsXC, Wave, YRS10
Model 310	Age, Height, Weight, Gender, BMT5, HrsTot, HrsXC, Wave, YRSALL
Model 311	Age, Height, Weight, Gender, BMT5, HrsTot, HrsXC, YRS10, YRSALL
Model 312	Age, Height, Weight, Gender, BMT5, HrsTot, RaceComp,RacePlnd, Wave
Model 313	Age, Height, Weight, Gender, BMT5, HrsTot, RaceComp, RacePlnd, YRS10
Model 314	Age, Height, Weight, Gender, BMT5, HrsTot, RaceComp, RacePlnd, YRSALL
Model 315	Age, Height, Weight, Gender, BMT5, HrsTot, RaceComp,Wave, YRS10
Model 316	Age, Height, Weight, Gender, BMT5, HrsTot,RaceComp, Wave, YRSALL
Model 317	Age, Height, Weight, Gender, BMT5, HrsTot, RaceComp,YRS10, YRSALL
Model 318	Age, Height, Weight, Gender, BMT5, HrsTot, RacePlnd, Wave, YRS10
Model 319	Age, Height, Weight, Gender, BMT5, HrsTot, RacePlnd, Wave, YRSALL

Table A.3.88. Overview of race time models along with quintuple combinations of the predictor variables

Models	**Predictor Variables**
Model 320	Age, Height, Weight, Gender, BMT5, HrsTot, RacePlnd, YRS10, YRSALL
Model 321	Age, Height, Weight, Gender, BMT5, HrsTot, Wave, YRS10, YRSALL
Model 322	Age, Height, Weight, Gender, BMT5, HrsXC, RaceComp, RacePlnd, Wave
Model 323	Age, Height, Weight, Gender, BMT5, HrsXC, RaceComp, RacePlnd, YRS10
Model 324	Age, Height, Weight, Gender, BMT5, HrsXC, RaceComp, RacePlnd, YRSALL
Model 325	Age, Height, Weight, Gender, BMT5, HrsXC, RaceComp,Wave, YRS10
Model 326	Age, Height, Weight, Gender, BMT5, HrsXC, RaceComp, Wave, YRSALL
Model 327	Age, Height, Weight, Gender, BMT5, HrsXC, RaceComp, YRS10, YRSALL
Model 328	Age, Height, Weight, Gender, BMT5, HrsXC,RacePlnd, Wave, YRS10
Model 329	Age, Height, Weight, Gender, BMT5, HrsXC,RacePlnd, Wave, YRSALL
Model 330	Age, Height, Weight, Gender, BMT5, HrsXC, RacePlnd,YRS10, YRSALL

Table A.3. 89. Overview of race time models along with quintuple combinations of the predictor variables

Models	**Predictor Variables**
Model 331	Age, Height, Weight, Gender, BMT5,HrsXC, Wave,YRS10, YRSALL
Model 332	Age, Height, Weight, Gender, BMT5, RaceComp, RacePlnd, Wave, YRS10
Model 333	Age, Height, Weight, Gender, BMT5, RaceComp, RacePlnd, Wave, YRSALL
Model 334	Age, Height, Weight, Gender, BMT5, RaceComp, RacePlnd, YRS10, YRSALL
Model 335	Age, Height, Weight, Gender, BMT5,RaceComp, Wave,YRS10, YRSALL
Model 336	Age, Height, Weight, Gender, BMT5,RacePlnd, Wave,YRS10, YRSALL
Model 337	Age, Height, Weight, Gender, HrsOther, HrsSP, HrsTot, HrsXC, RaceComp
Model 338	Age, Height, Weight, Gender, HrsOther, HrsSP,HrsTot, HrsXC, RacePlnd
Model 339	Age, Height, Weight, Gender, HrsOther, HrsSP,HrsTot, HrsXC, Wave
Model 340	Age, Height, Weight, Gender, HrsOther, HrsSP,HrsTot, HrsXC, YRS10
Model 341	Age, Height, Weight, Gender, HrsOther, HrsSP,HrsTot, HrsXC, YRSALL

Table A.3.90. Overview of race time models along with quintuple combinations of the predictor variables

Models	Predictor Variables
Model 342	Age, Height, Weight, Gender, HrsOther, HrsSP, HrsTot, RaceComp, RacePlnd
Model 343	Age, Height, Weight, Gender, HrsOther, HrsSP, HrsTot,RaceComp, Wave
Model 344	Age, Height, Weight, Gender, HrsOther , HrsSP, HrsTot, RaceComp, YRS10
Model 345	Age, Height, Weight, Gender, HrsOther, HrsSP, HrsTot, RaceComp, YRSALL
Model 346	Age, Height, Weight, Gender,HrsOther, HrsSP, HrsTot,RacePlnd, Wave
Model 347	Age, Height, Weight, Gender,HrsOther, HrsSP,HrsTot, RacePlnd, YRS10
Model 348	Age, Height, Weight, Gender, HrsOther, HrsSP, HrsTot, RacePlnd, YRSALL
Model 349	Age, Height, Weight, Gender, HrsOther, HrsSP, HrsTot,Wave, YRS10
Model 350	Age, Height, Weight, Gender, HrsOther, HrsSP, HrsTot, Wave, YRSALL
Model 351	Age, Height, Weight, Gender, HrsOther, HrsSP, HrsTot,YRS10, YRSALL
Model 352	Age, Height, Weight, Gender, HrsOther, HrsSP,HrsXC, RaceComp, RacePlnd

Table A.3.91. Overview of race time models along with quintuple combinations of the predictor variables

Models	**Predictor Variables**
Model 353	Age, Height, Weight, Gender,HrsOther, HrsSP,HrsXC, RaceComp, Wave
Model 354	Age, Height, Weight, Gender, HrsOther, HrsSP, HrsXC, RaceComp, YRS10
Model 355	Age, Height, Weight, Gender, HrsOther, HrsSP, HrsXC, RaceComp, YRSALL
Model 356	Age, Height, Weight, Gender,HrsOther, HrsSP, HrsXC,RacePlnd, Wave
Model 357	Age, Height, Weight, Gender,HrsOther, HrsSP,HrsXC, RacePlnd, YRS10
Model 358	Age, Height, Weight, Gender, HrsOther, HrsSP, HrsXC, RacePlnd, YRSALL
Model 359	Age, Height, Weight, Gender,HrsOther, HrsSP, HrsXC,Wave, YRS10
Model 360	Age, Height, Weight, Gender,HrsOther, HrsSP, HrsXC, Wave, YRSALL
Model 361	Age, Height, Weight, Gender,HrsOther, HrsSP, HrsXC,YRS10, YRSALL
Model 362	Age, Height, Weight, Gender, HrsOther, HrsSP, RaceComp, RacePlnd, Wave
Model 363	Age, Height, Weight, Gender,HrsOther, HrsSP, RaceComp, RacePlnd, YRS10

Table A.3.92. Overview of race time models along with quintuple combinations of the predictor variables

Models	**Predictor Variables**
Model 364	Age, Height, Weight, Gender, HrsOther, HrsSP, RaceComp, RacePlnd, YRSALL
Model 365	Age, Height, Weight, Gender,HrsOther, HrsSP, RaceComp,Wave, YRS10
Model 366	Age, Height, Weight, Gender, HrsOther, HrsSP, RaceComp, Wave, YRSALL
Model 367	Age, Height, Weight, Gender, HrsOther, HrsSP, RaceComp, YRS10, YRSALL
Model 368	Age, Height, Weight, Gender,HrsOther, HrsSP,RacePlnd, Wave, YRS10
Model 369	Age, Height, Weight, Gender,HrsOther, HrsSP,RacePlnd, Wave, YRSALL
Model 370	Age, Height, Weight, Gender, HrsOther, HrsSP, RacePlnd, YRS10, YRSALL
Model 371	Age, Height, Weight, Gender,HrsOther, HrsSP, Wave,YRS10, YRSALL
Model 372	Age, Height, Weight, Gender, HrsOther, HrsTot, HrsXC, RaceComp, RacePlnd
Model 373	Age, Height, Weight, Gender, HrsOther,HrsTot, HrsXC, RaceComp, Wave
Model 374	Age, Height, Weight, Gender, HrsOther, HrsTot, HrsXC, RaceComp, YRS10

Table A.3.93. Overview of race time models along with quintuple combinations of the predictor variables

Models	**Predictor Variables**
Model 375	Age, Height, Weight, Gender, HrsOther, HrsTot, HrsXC, RaceComp, YRSALL
Model 376	Age, Height, Weight, Gender, HrsOther, HrsTot, HrsXC,RacePlnd, Wave
Model 377	Age, Height, Weight, Gender, HrsOther, HrsTot, HrsXC, RacePlnd, YRS10
Model 378	Age, Height, Weight, Gender, HrsOther, HrsTot, HrsXC, RacePlnd, YRSALL
Model 379	Age, Height, Weight, Gender, HrsOther, HrsTot, HrsXC,Wave, YRS10
Model 380	Age, Height, Weight, Gender, HrsOther, HrsTot, HrsXC, Wave, YRSALL
Model 381	Age, Height, Weight, Gender, HrsOther, HrsTot, HrsXC,YRS10, YRSALL
Model 382	Age, Height, Weight, Gender, HrsOther, HrsTot, RaceComp, RacePlnd, Wave
Model 383	Age, Height, Weight, Gender, HrsOther, HrsTot, RaceComp, RacePlnd, YRS10
Model 384	Age, Height, Weight, Gender, HrsOther, HrsTot, RaceComp, RacePlnd, YRSALL
Model 385	Age, Height, Weight, Gender, HrsOther, HrsTot, RaceComp, Wave, YRS10

Table A.3.94. Overview of race time models along with quintuple combinations of the predictor variables

Models	**Predictor Variables**
Model 386	Age, Height, Weight, Gender, HrsOther, HrsTot, RaceComp, Wave, YRSALL
Model 387	Age, Height, Weight, Gender, HrsOther, HrsTot, RaceComp, YRS10, YRSALL
Model 388	Age, Height, Weight, Gender,HrsOther, HrsTot,RacePlnd, Wave, YRS10
Model 389	Age, Height, Weight, Gender, HrsOther, HrsTot, RacePlnd, Wave, YRSALL
Model 390	Age, Height, Weight, Gender, HrsOther, HrsTot, RacePlnd, YRS10, YRSALL
Model 391	Age, Height, Weight, Gender,HrsOther, HrsTot, Wave,YRS10, YRSALL
Model 392	Age, Height, Weight, Gender, HrsOther, HrsXC, RaceComp, RacePlnd, Wave
Model 393	Age, Height, Weight, Gender, HrsOther, HrsXC, RaceComp, RacePlnd, YRS10
Model 394	Age, Height, Weight, Gender, HrsOther, HrsXC, RaceComp, RacePlnd, YRSALL
Model 395	Age, Height, Weight, Gender,HrsOther, HrsXC, RaceComp,Wave, YRS10
Model 396	Age, Height, Weight, Gender, HrsOther, HrsXC, RaceComp, Wave, YRSALL

Table A.3.95. Overview of race time models along with quintuple combinations of the predictor variables

Models	**Predictor Variables**
Model 397	Age, Height, Weight, Gender, HrsOther, HrsXC, RaceComp,YRS10, YRSALL
Model 398	Age, Height, Weight, Gender, HrsOther, HrsXC,RacePlnd, Wave, YRS10
Model 399	Age, Height, Weight, Gender, HrsOther, HrsXC,RacePlnd, Wave, YRSALL
Model 400	Age, Height, Weight, Gender, HrsOther, HrsXC, RacePlnd,YRS10, YRSALL
Model 401	Age, Height, Weight, Gender, HrsOther, HrsXC, Wave,YRS10, YRSALL
Model 402	Age, Height, Weight, Gender, HrsOther, RaceComp,RacePlnd, Wave, YRS10
Model 403	Age, Height, Weight, Gender, HrsOther, RaceComp,RacePlnd, Wave, YRSALL
Model 404	Age, Height, Weight, Gender, HrsOther, RaceComp, RacePlnd,YRS10, YRSALL
Model 405	Age, Height, Weight, Gender, HrsOther, RaceComp, Wave,YRS10, YRSALL
Model 406	Age, Height, Weight, Gender, HrsOther, RacePlnd, Wave,YRS10, YRSALL
Model 407	Age, Height, Weight,Gender, HrsSP, HrsTot, HrsXC, RaceComp, RacePlnd

Table A.3.96. Overview of race time models along with quintuple combinations of the predictor variables

Models	Predictor Variables
Model 408	Age, Height, Weight,Gender, HrsSP,HrsTot, HrsXC, RaceComp, Wave
Model 409	Age, Height, Weight,Gender, HrsSP,HrsTot, HrsXC, RaceComp, YRS10
Model 410	Age, Height, Weight,Gender, HrsSP,HrsTot, HrsXC, RaceComp, YRSALL
Model 411	Age, Height, Weight,Gender, HrsSP,HrsTot, HrsXC,RacePlnd, Wave
Model 412	Age, Height, Weight,Gender, HrsSP,HrsTot, HrsXC, RacePlnd, YRS10
Model 413	Age, Height, Weight,Gender, HrsSP,HrsTot, HrsXC, RacePlnd, YRSALL
Model 414	Age, Height, Weight,Gender, HrsSP,HrsTot, HrsXC,Wave, YRS10
Model 415	Age, Height, Weight,Gender, HrsSP,HrsTot, HrsXC, Wave, YRSALL
Model 416	Age, Height, Weight,Gender, HrsSP,HrsTot, HrsXC,YRS10, YRSALL
Model 417	Age, Height, Weight, Gender, HrsSP, HrsTot, RaceComp, RacePlnd, Wave
Model 418	Age, Height, Weight, Gender, HrsSP, HrsTot, RaceComp, RacePlnd, YRS10

Table A.3.97. Overview of race time models along with quintuple combinations of the predictor variables

Models	Predictor Variables
Model 419	Age, Height, Weight, Gender, HrsSP, HrsTot, RaceComp, RacePlnd, YRSALL
Model 420	Age, Height, Weight,Gender, HrsSP, HrsTot, RaceComp,Wave, YRS10
Model 421	Age, Height, Weight,Gender, HrsSP, HrsTot,RaceComp, Wave, YRSALL
Model 422	Age, Height, Weight, Gender, HrsSP, HrsTot, RaceComp, YRS10, YRSALL
Model 423	Age, Height, Weight,Gender, HrsSP, HrsTot,RacePlnd, Wave, YRS10
Model 424	Age, Height, Weight,Gender, HrsSP, HrsTot,RacePlnd, Wave, YRSALL
Model 425	Age, Height, Weight,Gender, HrsSP,HrsTot, RacePlnd,YRS10, YRSALL
Model 426	Age, Height, Weight,Gender, HrsSP, HrsTot, Wave,YRS10, YRSALL
Model 427	Age, Height, Weight,Gender, HrsSP,HrsXC, RaceComp,RacePlnd, Wave
Model 428	Age, Height, Weight, Gender, HrsSP, HrsXC, RaceComp, RacePlnd, YRS10
Model 429	Age, Height, Weight, Gender, HrsSP, HrsXC, RaceComp, RacePlnd, YRSALL

Table A.3.98. Overview of race time models along with quintuple combinations of the predictor variables

Models	**Predictor Variables**
Model 430	Age, Height, Weight,Gender, HrsSP,HrsXC, RaceComp,Wave, YRS10
Model 431	Age, Height, Weight,Gender, HrsSP,HrsXC, RaceComp, Wave, YRSALL
Model 432	Age, Height, Weight, Gender, HrsSP, HrsXC, RaceComp, YRS10, YRSALL
Model 433	Age, Height, Weight,Gender, HrsSP, HrsXC,RacePlnd, Wave, YRS10
Model 434	Age, Height, Weight,Gender, HrsSP, HrsXC,RacePlnd, Wave, YRSALL
Model 435	Age, Height, Weight,Gender, HrsSP,HrsXC, RacePlnd,YRS10, YRSALL
Model 436	Age, Height, Weight,Gender, HrsSP, HrsXC, Wave,YRS10, YRSALL
Model 437	Age, Height, Weight, Gender, HrsSP, RaceComp, RacePlnd, Wave, YRS10
Model 438	Age, Height, Weight, Gender, HrsSP, RaceComp, RacePlnd, Wave, YRSALL
Model 439	Age, Height, Weight, Gender, HrsSP, RaceComp, RacePlnd, YRS10, YRSALL
Model 440	Age, Height, Weight,Gender, HrsSP, RaceComp, Wave,YRS10, YRSALL

Table A.3.99. Overview of race time models along with quintuple combinations of the predictor variables

Models	**Predictor Variables**
Model 441	Age, Height, Weight,Gender, HrsSP,RacePlnd, Wave,YRS10, YRSALL
Model 442	Age, Height, Weight, Gender , HrsTot, HrsXC, RaceComp, RacePlnd, Wave
Model 443	Age, Height, Weight, Gender, HrsTot, HrsXC, RaceComp, RacePlnd, YRS10
Model 444	Age, Height, Weight, Gender, HrsTot, HrsXC, RaceComp, RacePlnd, YRSALL
Model 445	Age, Height, Weight, Gender,HrsTot, HrsXC, RaceComp,Wave, YRS10
Model 446	Age, Height, Weight, Gender,HrsTot, HrsXC, RaceComp, Wave, YRSALL
Model 447	Age, Height, Weight, Gender, HrsTot, HrsXC, RaceComp, YRS10, YRSALL
Model 448	Age, Height, Weight, Gender,HrsTot, HrsXC,RacePlnd, Wave, YRS10
Model 449	Age, Height, Weight, Gender,HrsTot, HrsXC,RacePlnd, Wave, YRSALL
Model 450	Age, Height, Weight, Gender,HrsTot, HrsXC, RacePlnd,YRS10, YRSALL
Model 451	Age, Height, Weight, Gender,HrsTot, HrsXC, Wave,YRS10, YRSALL

Table A.3.100. Overview of race time models along with quintuple combinations of the predictor variables

Models	**Predictor Variables**
Model 452	Age, Height, Weight, Gender, HrsTot, RaceComp, RacePlnd, Wave, YRS10
Model 453	Age, Height, Weight, Gender, HrsTot, RaceComp, RacePlnd, Wave, YRSALL
Model 454	Age, Height, Weight, Gender, HrsTot, RaceComp, RacePlnd, YRS10, YRSALL
Model 455	Age, Height, Weight, Gender, HrsTot,RaceComp, Wave,YRS10, YRSALL
Model 456	Age, Height, Weight, Gender, HrsTot,RacePlnd, Wave,YRS10, YRSALL
Model 457	Age, Height, Weight, Gender, HrsXC, RaceComp, RacePlnd, Wave, YRS10
Model 458	Age, Height, Weight, Gender, HrsXC, RaceComp, RacePlnd, Wave, YRSALL
Model 459	Age, Height, Weight, Gender, HrsXC, RaceComp, RacePlnd, YRS10, YRSALL
Model 460	Age, Height, Weight,Gender, HrsXC, RaceComp, Wave,YRS10, YRSALL
Model 461	Age, Height, Weight,Gender, HrsXC,RacePlnd, Wave,YRS10, YRSALL
Model 462	Age, Height, Weight, Gender, RaceComp, RacePlnd, Wave, YRS10, YRSALL

A.6. Prediction Models Created Using Sextuple Combinations

By using sextuple combinations of the predictor variables, a total of 462 prediction models have been formed, respectively

Table A.3.101. Overview of race time models along with sextuple combinations of the predictor variables

Models	**Predictor Variables**
Model 1,	Age, Height, Weight, Gender, BMT5, BMT10, YRS10, YRSALL, HrsXC, HrsSP
Model 2,	Age, Height, Weight, Gender, BMT5, BMT10, YRS10, YRSALL, HrsXC, HrsOther
Model 3,	Age, Height, Weight, Gender, BMT5, BMT10, YRS10, YRSALL, HrsXC, HrsTot
Model 4,	Age, Height, Weight, Gender, BMT5, BMT10, YRS10, YRSALL, HrsXC, RaceComp
Model 5,	Age, Height, Weight, Gender, BMT5, BMT10, YRS10, YRSALL, HrsXC, RacePlnd
Model 6,	Age, Height,Weight, Gender, BMT5, BMT10,YRS10, YRSALL,HrsXC, Wave
Model 7,	Age, Height, Weight, Gender, BMT5, BMT10, YRS10, YRSALL, HrsSP, HrsOther
Model 8,	Age, Height,Weight, Gender, BMT5, BMT10,YRS10, YRSALL,HrsSP, HrsTot
Model 9,	Age, Height, Weight, Gender, BMT5, BMT10, YRS10, YRSALL, HrsSP, RaceComp
Model 10,	Age, Height, Weight, Gender, BMT5, BMT10, YRS10, YRSALL, HrsSP, RacePlnd
Model 11,	Age, Height, Weight, Gender, BMT5, BMT10, YRS10, YRSALL, HrsSP, Wave

Table A.3.102. Overview of race time models along with sextuple combinations of the predictor variables

Models	**Predictor Variables**
Model 12,	Age, Height,Weight, Gender, BMT5, BMT10,YRS10, YRSALL, HrsOther, HrsTot
Model13,	Age, Height,Weight, Gender, BMT5, BMT10,YRS10, YRSALL, HrsOther, RaceComp
Model 14,	Age, Height,Weight, Gender, BMT5, BMT10,YRS10, YRSALL, HrsOther, RacePlnd
Model 15,	Age, Height, Weight, Gender, BMT5, BMT10,YRS10, YRSALL,HrsOther, Wave
Model 16,	Age, Height, Weight, Gender, BMT5, BMT10, YRS10, YRSALL, HrsTot, RaceComp
Model 17,	Age, Height, Weight, Gender, BMT5, BMT10, YRS10, YRSALL, HrsTot, RacePlnd
Model 18,	Age, Height, Weight, Gender, BMT5, BMT10, YRS10, YRSALL, HrsTot, Wave
Model19,	Age, Height,Weight, Gender, BMT5, BMT10,YRS10, YRSALL, RaceComp, RacePlnd
Model 20,	Age, Height, Weight, Gender, BMT5, BMT10, YRS10, YRSALL, RaceComp, Wave
Model 21,	Age, Height, Weight, Gender, BMT5, BMT10, YRS10, YRSALL, RacePlnd, Wave
Model 22,	Age, Height, Weight, Gender, BMT5, BMT10, YRS10, HrsXC, HrsSP, HrsOther

Table A.3.103. Overview of race time models along with sextuple combinations of the predictor variables

Models	**Predictor Variables**
Model 23,	Age, Height,Weight, Gender, BMT5, BMT10, YRS10, HrsXC,HrsSP, HrsTot
Model 24,	Age, Height, Weight, Gender, BMT5, BMT10, YRS10, HrsXC, HrsSP, RaceComp
Model 25,	Age, Height, Weight, Gender, BMT5, BMT10, YRS10, HrsXC, HrsSP, RacePlnd
Model 26,	Age, Height,Weight, Gender, BMT5, BMT10, YRS10, HrsXC, HrsSP, Wave
Model 27,	Age, Height, Weight, Gender, BMT5, BMT10, YRS10, HrsXC, HrsOther, HrsTot
Model 28,	Age, Height, Weight, Gender, BMT5, BMT10, YRS10, HrsXC, HrsOther, RaceComp
Model 29,	Age, Height, Weight, Gender, BMT5, BMT10, YRS10, HrsXC, HrsOther, RacePlnd
Model 30,	Age, Height, Weight, Gender, BMT5, BMT10, YRS10, HrsXC, HrsOther, Wave
Model 31,	Age, Height, Weight, Gender, BMT5, BMT10, YRS10, HrsXC, HrsTot, RaceComp
Model 32,	Age, Height, Weight, Gender, BMT5, BMT10, YRS10, HrsXC, HrsTot, RacePlnd
Model 33,	Age, Height,Weight, Gender, BMT5, BMT10, YRS10, HrsXC, HrsTot, Wave

Table A.3.104. Overview of race time models along with sextuple combinations of the predictor variables

Models	Predictor Variables
Model 34,	Age, Height, Weight, Gender, BMT5, BMT10, YRS10, HrsXC, RaceComp, RacePlnd
Model 35,	Age, Height,Weight, Gender, BMT5, BMT10, YRS10, HrsXC, RaceComp, Wave
Model 36,	Age, Height, Weight, Gender, BMT5, BMT10, YRS10, HrsXC, RacePlnd, Wave
Model 37,	Age, Height, Weight, Gender, BMT5, BMT10, YRS10, HrsSP, HrsOther, HrsTot
Model 38,	Age, Height, Weight, Gender, BMT5, BMT10, YRS10, HrsSP, HrsOther, RaceComp
Model 39,	Age, Height, Weight, Gender, BMT5, BMT10, YRS10, HrsSP, HrsOther, RacePlnd
Model 40,	Age, Height, Weight, Gender, BMT5, BMT10, YRS10, HrsSP, HrsOther, Wave
Model 41,	Age, Height, Weight, Gender, BMT5, BMT10, YRS10, HrsSP, HrsTot, RaceComp
Model 42,	Age, Height, Weight, Gender, BMT5, BMT10, YRS10, HrsSP, HrsTot, RacePlnd
Model 43,	Age, Height,Weight, Gender, BMT5, BMT10, YRS10,HrsSP, HrsTot, Wave
Model 44,	Age, Height, Weight, Gender, BMT5, BMT10, YRS10, HrsSP, RaceComp, RacePlnd

Table A.3.105. Overview of race time models along with sextuple combinations of the predictor variables

Models	Predictor Variables
Model 45	Age, Height, Weight, Gender, BMT5, BMT10, YRS10, HrsSP, RaceComp, Wave
Model 46	Age, Height, Weight, Gender, BMT5, BMT10, YRS10, HrsSP, RacePlnd, Wave
Model 47	Age, Height, Weight, Gender, BMT5, BMT1 YRS10, HrsOther, HrsTot, RaceComp
Model 48	Age, Height, Weight, Gender, BMT5, BMT10, YRS10, HrsOther, HrsTot, RacePlnd
Model 49	Age, Height, Weight, Gender, BMT5, BMT10, YRS10, HrsOther, HrsTot, Wave
Model 50	Age, Height, Weight, Gender, BMT5, BMT10, YRS10, HrsOther, RaceComp, RacePlnd
Model 51	Age, Height, Weight, Gender, BMT5, BMT10, YRS10, HrsOther, RaceComp, Wave
Model 52	Age, Height, Weight, Gender, BMT5, BMT10, YRS10, HrsOther, RacePlnd, Wave
Model 53	Age, Height, Weight, Gender, BMT5, BMT10, YRS10, HrsTot, RaceComp, RacePlnd
Model 54	Age, Height, Weight, Gender, BMT5, BMT10, YRS10, HrsTot, RaceComp, Wave
Model 55	Age, Height, Weight, Gender, BMT5, BMT10, YRS10, HrsTot, RacePlnd, Wave

Table A.3.106. Overview of race time models along with sextuple combinations of the predictor variables

Models	**Predictor Variables**
Model 56	Age, Height, Weight, Gender, BMT5, BMT10, YRS10, RaceComp, RacePlnd, Wave
Model 57	Age, Height,Weight, Gender, BMT5, BMT10, YRSALL, HrsXC, HrsSP, HrsOther
Model 58	Age, Height,Weight, Gender, BMT5, BMT10, YRSALL, HrsXC,HrsSP, HrsTot
Model 59	Age, Height, Weight, Gender, BMT5, BMT10, YRSALL, HrsXC, HrsSP, RaceComp
Model 60	Age, Height, Weight, Gender, BMT5, BMT10, YRSALL, HrsXC, HrsSP, RacePlnd
Model 61	Age, Height,Weight, Gender, BMT5, BMT10, YRSALL, HrsXC, HrsSP, Wave
Model 62	Age, Height,Weight, Gender, BMT5, BMT10, YRSALL,HrsXC, HrsOther, HrsTot
Model 63	Age, Height, Weight, Gender, BMT5, BMT10, YRSALL, HrsXC, HrsOther, RaceComp
Model 64	Age, Height, Weight, Gender, BMT5, BMT10, YRSALL, HrsXC, HrsOther, RacePlnd
Model 65	Age Height,Weight, Gender, BMT5, BMT10, YRSALL,HrsXC, HrsOther, Wave
Model 66	Age, Height,Weight, Gender, BMT5, BMT10, YRSALL, HrsXC, HrsTot, RaceComp

Table A.3.107. Overview of race time models along with sextuple combinations of the predictor variables

Models	**Predictor Variables**
Model 67	Age, Height, Weight, Gender, BMT5, BMT10, YRSALL, HrsXC, HrsTot, RacePlnd
Model 68	Age, Height, Weight, Gender, BMT5, BMT10, YRSALL, HrsXC, HrsTot, Wave
Model 69	Age, Height, Weight, Gender, BMT5, BMT10, YRSALL, HrsXC, RaceComp, RacePlnd
Model 70	Age, Height, Weight, Gender, BMT5, BMT10, YRSALL, HrsXC, RaceComp, Wave
Model 71	Age, Height, Weight, Gender, BMT5, BMT10, YRSALL, HrsXC, RacePlnd, Wave
Model 72	Age, Height, Weight, Gender, BMT5, BMT10, YRSALL, HrsSP, HrsOther, HrsTot
Model 73	Age, Height, Weight, Gender, BMT5, BMT10, YRSALL, HrsSP, HrsOther RaceComp
Model 74	Age, Height, Weight, Gender, BMT5, BMT10, YRSALL, HrsSP, HrsOther, RacePlnd
Model 75	Age, Height, Weight, Gender, BMT5, BMT10, YRSALL, HrsSP, HrsOther, Wave
Model 76	Age, Height, Weight, Gender, BMT5, BMT10, YRSALL, HrsSP, HrsTot, RaceComp
Model 77	Age, Height, Weight, Gender, BMT5, BMT10, YRSALL, HrsSP, HrsTot, RacePlnd

Table A.3.108. Overview of race time models along with sextuple combinations of the predictor variables

Models	Predictor Variables
Model 78	Age, Height, Weight, Gender, BMT5, BMT10, YRSALL, HrsSP, HrsTot, Wave
Model 79	Age, Height, Weight, Gender, BMT5, BMT10, YRSALL, HrsSP, RaceComp, RacePlnd
Model 80	Age, Height, Weight, Gender, BMT5, BMT10, YRSALL, HrsSP, RaceComp, Wave
Model 81	Age, Height, Weight, Gender, BMT5, BMT10, YRSALL, HrsSP, RacePlnd, Wave
Model 82	Age, Height, Weight, Gender, BMT5, BMT10, YRSALL, HrsOther, HrsTot, RaceComp
Model 83	Age, Height, Weight, Gender, BMT5, BMT10, YRSALL, HrsOther, HrsTot, RacePlnd
Model 84	Age, Height, Weight, Gender, BMT5, BMT10, YRSALL, HrsOther, HrsTot, Wave
Model 85	Age, Height, Weight, Gender, BMT5, BMT10, YRSALL, HrsOther, RaceComp, RacePlnd
Model 86	Age, Height, Weight, Gender, BMT5, BMT10, YRSALL, HrsOther,RaceComp, Wave
Model 87	Age, Height, Weight, Gender, BMT5, BMT10, YRSALL, HrsOther,RacePlnd, Wave
Model 88	Age, Height, Weight, Gender, BMT5, BMT10, YRSALL, HrsTot, RaceComp, RacePlnd

Table A.3.109. Overview of race time models along with sextuple combinations of the predictor variables

Models	Predictor Variables
Model 89	Age, Height, Weight, Gender, BMT5, BMT10, YRSALL, HrsTot, RaceComp, Wave
Model 90	Age, Height, Weight, Gender, BMT5, BMT10, YRSALL, HrsTot, RacePlnd, Wave
Model 91	Age, Height, Weight, Gender, BMT5, BMT10, YRSALL, RaceComp, RacePlnd, Wave
Model 92	Age, Height, Weight, Gender, BMT5, BMT10, HrsXC, HrsSP, HrsOther, HrsTot
Model 93	Age ,Height, Weight, Gender BMT5, BMT10, HrsXC, HrsSP, HrsOther, RaceComp
Model 94	Age ,Height, Weight, Gender, BMT5, BMT10, HrsXC, HrsSP, HrsOther, RacePlnd
Model 95	Age, Height, Weight, Gender, BMT5, BMT10, HrsXC, HrsSP, HrsOther, Wave
Model 96	Age, Height, Weight, Gender, BMT5, BMT10, HrsXC, HrsSP, HrsTot, RaceComp
Model 97	Age, Height, Weight, Gender, BMT5, BMT10, HrsXC, HrsSP, HrsTot, RacePlnd
Model 98	Age, Height, Weight, Gender, BMT5, BMT10, HrsXC, HrsSP, HrsTot, Wave
Model 99	Age, Height, Weight, Gender, BMT5, BMT10, HrsXC, HrsSP, RaceComp, RacePlnd

Table A.3.110. Overview of race time models along with sextuple combinations of the predictor variables

Models	**Predictor Variables**
Model 100	Age, Height, Weight, Gender, BMT5, BMT10, HrsXC, HrsSP, RaceComp, Wave
Model 101	Age, Height, Weight, Gender, BMT5, BMT10, HrsXC, HrsSP, RacePlnd, Wave
Model 102	Age, Height, Weight, Gender, BMT5, BMT10, HrsXC, HrsOther, HrsTot, RaceComp
Model 103	Age, Height, Weight, Gender, BMT5, BMT10, HrsXC, HrsOther, HrsTot, RacePlnd
Model 104	Age, Height, Weight, Gender, BMT5, BMT10, HrsXC, HrsOther, HrsTot, Wave
Model 105	Age, Height, Weight, Gender, BMT5, BMT10, HrsXC, HrsOther, RaceComp, RacePlnd
Model 106	Age, Height, Weight, Gender, BMT5, BMT10, HrsXC, HrsOther, RaceComp, Wave
Model 107	Age, Height, Weight, Gender, BMT5, BMT10, HrsXC, HrsOther, RacePlnd, Wave
Model 108	Age, Height, Weight, Gender, BMT5, BMT10, HrsXC, HrsTot, RaceComp, RacePlnd
Model 109	Age, Height, Weight, Gender, BMT5, BMT10, HrsXC, HrsTot, RaceComp, Wave
Model 110	Age, Height, Weight, Gender, BMT5, BMT10, HrsXC, HrsTot, RacePlnd, Wave

Table A.3.111. Overview of race time models along with sextuple combinations of the predictor variables

Models	**Predictor Variables**
Model 111	Age, Height, Weight, Gender, BMT5, BMT10, HrsXC, RaceComp, RacePlnd, Wave
Model 112	Age, Height, Weight, Gender, BMT5, BMT10, HrsSP, HrsOther, HrsTot, RaceComp
Model 113	Age, Height, Weight, Gender, BMT5, BMT10, HrsSP, HrsOther, HrsTot, RacePlnd
Model 114	Age, Height, Weight, Gender, BMT5, BMT10, HrsSP, HrsOther, HrsTot, Wave
Model 115	Age, Height, Weight, Gender, BMT5, BMT10, HrsSP, HrsOther, RaceComp, RacePlnd
Model 116	Age, Height, Weight, Gender, BMT5, BMT10, HrsSP, HrsOther, RaceComp, Wave
Model 117	Age, Height, Weight, Gender, BMT5, BMT10, HrsSP, HrsOther, RacePlnd, Wave
Model 118	Age, Height, Weight, Gender, BMT5, BMT10, HrsSP, HrsTot, RaceComp, RacePlnd
Model 119	Age, Height, Weight, Gender, BMT5, BMT10, HrsSP, HrsTot, RaceComp, Wave
Model 120	Age, Height, Weight, Gender, BMT5, BMT10, HrsSP, HrsTot, RacePlnd, Wave
Model 121	Age, Height, Weight, Gender, BMT5, BMT10, HrsSP, RaceComp, RacePlnd, Wave

Table A.3.112. Overview of race time models along with sextuple combinations of the predictor variables

Models	**Predictor Variables**
Model 122	Age Height, Weight, Gender, BMT5, BMT10, HrsOther, HrsTot, RaceComp, RacePlnd
Model 123	Age, Height, Weight, Gender, BMT5, BMT10, HrsOther, HrsTot, RaceComp, Wave
Model 124	Age, Height, Weight, Gender, BMT5, BMT10, HrsOther, HrsTot, RacePlnd, Wave
Model 125	Age, Height, Weight, Gender, BMT5, BMT10, HrsOther, RaceComp, RacePlnd, Wave
Model 126	Age, Height, Weight, Gender, BMT5, BMT10, HrsTot, RaceComp, RacePlnd, Wave
Model 127	Age, Height, Weight, Gender, BMT5, YRS10, YRSALL, HrsXC, HrsSP, HrsOther
Model 128	Age, Height, Weight, Gender, BMT5, YRS10, YRSALL, HrsXC, HrsSP, HrsTot
Model 129	Age, Height, Weight, Gender, BMT5, YRS10, YRSALL, HrsXC, HrsSP, RaceComp
Model 130	Age, Height, Weight, Gender, BMT5, YRS10, YRSALL, HrsXC, HrsSP, RacePlnd
Model 131	Age, Height, Weight, Gender, BMT5, YRS10, YRSALL, HrsXC, HrsSP, Wave
Model 132	Age, Height, Weight, Gender, BMT5, YRS10, YRSALL, HrsXC, HrsOther, HrsTot

Table A.3.113. Overview of race time models along with sextuple combinations of the predictor variables

Models	Predictor Variables
Model 133	Age, Height, Weight, Gender, BMT5, YRS10, YRSALL, HrsXC, HrsOther, RaceComp
Model 134	Age, Height, Weight, Gender, BMT5, YRS10, YRSALL, HrsXC, HrsOther, RacePlnd
Model 135	Age, Height, Weight, Gender, BMT5, YRS10, YRSALL, HrsXC, HrsOther, Wave
Model 136	Age, Height, Weight, Gender, BMT5, YRS10, YRSALL, HrsXC, HrsTot, RaceComp
Model 137	Age, Height, Weight, Gender, BMT5, YRS10, YRSALL, HrsXC, HrsTot, RacePlnd
Model 138	Age, Height, Weight, Gender, BMT5, YRS10, YRSALL, HrsXC, HrsTot, Wave
Model 139	Age, Height, Weight, Gender, BMT5, YRS10, YRSALL, HrsXC, RaceComp, RacePlnd
Model 140	Age, Height, Weight, Gender, BMT5, YRS10, YRSALL, HrsXC, RaceComp, Wave
Model 141	Age, Height, Weight, Gender, BMT5, YRS10, YRSALL, HrsXC, RacePlnd, Wave
Model 142	Age, Height, Weight, Gender, BMT5, YRS10, YRSALL, HrsSP, HrsOther, HrsTot
Model 143	Age, Height, Weight, Gender, BMT5, YRS10, YRSALL, HrsSP, HrsOther, RaceComp

Table A.3.114. Overview of race time models along with sextuple combinations of the predictor variables

Models	**Predictor Variables**
Model 144	Age, Height, Weight, Gender, BMT5, YRS10, YRSALL, HrsSP, HrsOther, RacePlnd
Model 145	Age ,Height, Weight, Gender, BMT5, YRS10, YRSALL, HrsSP, HrsOther, Wave
Model 146	Age, Height, Weight, Gender, BMT5, YRS10, YRSALL, HrsSP, HrsTot, RaceComp
Model 147	Age ,Height, Weight, Gender, BMT5, YRS10, YRSALL, HrsSP, HrsTot, RacePlnd
Model 148	Age, Height, Weight, Gender, BMT5, YRS10, YRSALL, HrsSP, HrsTot, Wave
Model 149	Age, Height, Weight, Gender, BMT5, YRS10, YRSALL, HrsSP, RaceComp, RacePlnd
Model 150	Age, Height, Weight, Gender, BMT5, YRS10, YRSALL, HrsSP, RaceComp, Wave
Model 151	Age, Height, Weight, Gender, BMT5, YRS10, YRSALL, HrsSP, RacePlnd, Wave
Model 152	Age, Height, Weight, Gender, BMT5, YRS10, YRSALL, HrsOther, HrsTot, RaceComp
Model 153	Age, Height, Weight, Gender, BMT5, YRS10, YRSALL, HrsOther, HrsTot, RacePlnd
Model 154	Age, Height, Weight, Gender, BMT5, YRS10, YRSALL, HrsOther, HrsTot, Wave

Table A.3.115. Overview of race time models along with sextuple combinations of the predictor variables

Models	**Predictor Variables**
Model 155	Age, Height, Weight, Gender, BMT5, YRS10, YRSALL, HrsOther, RaceComp, RacePlnd
Model 156	Age, Height, Weight, Gender, BMT5, YRS10, YRSALL, HrsOther, RaceComp, Wave
Model 157	Age, Height, Weight, Gender, BMT5, YRS10, YRSALL, HrsOther, RacePlnd, Wave
Model 158	Age, Height, Weight, Gender, BMT5, YRS10, YRSALL, HrsTot, RaceComp, RacePlnd
Model 159	Age, Height, Weight, Gender, BMT5, YRS10, YRSALL, HrsTot, RaceComp, Wave
Model 160	Age, Height, Weight, Gender, BMT5, YRS10, YRSALL, HrsTot, RacePlnd, Wave
Model 161	Age, Height, Weight, Gender, BMT5, YRS10, YRSALL, RaceComp, RacePlnd, Wave
Model 162	Age, Height, Weight, Gender, BMT5, YRS10, HrsXC, HrsSP, HrsOther, HrsTot
Model 163	Age ,Height, Weight, Gender, BMT5, YRS10, HrsXC, HrsSP, HrsOther, RaceComp
Model 164	Age, Height, Weight, Gender, BMT5, YRS10, HrsXC, HrsSP, HrsOther, RacePlnd
Model 165	Age, Height, Weight, Gender, BMT5, YRS10, HrsXC, HrsSP, HrsOther, Wave

Table A.3.116. Overview of race time models along with sextuple combinations of the predictor variables

Models	**Predictor Variables**
Model 166	Age ,Height, Weight, Gender, BMT5, YRS10, HrsXC,HrsSP, HrsTot, RaceComp
Model 167	Age, Height, Weight, Gender, BMT5, YRS10, HrsXC,HrsSP, HrsTot, RacePlnd
Model 168	Age, Height ,Weight, Gender, BMT5, YRS10, HrsXC,HrsSP, HrsTot, Wave
Model 169	Age, Height, Weight, Gender, BMT5, YRS10, HrsXC, HrsSP, RaceComp, RacePlnd
Model 170	Age, Height, Weight, Gender, BMT5, YRS10, HrsXC, HrsSP, RaceComp, Wave
Model 171	Age, Height, Weight, Gender, BMT5, YRS10, HrsXC,HrsSP, RacePlnd, Wave
Model 172	Age, Height, Weight, Gender, BMT5, YRS10,HrsXC, HrsOther, HrsTot, RaceComp
Model 173	Age, Height, Weight, Gender, BMT5, YRS10,HrsXC, HrsOther, HrsTot, RacePlnd
Model 174	Age, Height, Weight, Gender, BMT5, YRS10,HrsXC, HrsOther, HrsTot, Wave
Model 175	Age, Height, Weight, Gender, BMT5, YRS10, HrsXC, HrsOther, RaceComp, RacePlnd
Model 176	Age, Height, Weight, Gender, BMT5, YRS10,HrsXC, HrsOther, RaceComp, Wave

Table A.3.117. Overview of race time models along with sextuple combinations of the predictor variables

Models	**Predictor Variables**
Model 177	Age, Height, Weight, Gender, BMT5, YRS10, HrsXC, HrsOther, RacePlnd, Wave
Model 178	Age, Height, Weight, Gender, BMT5, YRS10, HrsXC, HrsTot, RaceComp, RacePlnd
Model 179	Age, Height, Weight, Gender, BMT5, YRS10, HrsXC, HrsTot, RaceComp, Wave
Model 180	Age, Height, Weight, Gender, BMT5, YRS10, HrsXC, HrsTot, RacePlnd, Wave
Model 181	Age, Height, Weight, Gender, BMT5, YRS10, HrsXC, RaceComp, RacePlnd, Wave
Model 182	Age, Height, Weight, Gender, BMT5, YRS10, HrsSP, HrsOther, HrsTot, RaceComp
Model 183	Age, Height, Weight, Gender, BMT5, YRS10, HrsSP, HrsOther, HrsTot, RacePlnd
Model 184	Age, Height, Weight, Gender , BMT5, YRS10, HrsSP, HrsOther, HrsTot, Wave
Model 185	Age, Height, Weight, Gender, BMT5, YRS10, HrsSP, HrsOther, RaceComp, RacePlnd
Model 186	Age, Height, Weight, Gender, BMT5, YRS10, HrsSP, HrsOther, RaceComp, Wave
Model 187	Age, Height, Weight, Gender, BMT5, YRS10,HrsSP, HrsOther, RacePlnd, Wave

Table A.3.118. Overview of race time models along with sextuple combinations of the predictor variables

Models	**Predictor Variables**
Model 188	Age, Height, Weight, Gender, BMT5, YRS10,HrsSP, HrsTot, RaceComp, RacePlnd
Model 189	Age, Height, Weight, Gender, BMT5, YRS10,HrsSP, HrsTot, RaceComp, Wave
Model 190	Age, Height, Weight, Gender, BMT5, YRS10, HrsSP,HrsTot, RacePlnd, Wave
Model 191	Age, Height, Weight, Gender, BMT5, YRS10,HrsSP, RaceComp, RacePlnd, Wave
Model 192	Age, Height, Weight, Gender, BMT5, YRS10,HrsOther, HrsTot, RaceComp, RacePlnd
Model 193	Age, Height, Weight, Gender, BMT5, YRS10,HrsOther, HrsTot, RaceComp, Wave
Model 194	Age, Height, Weight, Gender, BMT5, YRS10,HrsOther, HrsTot, RacePlnd, Wave
Model 195	Age, Height, Weight, Gender, BMT5, YRS10, HrsOther, RaceComp, RacePlnd, Wave
Model 196	Age, Height, Weight, Gender, BMT5, YRS10, HrsTot, RaceComp, RacePlnd, Wave
Model 197	Age, Height, Weight, Gender, BMT5, YRSALL, HrsXC, HrsSP, HrsOther, HrsTot
Model 198	Age, Height, Weight, Gender, BMT5, YRSALL, HrsXC, HrsSP, HrsOther, RaceComp

Table A.3.119. Overview of race time models along with sextuple combinations of the predictor variables

Models	**Predictor Variables**
Model 199	Age, Height,Weight, Gender, BMT5, YRSALL, HrsXC, HrsSP, HrsOther, RacePlnd
Model 200	Age, Height,Weight, Gender, BMT5, YRSALL, HrsXC,HrsSP, HrsOther, Wave
Model 201	Age, Height,Weight, Gender, BMT5, YRSALL, HrsXC,HrsSP, HrsTot, RaceComp
Model 202	Age, Height,Weight, Gender, BMT5, YRSALL, HrsXC,HrsSP, HrsTot, RacePlnd
Model 203	Age, Height,Weight, Gender, BMT5, YRSALL, HrsXC,HrsSP, HrsTot, Wave
Model 204	Age, Height,Weight, Gender, BMT5, YRSALL, HrsXC,HrsSP, RaceComp, RacePlnd
Model 205	Age, Height,Weight, Gender, BMT5, YRSALL, HrsXC,HrsSP, RaceComp, Wave
Model 206	Age, Height,Weight, Gender, BMT5, YRSALL, HrsXC,HrsSP, RacePlnd, Wave
Model 207	Age, Height,Weight, Gender, BMT5, YRSALL,HrsXC, HrsOther, HrsTot, RaceComp
Model 208	Age, Height,Weight, Gender, BMT5, YRSALL,HrsXC, HrsOther, HrsTot, RacePlnd
Model 209	Age, Height,Weight, Gender, BMT5, YRSALL,HrsXC, HrsOther, HrsTot, Wave

Table A.3.120. Overview of race time models along with sextuple combinations of the predictor variables

Models	**Predictor Variables**
Model 210	Age, Height, Weight, Gender, BMT5, YRSALL,HrsXC, HrsOther, RaceComp, RacePlnd
Model 211	Age, Height, Weight, Gender, BMT5, YRSALL,HrsXC, HrsOther , RaceComp, Wave
Model 212	Age, Height, Weight, Gender, BMT5, YRSALL,HrsXC, HrsOther, RacePlnd, Wave
Model 213	Age, Height, Weight, Gender, BMT5, YRSALL, HrsXC, HrsTot, RaceComp, RacePlnd
Model 214	Age, Height, Weight, Gender, BMT5, YRSALL, HrsXC, HrsTot, RaceComp, Wave
Model 215	Age, Height, Weight, Gender, BMT5, YRSALL, HrsXC,HrsTot, RacePlnd, Wave
Model 216	Age, Height, Weight, Gender, BMT5, YRSALL,HrsXC, RaceComp, RacePlnd, Wave
Model 217	Age, Height, Weight, Gender, BMT5, YRSALL,HrsSP, HrsOther, HrsTot, RaceComp
Model 218	Age, Height, Weight, Gender, BMT5, YRSALL,HrsSP, HrsOther, HrsTot, RacePlnd
Model 219	Age, Height, Weight, Gender, BMT5, YRSALL,HrsSP, HrsOther, HrsTot, Wave
Model 220	Age, Height, Weight, Gender, BMT5, YRSALL,HrsSP, HrsOther, RaceComp, RacePlnd

Table A.3.121. Overview of race time models along with sextuple combinations of the predictor variables

Models	Predictor Variables
Model 221	Age, Height, Weight, Gender, BMT5, YRSALL,HrsSP, HrsOther, RaceComp, Wave
Model 222	Age, Height, Weight, Gender, BMT5, YRSALL,HrsSP, HrsOther, RacePlnd, Wave
Model 223	Age, Height, Weight, Gender, BMT5, YRSALL,HrsSP, HrsTot, RaceComp, RacePlnd
Model 224	Age, Height, Weight, Gender, BMT5, YRSALL,HrsSP, HrsTot, RaceComp, Wave
Model 225	Age, Height, Weight, Gender, BMT5, YRSALL, HrsSP,HrsTot, RacePlnd, Wave
Model 226	Age, Height, Weight, Gender, BMT5, YRSALL,HrsSP, RaceComp, RacePlnd, Wave
Model 227	Age, Height, Weight, Gender, BMT5, YRSALL,HrsOther, HrsTot, RaceComp, RacePlnd
Model 228	Age, Height, Weight, Gender, BMT5, YRSALL,HrsOther, HrsTot, RaceComp, Wave
Model 229	Age, Height, Weight, Gender, BMT5, YRSALL,HrsOther, HrsTot, RacePlnd, Wave
Model 230	Age, Height, Weight, Gender, BMT5, YRSALL, HrsOther, RaceComp, RacePlnd, Wave
Model 231	Age, Height, Weight, Gender, BMT5, YRSALL, HrsTot, RaceComp, RacePlnd, Wave

Table A.3.122. Overview of race time models along with sextuple combinations of the predictor variables

Models	Predictor Variables
Model 232	Age, Height, Weight, Gender, BMT5, HrsXC,HrsSP, HrsOther, HrsTot, RaceComp
Model 233	Age, Height, Weight, Gender, BMT5, HrsXC,HrsSP, HrsOther, HrsTot, RacePlnd
Model 234	Age, Height, Weight, Gender, BMT5, HrsXC,HrsSP, HrsOther, HrsTot, Wave
Model 235	Age, Height, Weight, Gender, BMT5, HrsXC,HrsSP, HrsOther, RaceComp, RacePlnd
Model 236	Age, Height, Weight, Gender, BMT5, HrsXC,HrsSP, HrsOther, RaceComp, Wave
Model 237	Age, Height, Weight, Gender, BMT5, HrsXC,HrsSP, HrsOther, RacePlnd, Wave
Model 238	Age, Height, Weight, Gender, BMT5, HrsXC,HrsSP, HrsTot, RaceComp, RacePlnd
Model 239	Age, Height, Weight, Gender, BMT5, HrsXC,HrsSP, HrsTot, RaceComp, Wave
Model 240	Age, Height, Weight, Gender, BMT5, HrsXC,HrsSP, HrsTot,RacePlnd, Wave
Model 241	Age, Height, Weight, Gender, BMT5, HrsXC,HrsSP, RaceComp, RacePlnd, Wave
Model 242	Age, Height, Weight, Gender, BMT5,HrsXC, HrsOther, HrsTot, RaceComp, RacePlnd

Table A.3.123. Overview of race time models along with sextuple combinations of the predictor variables

Models	Predictor Variables
Model 243	Age, Height, Weight, Gender, BMT5,HrsXC, HrsOther, HrsTot, RaceComp, Wave
Model 244	Age, Height, Weight, Gender, BMT5,HrsXC, HrsOther, HrsTot, RacePlnd, Wave
Model 245	Age, Height, Weight, Gender, BMT5,HrsXC, HrsOther, RaceComp, RacePlnd, Wave
Model 246	Age, Height, Weight, Gender, BMT5, HrsXC, HrsTot, RaceComp, RacePlnd, Wave
Model 247	Age, Height, Weight, Gender, BMT5,HrsSP, HrsOther, HrsTot, RaceComp, RacePlnd
Model 248	Age, Height, Weight, Gender, BMT5,HrsSP, HrsOther, HrsTot, RaceComp, Wave
Model 249	Age, Height, Weight, Gender, BMT5,HrsSP, HrsOther, HrsTot, RacePlnd, Wave
Model 250	Age, Height, Weight, Gender, BMT5,HrsSP, HrsOther, RaceComp, RacePlnd, Wave
Model 251	Age, Height, Weight, Gender, BMT5,HrsSP, HrsTot, RaceComp, RacePlnd, Wave
Model 252	Age, Height, Weight, Gender, BMT5,HrsOther, HrsTot, RaceComp, RacePlnd, Wave
Model 253	Age, Height, Weight,Gender, BMT10,YRS10, YRSALL, HrsXC, HrsSP, HrsOther

Table A.3.124. Overview of race time models along with sextuple combinations of the predictor variables

Models	**Predictor Variables**
Model 254,	Age, Height, Weight,Gender, BMT10,YRS10, YRSALL, HrsXC,HrsSP, HrsTot
Model 255,	Age, Height, Weight,Gender, BMT10,YRS10, YRSALL, HrsXC, HrsSP, RaceComp
Model 256,	Age, Height, Weight,Gender, BMT10,YRS10, YRSALL, HrsXC, HrsSP, RacePlnd
Model 257,	Age, Height, Weight,Gender, BMT10,YRS10, YRSALL, HrsXC, HrsSP, Wave
Model 258,	Age, Height, Weight,Gender, BMT10,YRS10, YRSALL,HrsXC, HrsOther, HrsTot
Model 259,	Age, Height, Weight,Gender, BMT10,YRS10, YRSALL, HrsXC, HrsOther, RaceComp
Model 260,	Age, Height, Weight,Gender, BMT10,YRS10, YRSALL,HrsXC, HrsOther, RacePlnd
Model 261,	Age, Height, Weight,Gender, BMT10,YRS10, YRSALL,HrsXC, HrsOther, Wave
Model 262,	Age, Height, Weight,Gender, BMT10,YRS10, YRSALL, HrsXC, HrsTot, Height, Weight,Gender, BMT10,YRS10, YRSALL, HrsXC,HrsTot, RacePlnd
Model 264,	Age, Height, Weight,Gender, BMT10,YRS10, YRSALL, HrsXC, HrsTot, Wave

Table A.3.125. Overview of race time models along with sextuple combinations of the predictor variables

Models	**Predictor Variables**
Model 265,	Age, Height, Weight, Gender, BMT10,YRS10, YRSALL, HrsXC, RaceComp, RacePlnd
Model 266,	Age, Height, Weight, Gender, BMT10,YRS10, YRSALL, HrsXC, RaceComp, Wave
Model 267,	Age, Height, Weight, Gender, BMT10,YRS10, YRSALL, HrsXC, RacePlnd, Wave
Model 268,	Age, Height, Weight, Gender, BMT10,YRS10, YRSALL, HrsSP, HrsOther, HrsTot
Model 269,	Age, Height, Weight, Gender, BMT10,YRS10, YRSALL, HrsSP, HrsOther, RaceComp
Model 270,	Age, Height, Weight, Gender, BMT10,YRS10, YRSALL, HrsSP, HrsOther, RacePlnd
Model 271,	Age, Height, Weight, Gender, BMT10,YRS10, YRSALL, HrsSP, HrsOther, Wave
Model 272,	Age, Height, Weight, Gender, BMT10,YRS10, YRSALL, HrsSP, HrsTot, RaceComp
Model 273,	Age, Height, Weight, Gender, BMT10,YRS10, YRSALL, HrsSP, HrsTot, RacePlnd
Model 274,	Age, Height, Weight, Gender, BMT10,YRS10, YRSALL, HrsSP, HrsTot, Wave
Model 275,	Age, Height, Weight, Gender, BMT10,YRS10, YRSALL, HrsSP, RaceComp, RacePlnd

Table A.3.126. Overview of race time models along with sextuple combinations of the predictor variables

Models	Predictor Variables
Model 276,	Age, Height, Weight,Gender, BMT10,YRS10, YRSALL, HrsSP, RaceComp, Wave
Model 277,	Age, Height, Weight,Gender, BMT10,YRS10, YRSALL, HrsSP, RacePlnd, Wave
Model 278,	Age, Height, Weight,Gender, BMT10,YRS10, YRSALL, HrsOther, HrsTot, RaceComp
Model 279,	Age, Height, Weight,Gender, BMT10,YRS10, YRSALL, HrsOther, HrsTot, RacePlnd
Model 280,	Age, Height, Weight,Gender, BMT10,YRS10, YRSALL, HrsOther, HrsTot, Wave
Model 281,	Age, Height, Weight,Gender, BMT10,YRS10, YRSALL, HrsOther, RaceComp, RacePlnd
Model 282,	Age, Height, Weight,Gender, BMT10,YRS10, YRSALL, HrsOther, RaceComp, Wave
Model 283,	Age, Height, Weight,Gender, BMT10,YRS10, YRSALL, HrsOther, RacePlnd, Wave
Model 284,	Age, Height, Weight,Gender, BMT10,YRS10, YRSALL, HrsTot, RaceComp, RacePlnd
Model 285,	Age, Height, Weight,Gender, BMT10,YRS10, YRSALL, HrsTot, RaceComp, Wave
Model 286,	Age, Height, Weight,Gender, BMT10,YRS10, YRSALL, HrsTot, RacePlnd, Wave

Table A.3.127. Overview of race time models along with sextuple combinations of the predictor variables

Models	**Predictor Variables**
Model 287	Age, Height, Weight, Gender, BMT10,YRS10, YRSALL, RaceComp, RacePlnd, Wave
Model 288	Age, Height, Weight, Gender, BMT10, YRS10, HrsXC,HrsSP, HrsOther, HrsTot
Model 289	Age, Height, Weight, Gender, BMT10, YRS10, HrsXC,HrsSP, HrsOther, RaceComp
Model 290	Age, Height, Weight, Gender, BMT10, YRS10, HrsXC,HrsSP, HrsOther, RacePlnd
Model 291	Age, Height, Weight, Gender, BMT10, YRS10, HrsXC,HrsSP, HrsOther, Wave
Model 292	Age, Height, Weight, Gender, BMT10, YRS10, HrsXC,HrsSP, HrsTot, RaceComp
Model 293	Age, Height, Weight, Gender, BMT10, YRS10, HrsXC,HrsSP, HrsTot, RacePlnd
Model 294	Age, Height, Weight, Gender, BMT10, YRS10, HrsXC,HrsSP, HrsTot, Wave
Model 295	Age, Height, Weight, Gender, BMT10, YRS10, HrsXC, HrsSP, RaceComp, RacePlnd
Model 296	Age, Height, Weight, Gender, BMT10, YRS10, HrsXC, HrsSP, RaceComp, Wave
Model 297	Age, Height, Weight, Gender, BMT10, YRS10, HrsXC,HrsSP, RacePlnd, Wave

Table A.3.128. Overview of race time models along with sextuple combinations of the predictor variables

Models	Predictor Variables
Model 298	Age, Height, Weight, Gender, BMT10, YRS10,HrsXC, HrsOther, HrsTot, RaceComp
Model 299	Age, Height, Weight, Gender, BMT10, YRS10,HrsXC, HrsOther, HrsTot, RacePlnd
Model 300	Age, Height, Weight, Gender, BMT10, YRS10,HrsXC, HrsOther, HrsTot, Wave
Model 301	Age, Height, Weight, Gender, BMT10, YRS10,HrsXC, HrsOther, RaceComp, RacePlnd
Model 302	Age, Height, Weight, Gender, BMT10, YRS10,HrsXC, HrsOther, RaceComp, Wave
Model 303	Age, Height, Weight, Gender, BMT10, YRS10,HrsXC, HrsOther, RacePlnd, Wave
Model 304	Age, Height, Weight, Gender, BMT10, YRS10, HrsXC, HrsTot, RaceComp, RacePlnd
Model 305	Age, Height, Weight, Gender, BMT10, YRS10, HrsXC, HrsTot, RaceComp, Wave
Model 306	Age, Height, Weight, Gender, BMT10, YRS10, HrsXC,HrsTot, RacePlnd, Wave
Model 307	Age, Height, Weight, Gender, BMT10, YRS10,HrsXC, RaceComp, RacePlnd, Wave
Model 308	Age, Height, Weight ,Gender, BMT10, YRS10,HrsSP, HrsOther, HrsTot, RaceComp

Table A.3.129. Overview of race time models along with sextuple combinations of the predictor variables

Models	Predictor Variables
Model 309	Age, Height, Weight, Gender, BMT10, YRS10,HrsSP, HrsOther, HrsTot, RacePlnd
Model 310	Age, Height, Weight, Gender, BMT10, YRS10,HrsSP, HrsOther, HrsTot, Wave
Model 311	Age, Height, Weight, Gender, BMT10, YRS10,HrsSP, HrsOther, RaceComp, RacePlnd
Model 312	Age, Height, Weight, Gender, BMT10, YRS10,HrsSP, HrsOther, RaceComp, Wave
Model 313	Age, Height, Weight, Gender, BMT10, YRS10,HrsSP, HrsOther, RacePlnd, Wave
Model 314	Age, Height, Weight, Gender, BMT10, YRS10,HrsSP, HrsTot, RaceComp, RacePlnd
Model 315	Age, Height, Weight, Gender, BMT10, YRS10,HrsSP, HrsTot, RaceComp, Wave
Model 316	Age, Height, Weight, Gender, BMT10, YRS10,HrsSP, HrsTot, RacePlnd, Wave
Model 317	Age, Height, Weight, Gender, BMT10, YRS10,HrsSP, RaceComp, RacePlnd, Wave
Model 318	Age, Height, Weight, Gender, BMT10, YRS10,HrsOther, HrsTot, RaceComp, RacePlnd
Model 319	Age, Height, Weight, Gender, BMT10, YRS10,HrsOther, HrsTot, RaceComp, Wave

Table A.3.130. Overview of race time models along with sextuple combinations of the predictor variables

Models	Predictor Variables
Model 320	Age, Height, Weight, Gender, BMT10, YRS10,HrsOther, HrsTot, RacePlnd, Wave
Model 321	Age, Height, Weight, Gender, BMT10, YRS10, HrsOther, RaceComp, RacePlnd, Wave
Model 322	Age, Height, Weight, Gender, BMT10, YRS10, HrsTot, RaceComp, RacePlnd, Wave
Model 323	Age, Height, Weight, Gender, BMT10, YRSALL, HrsXC, HrsSP, HrsOther, HrsTot
Model 324	Age, Height, Weight, Gender, BMT10, YRSALL, HrsXC, HrsSP, HrsOther, RaceComp
Model 325	Age, Height, Weight, Gender, BMT10, YRSALL, HrsXC, HrsSP, HrsOther, RacePlnd
Model 326	Age, Height, Weight, Gender, BMT10, YRSALL, HrsXC, HrsSP, HrsOther, Wave
Model 327	Age, Height, Weight, Gender, BMT10, YRSALL, HrsXC,HrsSP, HrsTot, RaceComp
Model 328	Age, Height, Weight, Gender, BMT10, YRSALL, HrsXC,HrsSP, HrsTot, RacePlnd
Model 329	Age, Height, Weight, Gender, BMT10, YRSALL, HrsXC,HrsSP, HrsTot, Wave
Model 330	Age, Height, Weight, Gender, BMT10, YRSALL, HrsXC, HrsSP, RaceComp, RacePlnd

Table A.3.131. Overview of race time models along with sextuple combinations of the predictor variables

Models	Predictor Variables
Model 331	Age, Height, Weight, Gender, BMT10, YRSALL, HrsXC, HrsSP, RaceComp, Wave
Model 332	Age, Height, Weight, Gender, BMT10, YRSALL, HrsXC, HrsSP, RacePlnd, Wave
Model 333	Age, Height, Weight, Gender, BMT10, YRSALL,HrsXC, HrsOther, HrsTot, RaceComp
Model 334	Age, Height, Weight, Gender, BMT10, YRSALL,HrsXC, HrsOther, HrsTot, RacePlnd
Model 335	Age, Height, Weight, Gender, BMT10, YRSALL,HrsXC, HrsOther, HrsTot, Wave
Model 336	Age, Height, Weight, Gender, BMT10, YRSALL,HrsXC, HrsOther, RaceComp, RacePlnd
Model 337	Age, Height, Weight, Gender, BMT10, YRSALL,HrsXC, HrsOther, RaceComp, Wave
Model 338	Age, Height, Weight, Gender, BMT10, YRSALL,HrsXC, HrsOther, RacePlnd, Wave
Model 339	Age, Height, Weight, Gender, BMT10, YRSALL, HrsXC, HrsTot, RaceComp, RacePlnd
Model 340	Age, Height, Weight, Gender, BMT10, YRSALL, HrsXC, HrsTot, RaceComp, Wave
Model 341	Age, Height, Weight, Gender, BMT10, YRSALL, HrsXC, HrsTot, RacePlnd, Wave

Table A.3.132. Overview of race time models along with sextuple combinations of the predictor variables

Models	**Predictor Variables**
Model 342,	Age, Height, Weight, Gender, BMT10, YRSALL,HrsXC, RaceComp, RacePlnd, Wave
Model 343,	Age, Height, Weight, Gender, BMT10, YRSALL,HrsSP, HrsOther, HrsTot, RaceComp
Model 344,	Age, Height, Weight, Gender, BMT10, YRSALL,HrsSP, HrsOther, HrsTot, RacePlnd
Model 345,	Age, Height, Weight, Gender, BMT10, YRSALL,HrsSP, HrsOther, HrsTot, Wave
Model 346,	Age, Height, Weight, Gender, BMT10, YRSALL,HrsSP, HrsOther, RaceComp, RacePlnd
Model 347,	Age, Height, Weight, Gender, BMT10, YRSALL,HrsSP, HrsOther, RaceComp, Wave
Model 348,	Age, Height, Weight, Gender, BMT10, YRSALL,HrsSP, HrsOther, RacePlnd, Wave
Model 349,	Age, Height, Weight, Gender, BMT10, YRSALL,HrsSP, HrsTot, RaceComp, RacePlnd
Model 350,	Age, Height, Weight, Gender, BMT10, YRSALL,HrsSP, HrsTot, RaceComp, Wave
Model 351,	Age, Height, Weight, Gender, BMT10, YRSALL,HrsSP, HrsTot, RacePlnd, Wave
Model 352,	Age, Height, Weight, Gender, BMT10, YRSALL,HrsSP, RaceComp, RacePlnd, Wave

Table A.3.133. Overview of race time models along with sextuple combinations of the predictor variables

Models	Predictor Variables
Model 353	Age, Height, Weight, Gender, BMT10, YRSALL,HrsOther, HrsTot, RaceComp, RacePlnd
Model 354	Age, Height, Weight, Gender, BMT10, YRSALL,HrsOther, HrsTot, RaceComp, Wave
Model 355	Age, Height, Weight, Gender, BMT10, YRSALL,HrsOther, HrsTot, RacePlnd, Wave
Model 356	Age, Height, Weight, Gender, BMT10, YRSALL, HrsOther, RaceComp, RacePlnd, Wave
Model 357	Age, Height, Weight, Gender, BMT10, YRSALL, HrsTot, RaceComp, RacePlnd, Wave
Model 358	Age, Height, Weight, Gender, BMT10, HrsXC,HrsSP, HrsOther, HrsTot, RaceComp
Model 359	Age, Height, Weight, Gender, BMT10, HrsXC,HrsSP, HrsOther, HrsTot, RacePlnd
Model 360	Age, Height, Weight, Gender, BMT10, HrsXC,HrsSP, HrsOther, HrsTot, Wave
Model 361	Age, Height, Weight, Gender, BMT10, HrsXC,HrsSP, HrsOther, RaceComp, RacePlnd
Model 362	Age, Height, Weight, Gender, BMT10, HrsXC,HrsSP, HrsOther, RaceComp, Wave
Model 363	Age, Height, Weight, Gender, BMT10, HrsXC,HrsSP, HrsOther, RacePlnd, Wave

Table A.3.134. Overview of race time models along with sextuple combinations of the predictor variables

Models	Predictor Variables
Model 364	Age, Height, Weight, Gender, BMT10, HrsXC,HrsSP, HrsTot, RaceComp, RacePlnd
Model 365	Age, Height, Weight, Gender, BMT10, HrsXC,HrsSP, HrsTot, RaceComp, Wave
Model 366	Age, Height, Weight, Gender, BMT10, HrsXC, HrsSP,HrsTot, RacePlnd, Wave
Model 367	Age, Height, Weight, Gender, BMT10, HrsXC,HrsSP, RaceComp, RacePlnd, Wave
Model 368	Age, Height, Weight, Gender, BMT10, HrsXC, HrsOther, HrsTot, RaceComp, RacePlnd
Model 369	Age, Height, Weight, Gender, BMT10, HrsXC, HrsOther, HrsTot, RaceComp, Wave
Model 370	Age, Height, Weight, Gender, BMT10, HrsXC, HrsOther, HrsTot, RacePlnd, Wave
Model 371	Age, Height, Weight, Gender, BMT10, HrsXC, HrsOther, RaceComp, RacePlnd, Wave
Model 372	Age, Height, Weight, Gender, BMT10, HrsXC, HrsTot, RaceComp, RacePlnd, Wave
Model 373	Age, Height, Weight, Gender, BMT10, HrsSP, HrsOther, HrsTot, RaceComp, RacePlnd
Model 374	Age, Height, Weight, Gender, BMT10, HrsSP, HrsOther, HrsTot, RaceComp, Wave

Table A.3.135. Overview of race time models along with sextuple combinations of the predictor variables

Models	Predictor Variables
Model 375,	Age, Height, Weight, Gender, BMT10,HrsSP, HrsOther, HrsTot, RacePlnd, Wave
Model 376,	Age, Height, Weight, Gender, BMT10,HrsSP, HrsOther, RaceComp, RacePlnd, Wave
Model 377,	Age, Height, Weight, Gender, BMT10, HrsSP, HrsTot, RaceComp, RacePlnd, Wave
Model 378,	Age, Height, Weight, Gender,BMT10, HrsOther, HrsTot, RaceComp, RacePlnd, Wave
Model 379,	Age, Height, Weight, Gender,YRS10, YRSALL, HrsXC, HrsSP, HrsOther, HrsTot
Model 380,	Age, Height, Weight, Gender,YRS10, YRSALL, HrsXC, HrsSP, HrsOther, RaceComp
Model 381,	Age, Height, Weight, Gender,YRS10, YRSALL, HrsXC, HrsSP, HrsOther, RacePlnd
Model 382,	Age, Height, Weight, Gender,YRS10, YRSALL, HrsXC, HrsSP, HrsOther, Wave
Model 383,	Age, Height, Weight, Gender,YRS10, YRSALL, HrsXC,HrsSP, HrsTot, RaceComp
Model 384,	Age, Height, Weight, Gender,YRS10, YRSALL, HrsXC,HrsSP, HrsTot, RacePlnd
Model 385,	Age, Height ,Weight, Gender,YRS10, YRSALL, HrsXC,HrsSP, HrsTot, Wave

Table A.3.136. Overview of race time models along with sextuple combinations of the predictor variables

Models	Predictor Variables
Model 386	Age, Height, Weight, Gender,YRS10, YRSALL, HrsXC, HrsSP, RaceComp, RacePlnd
Model 387	Age, Height, Weight, Gender,YRS10, YRSALL, HrsXC, HrsSP, RaceComp, Wave
Model 388	Age, Height, Weight, Gender,YRS10, YRSALL, HrsXC, HrsSP,RacePlnd, Wave
Model 389	Age, Height, Weight, Gender,YRS10, YRSALL,HrsXC, HrsOther, HrsTot, RaceComp
Model 390	Age, Height, Weight, Gender,YRS10, YRSALL,HrsXC, HrsOther, HrsTot, RacePlnd
Model 391	Age, Height, Weight, Gender,YRS10, YRSALL,HrsXC, HrsOther, HrsTot, Wave
Model 392	Age, Height, Weight, Gender,YRS10, YRSALL,HrsXC, HrsOther, RaceComp, RacePlnd
Model 393	Age, Height, Weight, Gender,YRS10, YRSALL,HrsXC, HrsOther, RaceComp, Wave
Model 394	Age, Height, Weight, Gender,YRS10, YRSALL,HrsXC, HrsOther,RacePlnd, Wave
Model 395	Age, Height, Weight, Gender,YRS10, YRSALL, HrsXC, HrsTot, RaceComp, RacePlnd
Model 396	Age, Height, Weight, Gender,YRS10, YRSALL, HrsXC, HrsTot,RaceComp, Wave

Table A.3.137. Overview of race time models along with sextuple combinations of the predictor variables

Models	**Predictor Variables**
Model 397	Age ,Height, Weight, Gender,YRS10, YRSALL, HrsXC, HrsTot, RacePlnd, Wave
Model 398	Age, Height, Weight, Gender,YRS10, YRSALL,HrsXC, RaceComp, RacePlnd, Wave
Model 399	Age, Height, Weight, Gender,YRS10, YRSALL,HrsSP, HrsOther, HrsTot, RaceComp
Model 400	Age, Height, Weight, Gender,YRS10, YRSALL,HrsSP, HrsOther, HrsTot, RacePlnd
Model 401	Age, Height, Weight, Gender,YRS10, YRSALL,HrsSP, HrsOther, HrsTot, Wave
Model 402	Age, Height, Weight, Gender,YRS10, YRSALL,HrsSP, HrsOther, RaceComp, RacePlnd
Model 403	Age, Height, Weight, Gender,YRS10, YRSALL,HrsSP, HrsOther, RaceComp, Wave
Model 404	Age, Height, Weight, Gender,YRS10, YRSALL,HrsSP, HrsOther, RacePlnd, Wave
Model 405	Age, Height, Weight, Gender,YRS10, YRSALL,HrsSP, HrsTot, RaceComp, RacePlnd
Model 406	Age, Height, Weight, Gender,YRS10, YRSALL,HrsSP, HrsTot, RaceComp, Wave
Model 407	Age, Height, Weight, Gender,YRS10, YRSALL,HrsSP, HrsTot, RacePlnd, Wave

Table A.3.138. Overview of race time models along with sextuple combinations of the predictor variables

Models	Predictor Variables
Model 408	Age, Height, Weight, Gender,YRS10, YRSALL,HrsSP, RaceComp, RacePlnd, Wave
Model 409	Age, Height, Weight, Gender,YRS10, YRSALL,HrsOther, HrsTot, RaceComp, RacePlnd
Model 410	Age, Height, Weight, Gender,YRS10, YRSALL,HrsOther, HrsTot, RaceComp, Wave
Model 411	Age, Height, Weight, Gender,YRS10, YRSALL,HrsOther, HrsTot, RacePlnd, Wave
Model 412	Age, Height, Weight, Gender,YRS10, YRSALL, HrsOther, RaceComp, RacePlnd, Wave
Model 413	Age, Height, Weight, Gender,YRS10, YRSALL, HrsTot, RaceComp, RacePlnd, Wave
Model 414	Age, Height, Weight, Gender, YRS10, HrsXC,HrsSP, HrsOther, HrsTot, RaceComp
Model 415	Age, Height, Weight, Gender, YRS10, HrsXC,HrsSP, HrsOther, HrsTot, RacePlnd
Model 416	Age, Height, Weight, Gender, YRS10, HrsXC,HrsSP, HrsOther, HrsTot, Wave
Model 417	Age, Height, Weight, Gender, YRS10, HrsXC,HrsSP, HrsOther, RaceComp, RacePlnd
Model 418	Age, Height, Weight, Gender, YRS10, HrsXC,HrsSP, HrsOther, RaceComp, Wave

Table A.3.139. Overview of race time models along with sextuple combinations of the predictor variables

Models	**Predictor Variables**
Model 419	Age, Height, Weight, Gender, YRS10, HrsXC,HrsSP, HrsOther, RacePlnd, Wave
Model 420	Age, Height, Weight, Gender, YRS10, HrsXC,HrsSP, HrsTot, RaceComp, RacePlnd
Model 421	Age, Height, Weight, Gender, YRS10, HrsXC,HrsSP, HrsTot, RaceComp, Wave
Model 422	Age, Height, Weight, Gender, YRS10, HrsXC, HrsSP,HrsTot, RacePlnd, Wave
Model 423	Age, Height, Weight, Gender, YRS10, HrsXC,HrsSP, RaceComp, RacePlnd, Wave
Model 424	Age, Height, Weight, Gender, YRS10,HrsXC, HrsOther, HrsTot, RaceComp, RacePlnd
Model 425	Age, Height, Weight, Gender, YRS10,HrsXC, HrsOther, HrsTot, RaceComp, Wave
Model 426	Age, Height, Weight, Gender, YRS10,HrsXC, HrsOther, HrsTot, RacePlnd, Wave
Model 427	Age, Height, Weight, Gender, YRS10,HrsXC, HrsOther, RaceComp, RacePlnd, Wave
Model 428	Age, Height, Weight, Gender, YRS10, HrsXC, HrsTot, RaceComp, RacePlnd, Wave
Model 429	Age, Height, Weight, Gender, YRS10,HrsSP, HrsOther, HrsTot, RaceComp, RacePlnd

Table A.3.140. Overview of race time models along with sextuple combinations of the predictor variables

Models	Predictor Variables
Model 430	Age, Height, Weight, Gender, YRS10,HrsSP, HrsOther, HrsTot,RaceComp, Wave
Model 431	Age, Height, Weight, Gender, YRS10,HrsSP, HrsOther, HrsTot,RacePlnd, Wave
Model 432	Age, Height, Weight, Gender, YRS10,HrsSP, HrsOther, RaceComp,RacePlnd, Wave
Model 433	Age, Height, Weight, Gender, YRS10,HrsSP, HrsTot, RaceComp,RacePlnd, Wave
Model 434	Age, Height, Weight, Gender, YRS10,HrsOther, HrsTot, RaceComp,RacePlnd, Wave
Model 435	Age, Height, Weight, Gender, YRSALL, HrsXC,HrsSP, HrsOther, HrsTot, RaceComp
Model 436	Age, Height, Weight, Gender, YRSALL, HrsXC,HrsSP, HrsOther, HrsTot, RacePlnd
Model 437	Age, Height, Weight, Gender, YRSALL, HrsXC,HrsSP, HrsOther, HrsTot, Wave
Model 438	Age, Height, Weight, Gender, YRSALL, HrsXC,HrsSP, HrsOther, RaceComp, RacePlnd
Model 439	Age, Height, Weight, Gender, YRSALL, HrsXC,HrsSP, HrsOther,RaceComp, Wave
Model 440	Age, Height, Weight, Gender, YRSALL, HrsXC,HrsSP, HrsOther,RacePlnd, Wave

Table A.3.141. Overview of race time models along with sextuple combinations of the predictor variables

Models	**Predictor Variables**
Model 441	Age, Height, Weight, Gender, YRSALL, HrsXC,HrsSP, HrsTot, RaceComp, RacePlnd
Model 442	Age, Height, Weight, Gender, YRSALL, HrsXC,HrsSP, HrsTot, RaceComp, Wave
Model 443	Age, Height, Weight, Gender, YRSALL, HrsXC,HrsSP, HrsTot, RacePlnd, Wave
Model 444	Age, Height, Weight, Gender, YRSALL, HrsXC,HrsSP, RaceComp, RacePlnd, Wave
Model 445	Age, Height, Weight, Gender, YRSALL,HrsXC, HrsOther, HrsTot, RaceComp, RacePlnd
Model 446	Age, Height, Weight, Gender, YRSALL,HrsXC, HrsOther, HrsTot, RaceComp, Wave
Model 447	Age, Height, Weight, Gender, YRSALL,HrsXC, HrsOther, HrsTot, RacePlnd, Wave
Model 448	Age, Height, Weight, Gender, YRSALL,HrsXC, HrsOther, RaceComp, RacePlnd, Wave
Model 449	Age, Height, Weight, Gender, YRSALL,HrsXC, HrsOther, RaceComp, RacePlnd, Wave
Model 450	Age, Height, Weight, Gender, YRSALL,HrsSP, HrsOther, HrsTot, RaceComp, RacePlnd
Model 451	Age, Height, Weight, Gender, YRSALL,HrsSP, HrsOther, HrsTot, RaceComp, Wave

Table A.3.142. Overview of race time models along with sextuple combinations of the predictor variables

Models	**Predictor Variables**
Model 452	Age, Height, Weight, Gender, YRSALL,HrsSP, HrsOther, HrsTot, RacePlnd, Wave
Model 453	Age, Height, Weight, Gender, YRSALL,HrsSP, HrsOther, RaceComp, RacePlnd, Wave
Model 454	Age, Height, Weight, Gender, YRSALL,HrsSP, HrsTot, RaceComp, RacePlnd, Wave
Model 455	Age, Height, Weight, Gender, YRSALL,HrsOther, HrsTot, RaceComp, RacePlnd, Wave
Model 456	Age, Height, Weight, Gender, HrsXC,HrsSP, HrsOther, HrsTot, RaceComp, RacePlnd
Model 457	Age, Height, Weight, Gender, HrsXC,HrsSP, HrsOther, HrsTot, RaceComp, Wave
Model 458	Age, Height, Weight, Gender, HrsXC,HrsSP, HrsOther, HrsTot, RacePlnd, Wave
Model 459	Age, Height, Weight, Gender, HrsXC,HrsSP, HrsOther, RaceComp, RacePlnd, Wave
Model 460	Age, Height, Weight, Gender, HrsXC,HrsSP, HrsTot, RaceComp, RacePlnd, Wave
Model 461	Age, Height, Weight, Gender, HrsXC, HrsOther, HrsTot, RaceComp, RacePlnd, Wave
Model 462	Age, Height, Weight, Gender, HrsSP, HrsOther, HrsTot, RaceComp, RacePlnd, Wave

A.7. Prediction Models Created Using Septuple Combinations

By using double combinations of the predictor variables, a total of 330 prediction models have been formed, respectively

Table A.3.143. Overview of race time models along with septuple combinations of the predictor variables

Models	**Predictor Variables**
Model 1	Age, Height, Weight, Gender, BMT5, BMT10, YRS10, YRSALL, HrsXC, HrsSP, HrsOther
Model 2	Age, Height, Weight, Gender, BMT5, BMT10, YRS10, YRSALL, HrsXC, HrsSP, HrsTot
Model 3	Age, Height, Weight, Gender, BMT5, BMT10 ,YRS10, YRSALL, HrsXC, HrsSP, RaceComp
Model 4	Age, Height, Weight, Gender, BMT5, BMT10, YRS10, YRSALL, HrsXC, HrsSP, RacePlnd
Model 5	Age, Height, Weight, Gender, BMT5, BMT10, YRS10, YRSALL, HrsXC, HrsSP, Wave
Model 6	Age, Height, Weight, Gender, BMT5, BMT10, YRS10, YRSALL, HrsXC, HrsOther, sTot
Model 7	Age, Height, Weight, Gender , BMT5, BMT10,YRS10, YRSALL, HrsXC, HrsOther, RaceComp
Model 8	Age, Height, Weight, Gender, BMT5, BMT10,YRS10, YRSALL, HrsXC, HrsOther, RacePlnd
Model 9	Age, Height, Weight, Gender, BMT5, BMT10,YRS10, YRSALL, HrsXC, HrsOther, Wave
Model 10	Age, Height, Weight, Gender, BMT5, BMT10,YRS10, YRSALL, HrsXC, HrsTot, RaceComp
Model 11	Age, Height, Weight, Gender, BMT5, BMT10,YRS10, YRSALL, HrsXC, HrsTot, RacePlnd

Table A.3.144. Overview of race time models along with septuple combinations of the predictor variables

Models	Predictor Variables
Model 12	Age, Height ,Weight, Gender, BMT5, BMT10,YRS10, YRSALL, HrsXC, HrsTot, Wave
Model 13	Age, Height, Weight, Gender, BMT5, BMT10, YRS10, YRSALL, HrsXC, RaceComp, RacePlnd
Model 14	Age, Height, Weight, Gender, BMT5, BMT10,YRS10, YRSALL, HrsXC, RaceComp, Wave
Model 15	Age, Height, Weight, Gender, BMT5, BMT10,YRS10, YRSALL, HrsXC, RacePlnd, Wave
Model 16	Age, Height, Weight, Gender, BMT5, BMT10,YRS10, YRSALL, HrsSP, HrsOther, HrsTot
Model 17	Age, Height, Weight, Gender, BMT5, BMT10,YRS10, YRSALL, HrsSP, HrsOther, RaceComp
Model 18	Age, Height , Weight, Gender, BMT5, BMT10,YRS10, YRSALL, HrsSP, HrsOther, RacePlnd
Model 19	Age, Height, Weight, Gender, BMT5, BMT10, YRS10, YRSALL, HrsSP, HrsOther, Wave
Model 20	Age, Height, Weight, Gender, BMT5, BMT10,YRS10, YRSALL, HrsSP, HrsTot, RaceComp
Model 21	Age, Height, Weight, Gender, BMT5, BMT10,YRS10, YRSALL, HrsSP, HrsTot, RacePlnd
Model 22	Age, Height, Weight, Gender, BMT5, BMT10,YRS10, YRSALL, HrsSP, HrsTot, Wave

Table A.3.145. Overview of race time models along with septuple combinations of the predictor variables

Models	Predictor Variables
Model 23	Age, Height,Weight, Gender, BMT5, BMT10,YRS10, YRSALL, HrsSP, RaceComp, RacePlnd
Model 24	Age, Height,Weight, Gender, BMT5, BMT10,YRS10, YRSALL, HrsSP, RaceComp, Wave
Model 25	Age, Height,Weight, Gender, BMT5, BMT10,YRS10, YRSALL, HrsSP, RacePlnd, Wave
Model 26	Age, Height,Weight, Gender, BMT5, BMT10,YRS10, YRSALL, HrsOther, HrsTot, RaceComp
Model 27	Age, Height,Weight, Gender, BMT5, BMT10,YRS10, YRSALL,HrsOther, HrsTot, RacePlnd
Model 28	Age, Height,Weight, Gender, BMT5, BMT10,YRS10, YRSALL,HrsOther, HrsTot, Wave
Model 29	Age, Height,Weight, Gender, BMT5, BMT10,YRS10, YRSALL, HrsOther, RaceComp, RacePlnd
Model 30	Age, Height,Weight, Gender, BMT5, BMT10,YRS10, YRSALL, HrsOther, RaceComp, Wave
Model 31	Age, Height,Weight, Gender, BMT5, BMT10, YRS10, YRSALL, HrsOther, RacePlnd, Wave
Model 32	Age, Height,Weight, Gender, BMT5, BMT10,YRS10, YRSALL, HrsTot, RaceComp, RacePlnd
Model 33	Age, Height,Weight, Gender, BMT5, BMT10,YRS10, YRSALL, HrsTot, RaceComp, Wave

Table A.3.146. Overview of race time models along with septuple combinations of the predictor variables

Models	**Predictor Variables**
Model 34	Age, Height, Weight, Gender, BMT5, BMT10, YRS10, YRSALL, HrsTot, RacePlnd, Wave
Model 35	Age, Height, Weight, Gender, BMT5, BMT10, YRS10, YRSALL, RaceComp, RacePlnd, Wave
Model 36	Age, Height,Weight, Gender, BMT5, BMT10, YRS10, HrsXC, HrsSP, HrsOther, HrsTot
Model 37	Age, Height,Weight, Gender, BMT5, BMT10, YRS10, HrsXC, HrsSP, HrsOther, RaceComp
Model 38	Age, Height,Weight, Gender, BMT5, BMT10, YRS10, HrsXC, HrsSP, HrsOther, RacePlnd
Model 39	Age, Height,Weight, Gender, BMT5, BMT10, YRS10, HrsXC, HrsSP, HrsOther, Wave
Model 40	Age, Height,Weight, Gender, BMT5, BMT10, YRS10, HrsXC, HrsSP, HrsTot, RaceComp
Model 41	Age, Height,Weight, Gender, BMT5, BMT10, YRS10, HrsXC, HrsSP,HrsTot, RacePlnd
Model 42	Age, Height,Weight, Gender, BMT5, BMT10, YRS10, HrsXC, HrsSP, HrsTot, Wave
Model 43	Age, Height,Weight, Gender, BMT5, BMT10, YRS10, HrsXC, HrsSP, RaceComp, RacePlnd
Model 44	Age, Height,Weight, Gender, BMT5, BMT10, YRS10, HrsXC, HrsSP, RaceComp, Wave

Table A.3.147. Overview of race time models along with septuple combinations of the predictor variables

Models	Predictor Variables
Model 45	Age, Height,Weight, Gender, BMT5, BMT10, YRS10, HrsXC, HrsSP, RacePlnd, Wave
Model 46	Age, Height,Weight, Gender, BMT5, BMT10, YRS10,HrsXC, HrsOther, HrsTot, RaceComp
Model 47	Age, Height,Weight, Gender, BMT5, BMT10, YRS10,HrsXC, HrsOther, HrsTot, RacePlnd
Model 48	Age, Height,Weight, Gender, BMT5, BMT10, YRS10,HrsXC, HrsOther, HrsTot, Wave
Model 49	Age, Height,Weight, Gender, BMT5, BMT10, YRS10,HrsXC, HrsOther, RaceComp, RacePlnd
Model 50	Age, Height,Weight, Gender, BMT5, BMT10, YRS10,HrsXC, HrsOther, RaceComp, Wave
Model 51	Age, Height, Weight, Gender, BMT5, BMT10, YRS10,HrsXC, HrsOther, RacePlnd, Wave
Model 52	Age, Height, Weight, Gender, BMT5, BMT10, YRS10, HrsXC, HrsTot, RaceComp, RacePlnd
Model 53	Age, Height, Weight, Gender, BMT5, BMT10, YRS10, HrsXC, HrsTot, RaceComp, Wave
Model 54	Age, Height, Weight, Gender, BMT5, BMT10, YRS10, HrsXC, HrsTot, RacePlnd, Wave
Model 55	Age, Height, Weight, Gender, BMT5, BMT10, YRS10,HrsXC, RaceComp, RacePlnd, Wave

Table A.3.148. Overview of race time models along with septuple combinations of the predictor variables

Models	Predictor Variables
Model 56	Age, Height, Weight, Gender, BMT5, BMT10, YRS10, HrsSP, HrsOther, HrsTot, RaceComp
Model 57	Age, Height, Weight, Gender, BMT5, BMT10, YRS10, HrsSP, HrsOther, HrsTot, RacePlnd
Model 58	Age, Height, Weight, Gender, BMT5, BMT10, YRS10, HrsSP, HrsOther, HrsTot, Wave
Model 59	Age, Height, Weight, Gender, BMT5, BMT10, YRS10, HrsSP, HrsOther, RaceComp, RacePlnd
Model 60	Age, Height, Weight, Gender, BMT5, BMT10, YRS10, HrsSP, HrsOther, RaceComp, Wave
Model 61	Age, Height, Weight, Gender, BMT5, BMT10, YRS10, HrsSP, HrsOther, RacePlnd, Wave
Model 62	Age, Height, Weight, Gender, BMT5, BMT10, YRS10, HrsSP, HrsTot, RaceComp, RacePlnd
Model 63	Age, Height, Weight, Gender, BMT5, BMT10, YRS10, HrsSP, HrsTot, RaceComp, Wave
Model 64	Age, Height, Weight, Gender, BMT5, BMT10, YRS10, HrsSP, HrsTot, RacePlnd, Wave
Model 65	Age, Height, Weight, Gender, BMT5, BMT10, YRS10, HrsSP, RaceComp, RacePlnd, Wave
Model 66	Age, Height, Weight, Gender, BMT5, BMT10, YRS10, HrsOther, HrsTot, RaceComp, RacePlnd

Table A.3.149. Overview of race time models along with septuple combinations of the predictor variables

Models	Predictor Variables
Model 67	Age, Height,Weight, Gender, BMT5, BMT10, YRS10,HrsOther, HrsTot,RaceComp, Wave
Model 68	Age, Height,Weight, Gender, BMT5, BMT10, YRS10,HrsOther, HrsTot, RacePlnd, Wave
Model 69	Age, Height,Weight, Gender, BMT5, BMT10, YRS10, HrsOther, RaceComp, RacePlnd, Wave
Model 70	Age, Height,Weight, Gender, BMT5, BMT10, YRS10, HrsTot, RaceComp, RacePlnd, Wave
Model 71	Age, Height,Weight, Gender, BMT5, BMT10, YRSALL, HrsXC, HrsSP, HrsOther, HrsTot
Model 72	Age, Height,Weight, Gender, BMT5, BMT10, YRSALL, HrsXC, HrsSP, HrsOther, RaceComp
Model 73	Age, Height,Weight, Gender, BMT5, BMT10, YRSALL, HrsXC, HrsSP, HrsOther, RacePlnd
Model 74	Age, Height,Weight, Gender, BMT5, BMT10, YRSALL, HrsXC, HrsSP, HrsOther, Wave
Model 75	Age, Height,Weight, Gender, BMT5, BMT10, YRSALL, HrsXC, HrsSP, HrsTot, RaceComp
Model 76	Age, Height,Weight, Gender, BMT5, BMT10, YRSALL, HrsXC, HrsSP, HrsTot, RacePlnd
Model 77	Age, Height,Weight, Gender, BMT5, BMT10, YRSALL, HrsXC, HrsSP, HrsTot, Wave

Table A.3.150. Overview of race time models along with septuple combinations of the predictor variables

Models	Predictor Variables
Model 78	Age, Height,Weight, Gender, BMT5, BMT10, YRSALL, HrsXC, HrsSP, RaceComp, RacePlnd
Model 79	Age, Height,Weight, Gender, BMT5, BMT10, YRSALL, HrsXC, HrsSP, RaceComp, Wave
Model 80	Age, Height,Weight, Gender, BMT5, BMT10, YRSALL, HrsXC, HrsSP, RacePlnd, Wave
Model 81	Age, Height,Weight, Gender, BMT5, BMT10, YRSALL,HrsXC, HrsOther, HrsTot, RaceComp
Model 82	Age, Height,Weight, Gender, BMT5, BMT10, YRSALL,HrsXC, HrsOther, HrsTot, RacePlnd
Model 83	Age, Height,Weight, Gender, BMT5, BMT10, YRSALL,HrsXC, HrsOther, HrsTot, Wave
Model 84	Age, Height,Weight, Gender, BMT5, BMT10, YRSALL,HrsXC, HrsOther, RaceComp, RacePlnd
Model 85	Age, Height,Weight, Gender, BMT5, BMT10, YRSALL,HrsXC, HrsOther, RaceComp, Wave
Model 86	Age, Height,Weight, Gender, BMT5, BMT10, YRSALL,HrsXC, HrsOther, RacePlnd, Wave
Model 87	Age, Height,Weight, Gender, BMT5, BMT10, YRSALL, HrsXC, HrsTot, RaceComp, RacePlnd
Model 88	Age, Height,Weight, Gender, BMT5, BMT10, YRSALL, HrsXC, HrsTot, RaceComp, Wave

Table A.3.151. Overview of race time models along with septuple combinations of the predictor variables

Models	**Predictor Variables**
Model 89	Age, Height,Weight, Gender, BMT5, BMT10, YRSALL, HrsXC, HrsTot, RacePlnd, Wave
Model 90	Age, Height,Weight, Gender, BMT5, BMT10, YRSALL, HrsXC, RaceComp, RacePlnd, Wave
Model 91	Age, Height,Weight, Gender, BMT5, BMT10, YRSALL,HrsSP, HrsOther, HrsTot, RaceComp
Model 92	Age, Height,Weight, Gender, BMT5, BMT10, YRSALL,HrsSP, HrsOther HrsTot, RacePlnd
Model 93	Age, Height,Weight, Gender, BMT5, BMT10, YRSALL,HrsSP, HrsOther, HrsTot, Wave
Model 94	Age, Height,Weight, Gender, BMT5, BMT10, YRSALL,HrsSP, HrsOther, RaceComp, RacePlnd
Model 95	Age, Height,Weight, Gender, BMT5, BMT10, YRSALL,HrsSP, HrsOther, RaceComp, Wave
Model 96	Age, Height,Weight, Gender, BMT5, BMT10, YRSALL,HrsSP, HrsOther, RacePlnd, Wave
Model 97	Age, Height,Weight, Gender, BMT5, BMT10, YRSALL,HrsSP, HrsTot, RaceComp, RacePlnd
Model 98	Age, Height,Weight, Gender, BMT5, BMT10, YRSALL,HrsSP, HrsTot, RaceComp, Wave
Model 99	Age, Height,Weight, Gender, BMT5, BMT10, YRSALL,HrsSP, HrsTot, RacePlnd, Wave

Table A.3.152. Overview of race time models along with septuple combinations of the predictor variables

Models	Predictor Variables
Model 100	Age, Height,Weight, Gender, BMT5, BMT10, YRSALL,HrsSP, RaceComp, RacePlnd, Wave
Model 101	Age, Height,Weight, Gender, BMT5, BMT10, YRSALL,HrsOther, HrsTot, RaceComp, RacePlnd
Model 102	Age, Height,Weight, Gender, BMT5, BMT10, YRSALL,HrsOther, HrsTot, RaceComp, Wave
Model 103,	Age, Height,Weight, Gender, BMT5, BMT10, YRSALL,HrsOther, HrsTot, RacePlnd, Wave
Model 104,	Age, Height,Weight, Gender, BMT5, BMT10, YRSALL, HrsOther, RaceComp, RacePlnd, Wave
Model 105	Age, Height,Weight, Gender, BMT5, BMT10, YRSALL, HrsTot, RaceComp, RacePlnd, Wave
Model 106	Age, Height,Weight, Gender, BMT5, BMT10, HrsXC,HrsSP, HrsOther, HrsTot, RaceComp
Model 107	Age, Height,Weight, Gender, BMT5, BMT10, HrsXC,HrsSP, HrsOther, HrsTot, RacePlnd
Model 108	Age, Height,Weight, Gender, BMT5, BMT10, HrsXC,HrsSP, HrsOther, HrsTot, Wave
Model 109	Age, Height,Weight, Gender, BMT5, BMT10, HrsXC,HrsSP, HrsOther, RaceComp, RacePlnd
Model 110	Age, Height,Weight, Gender, BMT5, BMT10, HrsXC,HrsSP, HrsOther, RaceComp, Wave

Table A.3.153. Overview of race time models along with septuple combinations of the predictor variables

Models	**Predictor Variables**
Model 111	Age, Height,Weight, Gender, BMT5, BMT10, HrsXC,HrsSP, HrsOther, RacePlnd, Wave
Model 112	Age, Height,Weight, Gender, BMT5, BMT10, HrsXC,HrsSP, HrsTot, RaceComp, RacePlnd
Model 113	Age, Height,Weight, Gender, BMT5, BMT10, HrsXC, HrsSP, HrsTot, RaceComp, Wave
Model 114	Age, Height,Weight, Gender, BMT5, BMT10, HrsXC, HrsSP,HrsTot, RacePlnd, Wave
Model 115	Age, Height,Weight, Gender, BMT5, BMT10, HrsXC, HrsSP, RaceComp, RacePlnd, Wave
Model 116	Age, Height,Weight, Gender, BMT5, BMT10, HrsXC, HrsOther, HrsTot, RaceComp, RacePlnd
Model 117	Age, Height,Weight, Gender, BMT5, BMT10,HrsXC, HrsOther, HrsTot, RaceComp, Wave
Model 118	Age, Height,Weight, Gender, BMT5, BMT10,HrsXC, HrsOther, HrsTot, RacePlnd, Wave
Model 119	Age, Height,Weight, Gender, BMT5, BMT10,HrsXC, HrsOther, RaceComp, RacePlnd, Wave
Model 120	Age, Height,Weight, Gender, BMT5, BMT10, HrsXC, HrsTot, RaceComp, RacePlnd, Wave
Model 121	Age, Height,Weight, Gender, BMT5, BMT10,HrsSP, HrsOther, HrsTot, RaceComp, RacePlnd

Table A.3.154. Overview of race time models along with septuple combinations of the predictor variables

Models	**Predictor Variables**
Model 122	Age, Height, Weight, Gender, BMT5, BMT10, HrsSP, HrsOther, HrsTot, RaceComp, Wave
Model 123	Age, Height, Weight, Gender, BMT5, BMT10, HrsSP, HrsOther , HrsTot, RacePlnd, Wave
Model 124	Age, Height, Weight, Gender, BMT5, BMT10, HrsSP, HrsOther, RaceComp, RacePlnd Wave
Model 125	Age, Height, Weight, Gender, BMT5, BMT10, HrsSP, HrsTot, RaceComp, RacePlnd, Wave
Model 126	Age, Height, Weight, Gender, BMT5, BMT10, HrsOther, HrsTot, RaceComp, RacePlnd, Wave
Model 127	Age, Height, Weight, Gender, BMT5, YRS10, YRSALL, HrsXC, HrsSP, HrsOther, HrsTot
Model 128	Age, Height, Weight, Gender, BMT5,YRS10, YRSALL, HrsXC, HrsSP, HrsOther, RaceComp
Model 129	Age, Height, Weight, Gender, BMT5,YRS10, YRSALL, HrsXC, HrsSP, HrsOther, RacePlnd
Model 130	Age, Height,Weight, Gender, BMT5,YRS10, YRSALL, HrsXC, HrsSP, HrsOther, Wave
Model 131	Age, Height,Weight, Gender, BMT5,YRS10, YRSALL, HrsXC,HrsSP, HrsTot, RaceComp
Model 132	Age, Height,Weight, Gender, BMT5,YRS10, YRSALL, HrsXC,HrsSP, HrsTot, RacePlnd

Table A.3.155. Overview of race time models along with septuple combinations of the predictor variables

Models	**Predictor Variables**
Model 133	Age, Height,Weight, Gender, BMT5,YRS10, YRSALL, HrsXC, HrsSP, HrsTot, Wave
Model 134	Age, Height,Weight, Gender, BMT5,YRS10, YRSALL, HrsXC,HrsSP, RaceComp, RacePlnd
Model 135	Age, Height,Weight, Gender, BMT5,YRS10, YRSALL, HrsXC,HrsSP, RaceComp, Wave
Model 136	Age, Height,Weight, Gender, BMT5,YRS10, YRSALL, HrsXC,HrsSP, RacePlnd, Wave
Model 137	Age, Height,Weight, Gender, BMT5,YRS10, YRSALL,HrsXC, HrsOther, HrsTot, RaceComp
Model 138	Age, Height,Weight, Gender, BMT5,YRS10, YRSALL,HrsXC, HrsOther, HrsTot, RacePlnd
Model 139	Age, Height,Weight, Gender, BMT5,YRS10, YRSALL,HrsXC, HrsOther, HrsTot, Wave
Model 140	Age , Height,Weight, Gender, BMT5,YRS10, YRSALL,HrsXC, HrsOther, RaceComp, RacePlnd
Model 141	Age, Height,Weight, Gender, BMT5,YRS10, YRSALL,HrsXC, HrsOther, RaceComp, Wave
Model 142,	Age, Height,Weight, Gender, BMT5, YRS10, YRSALL, HrsXC, HrsOther, RacePlnd, Wave
Model 143	Age, Height,Weight, Gender, BMT5,YRS10, YRSALL, HrsXC, HrsTot, RaceComp, RacePlnd

Table A.3.156. Overview of race time models along with septuple combinations of the predictor variables

Models	**Predictor Variables**
Model 144	Age, Height, Weight , Gender, BMT5, YRS10, YRSALL, HrsXC, HrsTot , RaceComp, Wave
Model 145	Age, Height, Weight, Gender, BMT5, YRS10, YRSALL, HrsXC, HrsTot, RacePlnd, Wave
Model 146	Age, Height, Weight, Gender, BMT5, YRS10, YRSALL, HrsXC, RaceComp, RacePlnd, Wave
Model 147	Age, Height, Weight, Gender, BMT5,YRS10, YRSALL, HrsSP, HrsOther, HrsTot, RaceComp
Model 148	Age, Height, Weight, Gender, BMT5,YRS10, YRSALL, HrsSP, HrsOther, HrsTot, RacePlnd
Model 149	Age, Height,Weight, Gender, BMT5,YRS10, YRSALL, HrsSP, HrsOther, HrsTot, Wave
Model 150	Age, Height,Weight, Gender, BMT5,YRS10, YRSALL, HrsSP, HrsOther, RaceComp, RacePlnd
Model 151	Age, Height, Weight, Gender, BMT5, YRS10, YRSALL, HrsSP, HrsOther, RaceComp, Wave
Model 152	Age, Height,Weight, Gender, BMT5,YRS10, YRSALL, HrsSP, HrsOther, RacePlnd, Wave
Model 153	Age, Height,Weight, Gender, BMT5,YRS10, YRSALL,HrsSP, HrsTot, RaceComp, RacePlnd
Model 154	Age, Height,Weight, Gender, BMT5,YRS10, YRSALL,HrsSP, HrsTot, RaceComp, Wave

Table A.3.157. Overview of race time models along with septuple combinations of the predictor variables

Models	Predictor Variables
Model 155	Age, Height, Weight, Gender, BMT5,YRS10, YRSALL, HrsSP,HrsTot, RacePlnd, Wave
Model 156	Age, Height, Weight, Gender, BMT5,YRS10, YRSALL,HrsSP, RaceComp, RacePlnd, Wave
Model 157	Age, Height, Weight, Gender, BMT5,YRS10, YRSALL,HrsOther, HrsTot, RaceComp, RacePlnd
Model 158	Age, Height, Weight, Gender, BMT5,YRS10, YRSALL,HrsOther, HrsTot, RaceComp, Wave
Model 159	Age, Height, Weight, Gender, BMT5,YRS10, YRSALL,HrsOther, HrsTot, RacePlnd, Wave
Model 160,	Age, Height, Weight, Gender, BMT5,YRS10, YRSALL, HrsOther, RaceComp, RacePlnd, Wave
Model 161	Age, Height, Weight, Gender, BMT5,YRS10, YRSALL, HrsTot, RaceComp, RacePlnd, Wave
Model 162	Age, Height,Weight, Gender, BMT5, YRS10, HrsXC,HrsSP, HrsOther, HrsTot, RaceComp
Model 163	Age, Height,Weight, Gender, BMT5, YRS10, HrsXC,HrsSP, HrsOther, HrsTot, RacePlnd
Model 164	Age, Height,Weight, Gender, BMT5, YRS10, HrsXC,HrsSP, HrsOther, HrsTot, Wave
Model 165	Age, Height,Weight, Gender, BMT5, YRS10, HrsXC,HrsSP, HrsOther, RaceComp, RacePlnd

Table A.3.158. Overview of race time models along with septuple combinations of the predictor variables

Models	Predictor Variables
Model 166	Age, Height, Weight, Gender, BMT5, YRS10, HrsXC,HrsSP, HrsOther, RaceComp, Wave
Model 167	Age, Height, Weight, Gender, BMT5, YRS10, HrsXC,HrsSP, HrsOther, RacePlnd, Wave
Model 168	Age, Height, Weight, Gender, BMT5, YRS10, HrsXC,HrsSP, HrsTot, RaceComp, RacePlnd
Model 169	Age, Height, Weight, Gender, BMT5, YRS10, HrsXC,HrsSP, HrsTot, RaceComp, Wave
Model 170	Age, Height, Weight, Gender, BMT5, YRS10, HrsXC, HrsSP,HrsTot, RacePlnd, Wave
Model 171	Age, Height, Weight, Gender, BMT5, YRS10, HrsXC,HrsSP, RaceComp, RacePlnd, Wave
Model 172	Age, Height, Weight, Gender, BMT5, YRS10,HrsXC, HrsOther, HrsTot, RaceComp, RacePlnd
Model 173	Age, Height, Weight, Gender, BMT5, YRS10,HrsXC, HrsOther, HrsTot, RaceComp, Wave
Model 174	Age, Height, Weight, Gender, BMT5, YRS10,HrsXC, HrsOther, HrsTot, RacePlnd, Wave
Model 175	Age, Height,Weight, Gender, BMT5, YRS10,HrsXC, HrsOther, RaceComp, RacePlnd, Wave
Model 176	Age, Height,Weight, Gender, BMT5, YRS10, HrsXC, HrsTot, RaceComp, RacePlnd, Wave

Table A.3.159. Overview of race time models along with septuple combinations of the predictor variables

Models	Predictor Variables
Model 177	Age, Height, Weight, Gender, BMT5, YRS10,HrsSP, HrsOther, HrsTot,Race Comp, RacePlnd
Model 178	Age, Height, Weight, Gender, BMT5, YRS10,HrsSP, HrsOther, HrsTot, RaceComp, Wave
Model 179	Age, Height, Weight, Gender, BMT5, YRS10,HrsSP, HrsOther, HrsTot, RacePlnd, Wave
Model 180	Age, Height, Weight, Gender, BMT5, YRS10,HrsSP, HrsOther, RaceComp, RacePlnd, Wave
Model 181	Age, Height, Weight, Gender, BMT5, YRS10,HrsSP, HrsTot, RaceComp, RacePlnd, Wave
Model 182	Age, Height, Weight, Gender, BMT5, YRS10,HrsOther, HrsTot, RaceComp, RacePlnd, Wave
Model 183	Age, Height, Weight, Gender, BMT5, YRSALL, HrsXC,HrsSP, HrsOther, HrsTot, RaceComp
Model 184	Age, Height, Weight, Gender, BMT5, YRSALL, HrsXC,HrsSP, HrsOther, HrsTot, RacePlnd
Model 185	Age, Height, Weight, Gender, BMT5, YRSALL, HrsXC,HrsSP, HrsOther, HrsTot, Wave
Model 186	Age, Height, Weight, Gender, BMT5, YRSALL, HrsXC,HrsSP, HrsOther, RaceComp, RacePlnd
Model 187	Age, Height,Weight, Gender, BMT5, YRSALL, HrsXC,HrsSP, HrsOther, RaceComp, Wave

Table A.3.160. Overview of race time models along with septuple combinations of the predictor variables

Models	Predictor Variables
Model 188	Age, Height,Weight, Gender, BMT5, YRSALL, HrsXC,HrsSP, HrsOther, RacePlnd, Wave
Model 189	Age, Height,Weight, Gender, BMT5, YRSALL, HrsXC,HrsSP, HrsTot, RaceComp, RacePlnd
Model 190	Age, Height,Weight, Gender, BMT5, YRSALL, HrsXC,HrsSP, HrsTot, RaceComp, Wave
Model 191	Age, Height,Weight, Gender, BMT5, YRSALL, HrsXC, HrsSP,HrsTot, RacePlnd, Wave
Model 192	Age, Height,Weight, Gender, BMT5, YRSALL, HrsXC,HrsSP, RaceComp, RacePlnd, Wave
Model 193	Age, Height,Weight, Gender, BMT5, YRSALL,HrsXC, HrsOther, HrsTot, RaceComp, RacePlnd
Model 194	Age, Height,Weight, Gender, BMT5, YRSALL,HrsXC, HrsOther, HrsTot, RaceComp, Wave
Model 195	Age, Height,Weight, Gender, BMT5, YRSALL,HrsXC, HrsOther, HrsTot, RacePlnd, Wave
Model 196	Age, Height,Weight, Gender, BMT5, YRSALL,HrsXC, HrsOther, RaceComp, RacePlnd, Wave
Model 197	Age, Height,Weight, Gender, BMT5, YRSALL, HrsXC, HrsTot, RaceComp, RacePlnd, Wave
Model198,	Age, Height,Weight, Gender, BMT5, YRSALL,HrsSP, HrsOther, HrsTot, RaceComp, RacePlnd

Table A.3.161. Overview of race time models along with septuple combinations of the predictor variables

Models	Predictor Variables
Model 199	Age, Height, Weight, Gender, BMT5, YRSALL,HrsSP, HrsOther, HrsTot, RaceComp, Wave
Model 200	Age, Height, Weight, Gender, BMT5, YRSALL,HrsSP, HrsOther, HrsTot, RacePlnd, Wave
Model 201	Age, Height, Weight, Gender, BMT5, YRSALL,HrsSP, HrsOther, RaceComp, RacePlnd, Wave
Model 202	Age, Height, Weight, Gender, BMT5, YRSALL,HrsSP, HrsTot, RaceComp, RacePlnd, Wave
Model 203	Age, Height, Weight, Gender, BMT5, YRSALL,HrsOther, HrsTot, RaceComp, RacePlnd, Wave
Model 204	Age, Height,Weight, Gender, BMT5, HrsXC,HrsSP, HrsOther, HrsTot, RaceComp, RacePlnd
Model 205	Age, Height,Weight, Gender, BMT5, HrsXC,HrsSP, HrsOther, HrsTot, RaceComp, Wave
Model 206	Age, Height,Weight, Gender, BMT5, HrsXC,HrsSP, HrsOther, HrsTot, RacePlnd, Wave
Model 207	Age, Height,Weight, Gender, BMT5, HrsXC,HrsSP, HrsOther, RaceComp, RacePlnd, Wave
Model 208	Age, Height,Weight, Gender, BMT5, HrsXC,HrsSP, HrsTot, RaceComp, RacePlnd, Wave
Model 209	Age, Height,Weight, Gender, BMT5,HrsXC, HrsOther, HrsTot, RaceComp, RacePlnd, Wave

Table A.3.162. Overview of race time models along with septuple combinations of the predictor variables

Models	**Predictor Variables**
Model 210	Age, Height,Weight, Gender, BMT5,HrsSP, HrsOther, HrsTot, RaceComp, RacePlnd, Wave
Model 211	Age, Height, Weight,Gender, BMT10,YRS10, YRSALL, HrsXC,HrsSP, HrsOther, HrsTot
Model 212	Age, Height, Weight,Gender, BMT10,YRS10, YRSALL, HrsXC,HrsSP, HrsOther, RaceComp
Model 213	Age, Height, Weight,Gender, BMT10,YRS10, YRSALL, HrsXC,HrsSP, HrsOther, RacePlnd
Model 214	Age, Height, Weight,Gender, BMT10,YRS10, YRSALL, HrsXC,HrsSP, HrsOther, Wave
Model 215	Age, Height, Weight,Gender, BMT10,YRS10, YRSALL, HrsXC,HrsSP, HrsTot RaceComp
Model 216	Age, Height, Weight,Gender, BMT10,YRS10, YRSALL, HrsXC,HrsSP, HrsTot, RacePlnd
Model 217	Age, Height, Weight,Gender, BMT10,YRS10, YRSALL, HrsXC,HrsSP, HrsTot, Wave
Model 218	Age, Height, Weight,Gender, BMT10,YRS10, YRSALL, HrsXC, HrsSP, RaceComp, RacePlnd
Model 219	Age, Height, Weight,Gender, BMT10,YRS10, YRSALL, HrsXC, HrsSP, RaceComp, Wave
Model 220	Age, Height, Weight,Gender, BMT10,YRS10, YRSALL, HrsXC,HrsSP, RacePlnd, Wave

Table A.3.163. Overview of race time models along with septuple combinations of the predictor variables

Models	Predictor Variables
Model 221	Age, Height, Weight,Gender, BMT10,YRS10, YRSALL,HrsXC, HrsOther, HrsTot, RaceComp
Model 222	Age, Height, Weight,Gender, BMT10,YRS10, YRSALL,HrsXC, HrsOther, HrsTot, RacePlnd
Model 223	Age, Height, Weight,Gender, BMT10,YRS10, YRSALL,HrsXC, HrsOther, HrsTot, Wave
Model224	Age, Height, Weight,Gender, BMT10,YRS10, YRSALL,HrsXC, HrsOther, RaceComp, RacePlnd
Model 225	Age, Height, Weight,Gender, BMT10,YRS10, YRSALL,HrsXC, HrsOther, RaceComp, Wave
Model 226	Age, Height, Weight,Gender, BMT10,YRS10, YRSALL,HrsXC, HrsOther, RacePlnd, Wave
Model 227	Age, Height, Weight,Gender, BMT10,YRS10, YRSALL, HrsXC, HrsTot, RaceComp, RacePlnd
Model 228	Age, Height, Weight,Gender, BMT10,YRS10, YRSALL, HrsXC, HrsTot, RaceComp, Wave
Model 229	Age, Height, Weight,Gender, BMT10,YRS10, YRSALL, HrsXC,HrsTot, RacePlnd, Wave
Model 230,	Age ,Height, Weight,Gender, BMT10,YRS10, YRSALL,HrsXC, RaceComp, RacePlnd, Wave
Model 231,	Age, Height, Weight,Gender, BMT10,YRS10, YRSALL,HrsSP, HrsOther, HrsTot,RaceComp
Model 232,	Age, Height, Weight,Gender, BMT10,YRS10, YRSALL,HrsSP, HrsOther, HrsTot, RacePlnd

Table A.3.164. Overview of race time models along with septuple combinations of the predictor variables

Models	**Predictor Variables**
Model 233	Age, Height, Weight, Gender, BMT10, YRS10, YRSALL, HrsSP, HrsOther, HrsTot, Wave
Model 234	Age, Height, Weight, Gender, BMT10, YRS10, YRSALL, HrsSP, HrsOther, RaceComp RacePlnd
Model 235	Age, Height, Weight, Gender, BMT10, YRS10, YRSALL, HrsSP, HrsOther RaceComp Wave
Model 236	Age, Height, Weight, Gender, BMT10, YRS10, YRSALL, HrsSP, HrsOther, RacePlnd, Wave
Model 237	Age, Height,Weight, Gender, BMT10, YRS10, YRSALL, HrsSP, HrsTot, RaceComp, RacePlnd
Model 238	Age, Height,Weight, Gender, BMT10 , YRS10, YRSALL, HrsSP, HrsTot, RaceComp, Wave
Model 239	Age, Height,Weight, Gender, BMT10, YRS10, YRSALL, HrsSP, HrsTot, RacePlnd, Wave
Model 240	Age, Height,Weight, Gender, BMT10, YRS10, YRSALL, HrsSP, RaceComp, RacePlnd, Wave
Model 241	Age, Height,Weight, Gender, BMT10, YRS10, YRSALL, HrsOther, HrsTot, RaceComp, RacePlnd
Model 42	Age, Height,Weight, Gender, BMT10, YRS10, YRSALL, HrsOther, HrsTot, RaceComp, Wave
Model 243	Age, Height,Weight, Gender, BMT10, YRS10, YRSALL, HrsOther, HrsTot, RacePlnd, Wave

Table A.3.165. Overview of race time models along with septuple combinations of the predictor variables

Models	Predictor Variables
Model 244	Age, Height, Weight,Gender, BMT10,YRS10, YRSALL, HrsOther, RaceComp, RacePlnd, Wave
Model 245	Age, Height, Weight,Gender, BMT10,YRS10, YRSALL, HrsTot, RaceComp, RacePlnd, Wave
Model 246	Age, Height, Weight,Gender, BMT10, YRS10, HrsXC,HrsSP, HrsOther, HrsTot, RaceComp
Model 247	Age, Height, Weight,Gender, BMT10, YRS10, HrsXC,HrsSP, HrsOther, HrsTot, RacePlnd
Model 248	Age, Height, Weight,Gender, BMT10, YRS10, HrsXC,HrsSP, HrsOther, HrsTot, Wave
Model 249	Age, Height, Weight,Gender, BMT10, YRS10, HrsXC,HrsSP, HrsOther, RaceComp, RacePlnd
Model 250	Age, Height, Weight,Gender, BMT10, YRS10, HrsXC,HrsSP, HrsOther, RaceComp, Wave
Model 251	Age, Height, Weight,Gender, BMT10, YRS10, HrsXC,HrsSP, HrsOther, RacePlnd, Wave
Model 252	Age, Height, Weight,Gender, BMT10, YRS10, HrsXC,HrsSP, HrsTot, RaceComp, RacePlnd
Model 253	Age, Height, Weight,Gender, BMT10, YRS10, HrsXC,HrsSP, HrsTot, RaceComp, Wave
Model 254	Age, Height, Weight,Gender, BMT10, YRS10, HrsXC, HrsSP,HrsTot, RacePlnd, Wave

Table A.3.166. Overview of race time models along with septuple combinations of the predictor variables

Models	Predictor Variables
Model 255	Age, Height, Weight, Gender, BMT10, YRS10, HrsXC, HrsSP, RaceComp, RacePlnd, Wave
Model 256	Age, Height, Weight, Gender, BMT10, YRS10,HrsXC, HrsOther, HrsTot, RaceComp, RacePlnd
Model 257	Age, Height, Weight, Gender, BMT10, YRS10,HrsXC, HrsOther, HrsTot, RaceComp, Wave
Model 258	Age, Height, Weight, Gender, BMT10, YRS10,HrsXC, HrsOther, HrsTot, RacePlnd, Wave
Model 259	Age, Height, Weight, Gender, BMT10, YRS10,HrsXC, HrsOther, RaceComp, RacePlnd, Wave
Model 260	Age, Height, Weight, Gender, BMT10, YRS10, HrsXC, HrsTot, RaceComp, RacePlnd, Wave
Model 261	Age, Height, Weight, Gender, BMT10, YRS10,HrsSP, HrsOther, HrsTot, RaceComp, RacePlnd
Model 262	Age, Height, Weight, Gender, BMT10, YRS10,HrsSP, HrsOther, HrsTot, RaceComp, Wave
Model 263	Age, Height, Weight, Gender, BMT10, YRS10,HrsSP, HrsOther, HrsTot, RacePlnd,Wave
Model 264	Age, Height, Weight, Gender, BMT10, YRS10,HrsSP, HrsOther, RaceComp, RacePlnd Wave
Model 265	Age, Height, Weight, Gender, BMT10, YRS10,HrsSP, HrsTot, RaceComp, RacePlnd, Wave

Table A.3.167. Overview of race time models along with septuple combinations of the predictor variables

Models	**Predictor Variables**
Model 266	Age, Height, Weight, Gender, BMT10, YRS10, HrsOther, HrsTot, RaceComp, RacePlnd, Wave
Model 267	Age, Height, Weight, Gender, BMT10, YRSALL, HrsXC, HrsSP, HrsOther, HrsTot, RaceComp
Model 268	Age, Height, Weight, Gender, BMT10, YRSALL, HrsXC, HrsSP, HrsOther, HrsTot, RacePlnd
Model 269	Age, Height, Weight, Gender, BMT10, YRSALL, HrsXC, HrsSP, HrsOther, HrsTot, Wave
Model 270	Age, Height, Weight, Gender, BMT10, YRSALL, HrsXC, HrsSP, HrsOther, RaceComp, RacePlnd
Model 271	Age, Height, Weight, Gender, BMT10, YRSALL, HrsXC, HrsSP, HrsOther, RaceComp, Wave
Model 272	Age, Height, Weight, Gender, BMT10, YRSALL, HrsXC, HrsSP, HrsOther, RacePlnd, Wave
Model 273	Age, Height, Weight, Gender, BMT10, YRSALL, HrsXC, HrsSP, HrsTot, RaceComp, RacePlnd
Model 274	Age, Height, Weight, Gender, BMT10, YRSALL, HrsXC, HrsSP, HrsTot, RaceComp, Wave
Model 275	Age, Height, Weight, Gender, BMT10, YRSALL, HrsXC, HrsSP, HrsTot, RacePlnd, Wave
Model 276	Age, Height, Weight, Gender, BMT10, YRSALL, HrsXC, HrsSP, RaceComp, RacePlnd, Wave

Table A.3.168. Overview of race time models along with septuple combinations of the predictor variables

Models	Predictor Variables
Model 277	Age, Height, Weight,Gender, BMT10, YRSALL,HrsXC, HrsOther, HrsTot, RaceComp, RacePlnd
Model 278	Age, Height, Weight,Gender, BMT10, YRSALL,HrsXC, HrsOther, HrsTot, RaceComp, Wave
Model 279	Age, Height, Weight,Gender, BMT10, YRSALL,HrsXC, HrsOther, HrsTot, RacePlnd, Wave
Model 280	Age, Height, Weight,Gender, BMT10, YRSALL,HrsXC, HrsOther, RaceComp, RacePlnd, Wave
Model 281	Age, Height, Weight,Gender, BMT10, YRSALL, HrsXC, HrsTot, RaceComp, RacePlnd, Wave
Model 282	Age, Height, Weight,Gender, BMT10, YRSALL,HrsSP, HrsOther, HrsTot, RaceComp, RacePlnd
Model 283	Age, Height, Weight,Gender, BMT10, YRSALL,HrsSP, HrsOther, HrsTot, RaceComp, Wave
Model 284	Age, Height, Weight,Gender, BMT10, YRSALL,HrsSP, HrsOther, HrsTot, RacePlnd, Wave
Model 285	Age, Height, Weight,Gender, BMT10, YRSALL,HrsSP, HrsOther, RaceComp, RacePlnd, Wave
Model 286	Age, Height, Weight,Gender, BMT10, YRSALL,HrsSP, HrsTot, RaceComp, RacePlnd, Wave
Model 287	Age, Height, Weight,Gender, BMT10, YRSALL,HrsOther, HrsTot, RaceComp, RacePlnd, Wave

Table A.3.169. Overview of race time models along with septuple combinations of the predictor variables

Models	**Predictor Variables**
Model 288	Age, Height, Weight, Gender, BMT10, HrsXC,HrsSP, HrsOther, HrsTot, RaceComp, RacePlnd
Model 289	Age, Height, Weight, Gender, BMT10, HrsXC,HrsSP, HrsOther, HrsTot, RaceComp, Wave
Model 290	Age, Height, Weight, Gender, BMT10, HrsXC,HrsSP, HrsOther, HrsTot, RacePlnd, Wave
Model 291	Age, Height, Weight, Gender, BMT10, HrsXC,HrsSP, HrsOther, RaceComp, RacePlnd, Wave
Model 292	Age, Height, Weight, Gender, BMT10, HrsXC,HrsSP, HrsTot, RaceComp, RacePlnd, Wave
Model 293	Age, Height, Weight, Gender, BMT10, HrsXC, HrsOther, HrsTot, RaceComp, RacePlnd, Wave
Model 294	Age, Height, Weight, Gender, BMT10, HrsSP, HrsOther, HrsTot, RaceComp, RacePlnd, Wave
Model 295	Age, Height, Weight, Gender, YRS10, YRSALL, HrsXC,HrsSP, HrsOther, HrsTot, RaceComp
Model 296	Age, Height, Weight, Gender, YRS10, YRSALL, HrsXC,HrsSP, HrsOther, HrsTot, RacePlnd
Model 297	Age, Height, Weight, Gender, YRS10, YRSALL, HrsXC,HrsSP, HrsOther, HrsTot, Wave
Model 298	Age, Height, Weight, Gender, YRS10, YRSALL, HrsXC,HrsSP, HrsOther, RaceComp, RacePlnd

Table A.3.170. Overview of race time models along with septuple combinations of the predictor variables

Models	Predictor Variables
Model 299	Age, Height,Weight, Gender,YRS10, YRSALL, HrsXC,HrsSP, HrsOther, RaceComp, Wave
Model 300	Age, Height,Weight, Gender,YRS10, YRSALL, HrsXC,HrsSP, HrsOther, RacePlnd,Wave
Model 301	Age, Height,Weight, Gender,YRS10, YRSALL, HrsXC,HrsSP, HrsTot, RaceComp, RacePlnd
Model 302	Age, Height,Weight, Gender,YRS10, YRSALL, HrsXC,HrsSP, HrsTot, RaceComp, Wave
Model 303	Age, Height,Weight, Gender,YRS10, YRSALL, HrsXC, HrsSP,HrsTot, RacePlnd, Wave
Model 304	Age, Height,Weight, Gender,YRS10, YRSALL, HrsXC,HrsSP, RaceComp, RacePlnd, Wave
Model 305	Age, Height,Weight, Gender,YRS10, YRSALL,HrsXC, HrsOther, HrsTot, RaceComp, RacePlnd
Model 306	Age, Height,Weight, Gender,YRS10, YRSALL,HrsXC, HrsOther, HrsTot, RaceComp, Wave
Model 307	Age, Height,Weight, Gender,YRS10, YRSALL,HrsXC, HrsOther, HrsTot, RacePlnd, Wave
Model 308	Age, Height,Weight, Gender,YRS10, YRSALL,HrsXC, HrsOther, RaceComp, RacePlnd, Wave
Model 309	Age, Height,Weight, Gender,YRS10, YRSALL, HrsXC, HrsTot, RaceComp, RacePlnd, Wave

Table A.3.171. Overview of race time models along with septuple combinations of the predictor variables

Models	Predictor Variables
Model 310	Age, Height, Weight, Gender, YRS10, YRSALL,HrsSP, HrsOther, HrsTot, RaceComp, RacePlnd
Model 311	Age, Height, Weight, Gender, YRS10, YRSALL,HrsSP, HrsOther, HrsTot, RaceComp, Wave
Model 312	Age, Height, Weight, Gender, YRS10, YRSALL,HrsSP, HrsOther, HrsTot, RacePlnd, Wave
Model 313	Age, Height, Weight, Gender, YRS10, YRSALL,HrsSP, HrsOther, RaceComp, RacePlnd, Wave
Model 314	Age, Height, Weight, Gender, YRS10, YRSALL,HrsSP, HrsTot, RaceComp, RacePlnd, Wave
Model 315	Age, Height, Weight, Gender, YRS10, YRSALL,HrsOther, HrsTot, RaceComp, RacePlnd, Wave
Model 316	Age, Height, Weight, Gender, YRS10, HrsXC,HrsSP, HrsOther, HrsTot, RaceComp, RacePlnd
Model 317	Age, Height, Weight, Gender, YRS10, HrsXC,HrsSP, HrsOther, HrsTot, RaceComp, Wave
Model 318	Age, Height, Weight, Gender, YRS10, HrsXC,HrsSP, HrsOther, HrsTot, RacePlnd, Wave
Model 319	Age, Height, Weight, Gender, YRS10, HrsXC,HrsSP, HrsOther, RaceComp, RacePlnd, Wave
Model 320	Age, Height,Weight, Gender, YRS10, HrsXC,HrsSP, HrsTot, RaceComp, RacePlnd, Wave

Table A.3.172. Overview of race time models along with septuple combinations of the predictor variables

Models	Predictor Variables
Model 321	Age, Height, Weight, Gender, YRS10,HrsXC, HrsOther, HrsTot, RaceComp, RacePlnd, Wave
Model 322	Age, Height, Weight, Gender, YRS10,HrsSP, HrsOther, HrsTot, RaceComp, RacePlnd, Wave
Model 323	Age, Height, Weight, Gender, YRSALL, HrsXC,HrsSP, HrsOther, HrsTot, RaceComp, RacePlnd
Model 324	Age, Height, Weight, Gender, YRSALL, HrsXC,HrsSP, HrsOther, HrsTot, RaceComp, Wave
Model 325	Age, Height, Weight, Gender, YRSALL, HrsXC,HrsSP, HrsOther, HrsTot, RacePlnd, Wave
Model 326	Age, Height, Weight, Gender, YRSALL, HrsXC,HrsSP, HrsOther, RaceComp, RacePlnd, Wave
Model 327	Age, Height, Weight, Gender, YRSALL, HrsXC,HrsSP, HrsTot, RaceComp, RacePlnd, Wave
Model 328	Age, Height,Weight, Gender, YRSALL, HrsXC, HrsOther, HrsTot, RaceComp, RacePlnd, Wave
Model 329	Age, Height,Weight, Gender, YRSALL,HrsSP, HrsOther, HrsTot, RaceComp, RacePlnd, Wave
Model 330	Age, Height, Weight,Gender, HrsXC,HrsSP, HrsOther, HrsTot, RaceComp, RacePlnd, Wave

A.8. Prediction Models Created Using Octuple Combinations

By using octuple combinations of the predictor variables, a total of 165 prediction models have been formed, respectively

Table A.3.173. Overview of race time models along with octuple combinations of the predictor variables

Models	Predictor Variables
Model 1	Age, Height, Weight, Gender, BMT5, BMT10, YRS10, YRSALL, HrsXC, HrsSP, HrsOther, HrsTot
Model 2	Age, Height ,Weight, Gender, BMT5, BMT10, YRS10, YRSALL, HrsXC, HrsSP, HrsOther, RaceComp
Model 3	Age, Height, Weight, Gender, BMT5, BMT10, YRS10, YRSALL, HrsXC, HrsSP, HrsOther, RacePlnd
Model 4	Age, Height, Weight, Gender, BMT5, BMT10, YRS10, YRSALL, HrsXC, HrsSP, HrsOther, Wave
Model 5	Age, Height, Weight, Gender, BMT5, BMT10, YRS10, YRSALL, HrsXC , HrsSP, HrsTot, RaceComp
Model 6	Age, Height, Weight, Gender, BMT5, BMT10, YRS10, YRSALL, HrsXC, HrsSP, HrsTot, RacePlnd,
Model 7	Age, Height, Weight, Gender, BMT5, BMT10, YRS10, YRSALL, HrsXC, HrsSP, HrsTot, Wave
Model 8	Age, Height, Weight, Gender, BMT5, BMT10, YRS10, YRSALL, HrsXC, HrsSP, RaceComp, RacePlnd
Model 9	Age, Height, Weight, Gender, BMT5, BMT10, YRS10, YRSALL, HrsXC, HrsSP, RaceComp, Wave
Model 10	Age, Height, Weight, Gender, BMT5, BMT10, YRS10, YRSALL, HrsXC, HrsSP, RacePlnd, Wave
Model 11	Age, Height, Weight, Gender, BMT5, BMT10,YRS10, YRSALL, HrsXC, HrsOther, HrsTot, RaceComp,

Table A.3.174. Overview of race time models along with octuple combinations of the predictor variables

Models	Predictor Variables
Model 12	Age, Height, Weight, Gender, BMT5, BMT10, YRS10, YRSALL, HrsXC, HrsOther, HrsTot, RacePlnd
Model 13	Age, Height,Weight, Gender, BMT5, BMT10,YRS10, YRSALL,HrsXC, HrsOther, HrsTot, Wave
Model 14	Age, Height, Weight, Gender, BMT5, BMT10, YRS10, YRSALL, HrsXC, HrsOther, RaceComp, RacePlnd,
Model 15	Age, Height, Weight, Gender, BMT5, BMT10, YRS10, YRSALL, HrsXC, HrsOther, RaceComp, Wave,
Model 16	Age, Height, Weight, Gender, BMT5, BMT10, YRS10, YRSALL, HrsXC, HrsOther, RacePlnd, Wave
Model 17	Age, Height, Weight, Gender, BMT5, BMT10,YRS10, YRSALL, HrsXC, HrsTot, RaceComp, RacePlnd,
Model 18	Age, Height, Weight, Gender, BMT5, BMT10,YRS10, YRSALL, HrsXC, HrsTot,RaceComp, Wave,
Model 19	Age, Height,Weight, Gender, BMT5, BMT10,YRS10, YRSALL, HrsXC, HrsTot, RacePlnd, Wave
Model 20	Age, Height, Weight, Gender, BMT5, BMT10, YRS10, YRSALL, HrsXC, RaceComp, RacePlnd, Wave
Model 21	Age, Height,Weight, Gender, BMT5, BMT10,YRS10, YRSALL,HrsSP, HrsOther, HrsTot, RaceComp
Model 22	Age, Height, Weight, Gender, BMT5, BMT10, YRS10, YRSALL, HrsSP, HrsOther, HrsTot, RacePlnd

Table A.3.175. Overview of race time models along with octuple combinations of the predictor variables

Models	**Predictor Variables**
Model 23	Age, Height, Weight, Gender, BMT5, BMT10, YRS10, YRSALL, HrsSP, HrsOther, HrsTot, Wave
Model 24	Age, Height, Weight, Gender, BMT5, BMT10, YRS10, YRSALL, HrsSP, HrsOther, RaceComp, RacePlnd,
Model 25	Age, Height, Weight, Gender, BMT5, BMT10, YRS10, YRSALL, HrsSP, HrsOther, RaceComp, Wave
Model 26	Age, Height,Weight, Gender, BMT5, BMT10,YRS10, YRSALL,HrsSP, HrsOther, RacePlnd, Wave,
Model 27	Age, Height,Weight, Gender, BMT5, BMT10,YRS10, YRSALL,HrsSP, HrsTot,RaceComp, RacePlnd
Model 28	Age, Height, Weight, Gender, BMT5, BMT10, YRS10, YRSALL, HrsSP, HrsTot,RaceComp, Wave
Model 29	Age, Height, Weight, Gender, BMT5, BMT10, YRS10, YRSALL, HrsSP, HrsTot, RacePlnd, Wave
Model 30	Age, Height, Weight, Gender, BMT5, BMT10, YRS10, YRSALL, HrsSP, RaceComp, RacePlnd, Wave
Model 31	Age, Height,Weight, Gender, BMT5, BMT10, YRS10, YRSALL, HrsOther, HrsTot, RaceComp, RacePlnd
Model 32	Age, Height,Weight, Gender, BMT5, BMT10,YRS10, YRSALL,HrsOther, HrsTot, RaceComp, Wave
Model 33	Age, Height, Weight, Gender, BMT5, BMT10, YRS10, YRSALL, HrsOther, HrsTot, RacePlnd, Wave

Table A.3.176. Overview of race time models along with octuple combinations of the predictor variables

Models	**Predictor Variables**
Model 34	Age, Height, Weight, Gender, BMT5, BMT10, YRS10, YRSALL, HrsOther, RaceComp, RacePlnd, Wave
Model 35	Age, Height, Weight, Gender, BMT5, BMT10, YRS10, YRSALL, HrsTot, RaceComp, RacePlnd, Wave
Model 36	Age, Height, Weight, Gender, BMT5, BMT10, YRS10, HrsXC, HrsSP, HrsOther, HrsTot, RaceComp
Model 37	Age, Height, Weight, Gender, BMT5, BMT10, YRS10, HrsXC, HrsSP, HrsOther, HrsTot, RacePlnd
Model 38	Age, Height, Weight, Gender, BMT5, BMT10, YRS10, HrsXC, HrsSP, HrsOther,HrsTot, Wave
Model 39	Age, Height, Weight, Gender, BMT5, BMT10, YRS10, HrsXC, HrsSP, HrsOther, RaceComp, RacePlnd,
Model 40	Age, Height, Weight, Gender, BMT5, BMT10, YRS10, HrsXC, HrsSP, HrsOther, RaceComp, Wave
Model 41	Age, Height, Weight, Gender, BMT5, BMT10, YRS10, HrsXC, HrsSP, HrsOther, RacePlnd, Wave
Model 42	Age, Height, Weight, Gender, BMT5, BMT10, YRS10, HrsXC, HrsSP, HrsTot, RaceComp, RacePlnd
Model 43	Age, Height, Weight, Gender, BMT5, BMT10, YRS10, HrsXC, HrsSP, HrsTot, RaceComp, Wave
Model 44	Age, Height, Weight, Gender, BMT5, BMT10, YRS10, HrsXC, HrsSP, HrsTot, RacePlnd, Wave

Table A.3.177. Overview of race time models along with octuple combinations of the predictor variables

Models	**Predictor Variables**
Model 45	Age, Height, Weight, Gender, BMT5, BMT10, YRS10, HrsXC, HrsSP, RaceComp, RacePlnd, Wave
Model 46	Age, Height, Weight, Gender, BMT5, BMT10, YRS10, HrsXC, HrsOther, HrsTot,RaceComp, RacePlnd
Model 47	Age, Height, Weight, Gender, BMT5, BMT10, YRS10, HrsXC, HrsOther, HrsTot, RaceComp, Wave
Model 48	Age, Height, Weight, Gender, BMT5, BMT10, YRS10, HrsXC, HrsOther, HrsTot,RacePlnd, Wave
Model 49	Age, Height, Weight, Gender, BMT5, BMT10, YRS10, HrsXC, HrsOther, RaceComp, RacePlnd, Wave
Model 50	Age, Height, Weight, Gender, BMT5, BMT10, YRS10, HrsXC, HrsTot, RaceComp, RacePlnd, Wave
Model 51	Age, Height, Weight, Gender, BMT5, BMT10, YRS10, HrsSP, HrsOther, HrsTot, RaceComp, RacePlnd
Model 52	Age, Height, Weight, Gender, BMT5, BMT10, YRS10, HrsSP, HrsOther, HrsTot,RaceComp, Wave
Model 53	Age, Height, Weight, Gender, BMT5, BMT10, YRS10, HrsSP, HrsOther, HrsTot, RacePlnd, Wave
Model 54	Age, Height, Weight, Gender, BMT5, BMT10, YRS10, HrsSP, HrsOther, RaceComp, RacePlnd, Wave
Model 55	Age, Height, Weight, Gender, BMT5, BMT10, YRS10, HrsSP, HrsTot, RaceComp, RacePlnd, Wave

Table A.3.178. Overview of race time models along with octuple combinations of the predictor variables

Models	Predictor Variables
Model 56	Age, Height, Weight, Gender, BMT5, BMT10, YRS10, HrsOther, HrsTot, RaceComp, RacePlnd, Wave
Model 57	Age, Height, Weight, Gender, BMT5, BMT10, YRSALL, HrsXC, HrsSP, HrsOther, HrsTot, RaceComp
Model 58	Age, Height,Weight, Gender, BMT5, BMT10, YRSALL, HrsXC,HrsSP, HrsOther, HrsTot, RacePlnd
Model 59	Age, Height, Weight, Gender, BMT5, BMT10, YRSALL, HrsXC, HrsSP, HrsOther, HrsTot, Wave
Model 60	Age, Height, Weight, Gender, BMT5, BMT10, YRSALL, HrsXC, HrsSP, HrsOther, RaceComp, RacePlnd
Model 61	Age, Height, Weight, Gender, BMT5, BMT10, YRSALL, HrsXC, HrsSP, HrsOther, RaceComp, Wave
Model 62	Age, Height, Weight, Gender, BMT5, BMT10, YRSALL, HrsXC, HrsSP, HrsOther, RacePlnd, Wave
Model 63	Age, Height,Weight, Gender, BMT5, BMT10, YRSALL, HrsXC, HrsSP, HrsTot, RaceComp, RacePlnd
Model 64	Age, Height, Weight, Gender, BMT5, BMT10, YRSALL, HrsXC, HrsSP, HrsTot, RaceComp, Wave
Model 65	Age, Height, Weight, Gender, BMT5, BMT10, YRSALL, HrsXC, HrsSP, HrsTot, RacePlnd, Wave
Model 66	Age, Height, Weight, Gender, BMT5, BMT10, YRSALL, HrsXC, HrsSP, RaceComp, RacePlnd, Wave

Table A.3.179. Overview of race time models along with octuple combinations of the predictor variables

Models	**Predictor Variables**
Model 67	Age, Height, Weight, Gender, BMT5, BMT10, YRSALL, HrsXC, HrsOther, HrsTot, RaceComp, RacePlnd
Model 68	Age, Height, Weight, Gender, BMT5, BMT10, YRSALL, HrsXC, HrsOther, HrsTot, RaceComp, Wave
Model 69	Age, Height, Weight, Gender, BMT5, BMT10, YRSALL, HrsXC, HrsOther, HrsTot, RacePlnd, Wave
Model 70	Age, Height, Weight, Gender, BMT5, BMT10, YRSALL, HrsXC, HrsOther, RaceComp, RacePlnd, Wave
Model 71	Age, Height, Weight, Gender, BMT5, BMT10, YRSALL, HrsXC, HrsTot, RaceComp, RacePlnd, Wave
Model 72	Age, Height, Weight, Gender, BMT5, BMT10, YRSALL, HrsSP, HrsOther, HrsTot, RaceComp, RacePlnd
Model 73	Age, Height, Weight, Gender, BMT5, BMT10, YRSALL, HrsSP, HrsOther , HrsTot, RaceComp, Wave
Model 74	Age, Height, Weight, Gender, BMT5, BMT10, YRSALL, HrsSP, HrsOther, HrsTot, RacePlnd, Wave
Model 75	Age, Height, Weight, Gender, BMT5, BMT10, YRSALL, HrsSP, HrsOther, RaceComp, RacePlnd, Wave
Model 76	Age, Height, Weight, Gender, BMT5, BMT10, YRSALL, HrsSP, HrsTot, RaceComp, RacePlnd, Wave
Model 77	Age, Height,Weight, Gender, BMT5, BMT10, YRSALL,HrsOther, HrsTot, RaceComp, RacePlnd, Wave

Table A.3.180. Overview of race time models along with octuple combinations of the predictor variables

Models	**Predictor Variables**
Model 78	Age, Height, Weight, Gender, BMT5, BMT10, HrsXC, HrsSP, HrsOther, HrsTot, RaceComp, RacePlnd
Model 79	Age, Height,Weight, Gender, BMT5, BMT10, HrsXC,HrsSP, HrsOther, HrsTot, RaceComp, Wave
Model 80	Age, Height,Weight, Gender, BMT5, BMT10, HrsXC,HrsSP, HrsOther, HrsTot, RacePlnd, Wave
Model 81	Age, Height, Weight, Gender, BMT5, BMT10, HrsXC, HrsSP, HrsOther, RaceComp, RacePlnd, Wave
Model 82	Age, Height, Weight, Gender, BMT5, BMT10, HrsXC,HrsSP, HrsTot, RaceComp, RacePlnd, Wave
Model 83	Age, Height, Weight, Gender, BMT5, BMT10,HrsXC, HrsOther, HrsTot, RaceComp, RacePlnd, Wave
Model 84	Age, Height, Weight, Gender, BMT5, BMT10, HrsSP, HrsOther, HrsTot, RaceComp, RacePlnd, Wave,
Model 85	Age, Height, Weight, Gender, BMT5,YRS10, YRSALL, HrsXC, HrsSP, HrsOther, HrsTot, RaceComp
Model 86	Age, Height,Weight, Gender, BMT5,YRS10, YRSALL, HrsXC,HrsSP, HrsOther, HrsTot, RacePlnd
Model 87	Age, Height, Weight, Gender, BMT5, YRS10, YRSALL, HrsXC, HrsSP, HrsOther, HrsTot, Wave,
Model 88	Age, Height,Weight, Gender, BMT5,YRS10, YRSALL, HrsXC,HrsSP, HrsOther, RaceComp, RacePlnd

Table A.3.181. Overview of race time models along with octuple combinations of the predictor variables

Models	Predictor Variables
Model 89	Age, Height, Weight, Gender, BMT5, YRS10, YRSALL, HrsXC, HrsSP, HrsOther, RaceComp, Wave
Model 90	Age, Height,Weight, Gender, BMT5, YRS10, YRSALL, HrsXC, HrsSP, HrsOther, RacePlnd, Wave
Model 91	Age, Height, Weight, Gender, BMT5, YRS10, YRSALL, HrsXC, HrsSP, HrsTot, RaceComp, RacePlnd
Model 92	Age, Height, Weight, Gender, BMT5, YRS10, YRSALL, HrsXC, HrsSP, HrsTot, RaceComp, Wave
Model 93	Age, Height, Weight, Gender, BMT5, YRS10, YRSALL, HrsXC, HrsSP, HrsTot, RacePlnd, Wave
Model 94	Age, Height,Weight, Gender, BMT5,YRS10, YRSALL, HrsXC,HrsSP, RaceComp, RacePlnd, Wave
Model 95	Age, Height,Weight, Gender, BMT5,YRS10, YRSALL,HrsXC, HrsOther, HrsTot, RaceComp, RacePlnd
Model 96	Age, Height, Weight, Gender, BMT5, YRS10, YRSALL, HrsXC, HrsOther, HrsTot, RaceComp, Wave
Model 97	Age, Height,Weight, Gender, BMT5,YRS10, YRSALL,HrsXC, HrsOther, HrsTot, RacePlnd, Wave
Model 98	Age, Height, Weight, Gender, BMT5, YRS10, YRSALL, HrsXC, HrsOther, RaceComp, RacePlnd, Wave
Model 99	Age, Height, Weight, Gender, BMT5, YRS10, YRSALL, HrsXC, HrsTot, RaceComp, RacePlnd, Wave

Table A.3.182. Overview of race time models along with octuple combinations of the predictor variables

Models	**Predictor Variables**
Model 100	Age, Height, Weight, Gender, BMT5, YRS10, YRSALL, HrsSP, HrsOther, HrsTot, RaceComp, RacePlnd
Model 101	Age, Height, Weight, Gender, BMT5, YRS10, YRSALL, HrsSP, HrsOther, rsTot, RaceComp, Wave
Model 102	Age, Height, Weight, Gender, BMT5, YRS10, YRSALL, HrsSP, HrsOther, HrsTot, RacePlnd, Wave
Model 103	Age, Height, Weight, Gender, BMT5, YRS10, YRSALL, HrsSP, HrsOther, RaceComp, RacePlnd, Wave
Model 104	Age, Height, Weight, Gender, BMT5, YRS10, YRSALL, HrsSP, HrsTot, RaceComp, RacePlnd, Wave
Model 105	Age, Height,Weight, Gender BMT5,YRS10, YRSALL,HrsOther, HrsTot, RaceComp, RacePlnd, Wave,
Model 106	Age, Height, Weight, Gender, BMT5, YRS10, HrsXC, HrsSP, HrsOther, HrsTot, RaceComp, RacePlnd
Model 107	Age, Height, Weight, Gender, BMT5, YRS10, HrsXC, HrsSP, HrsOther, HrsTot, RaceComp, Wave
Model 108	Age, Height, Weight, Gender, BMT5, YRS10, HrsXC, HrsSP, HrsOther, HrsTot, RacePlnd, Wave
Model 109	Age, Height, Weight, Gender, BMT5, YRS10, HrsXC, HrsSP, HrsOther, RaceComp, RacePlnd, Wave
Model 110	Age, Height, Weight, Gender, BMT5, YRS10, HrsXC, HrsSP, HrsTot, RaceComp, RacePlnd, Wave

Table A.3.183. Overview of race time models along with octuple combinations of the predictor variables

Models	Predictor Variables
Model 111	Age, Height, Weight, Gender, BMT5, YRS10, HrsXC, HrsOther, HrsTot, RaceComp, RacePlnd, Wave
Model 112	Age, Height, Weight, Gender, BMT5, YRS10, HrsSP, HrsOther, HrsTot, RaceComp, RacePlnd, Wave
Model 113	Age, Height, Weight, Gender, BMT5, YRSALL, HrsXC, HrsSP, HrsOther, HrsTot, RaceComp, RacePlnd
Model 114	Age, Height, Weight, Gender, BMT5, YRSALL, HrsXC, HrsSP, HrsOther, HrsTot, RaceComp, Wave
Model 115	Age, Height, Weight, Gender, BMT5, YRSALL, HrsXC, HrsSP, HrsOther, HrsTot, RacePlnd, Wave
Model 116	Age, Height,Weight, Gender, BMT5, YRSALL, HrsXC,HrsSP, HrsOther, RaceComp, RacePlnd, Wave
Model 117	Age, Height, Weight, Gender, BMT5, YRSALL, HrsXC, HrsSP, HrsTot, RaceComp, RacePlnd, Wave
Model 118	Age, Height,Weight, Gender, BMT5, YRSALL, HrsXC, HrsOther, HrsTot, RaceComp, RacePlnd, Wave
Model 119	Age, Height, Weight, Gender, BMT5, YRSALL, HrsSP, HrsOther, HrsTot, RaceComp, RacePlnd, Wave
Model 120	Age, Height, Weight, Gender, BMT5, HrsXC, HrsSP, HrsOther, HrsTot, RaceComp, RacePlnd, Wave

Table A.3.184. Overview of race time models along with octuple combinations of the predictor variables

Models	Predictor Variables
Model 121	Age, Height, Weight, Gender, BMT10, YRS10, YRSALL, HrsXC, HrsSP, HrsOther, HrsTot, RaceComp
Model 122	Age, Height, Weight, Gender, BMT10, YRS10, YRSALL, HrsXC, HrsSP, HrsOther, HrsTot, RacePlnd
Model 123	Age, Height, Weight, Gender, BMT10, YRS10, YRSALL, HrsXC, HrsSP, HrsOther, HrsTot, Wave
Model 124	Age, Height, Weight, Gender, BMT10, YRS10, YRSALL, HrsXC, HrsSP, HrsOther, RaceComp, RacePlnd
Model 125	Age, Height, Weight, Gender, BMT10, YRS10, YRSALL, HrsXC, HrsSP, HrsOther, RaceComp, Wave
Model 126	Age, Height, Weight, Gender, BMT10, YRS10, YRSALL, HrsXC, HrsSP, HrsOther, RacePlnd, Wave
Model 127	Age, Height, Weight, Gender, BMT10, YRS10, YRSALL, HrsXC, HrsSP, HrsTot, RaceComp, RacePlnd
Model 128	Age, Height, Weight, Gender, BMT10, YRS10, YRSALL, HrsXC, HrsSP, HrsTot, RaceComp, Wave
Model 129	Age, Height, Weight,Gender, BMT10,YRS10, YRSALL, HrsXC,HrsSP, HrsTot,RacePlnd, Wave
Model 130	Age, Height, Weight,Gender, BMT10,YRS10, YRSALL, HrsXC, HrsSP, RaceComp, RacePlnd, Wave
Model 131	Age, Height, Weight,Gender, BMT10,YRS10, YRSALL,HrsXC, HrsOther, HrsTot, RaceComp, RacePlnd

Table A.3.185. Overview of race time models along with octuple combinations of the predictor variables

Models	Predictor Variables
Model 132	Age, Height, Weight, Gender, BMT10, YRS10, YRSALL, HrsXC, HrsOther, HrsTot, RaceComp, Wave
Model 133	Age, Height, Weight,Gender, BMT10,YRS10, YRSALL,HrsXC, HrsOther, HrsTot, RacePlnd, Wave
Model 134	Age, Height, Weight, Gender, BMT10, YRS10, YRSALL, HrsXC, HrsOther, RaceComp, RacePlnd, Wave
Model 135	Age, Height, Weight, Gender, BMT10, YRS10, YRSALL, HrsXC, HrsTot, RaceComp, RacePlnd, Wave
Model 136	Age, Height, Weight, Gender, BMT10, YRS10, YRSALL, HrsSP, HrsOther, HrsTot, RaceComp, RacePlnd
Model 137	Age, Height, Weight, Gender, BMT10, YRS10, YRSALL, HrsSP, HrsOther, HrsTot, RaceComp , Wave
Model 138	Age, Height, Weight, Gender, BMT10, YRS10, YRSALL, HrsSP, HrsOther, HrsTot, RacePlnd, Wave
Model 139	Age, Height, Weight, Gender, BMT10, YRS10, YRSALL, HrsSP, HrsOther, RaceComp, RacePlnd, Wave
Model 140	Age, Height, Weight, Gender, BMT10, YRS10, YRSALL, HrsSP, HrsTot, RaceComp, RacePlnd, Wave
Model 141	Age, Height, Weight, Gender, BMT10, YRS10, YRSALL, HrsOther, HrsTot, RaceComp, RacePlnd, Wave
Model 142	Age, Height, Weight, Gender, BMT10, YRS10, HrsXC, HrsSP, HrsOther, HrsTot, RaceComp, RacePlnd

Table A.3.186. Overview of race time models along with octuple combinations of the predictor variables

Models	**Predictor Variables**
Model 143	Age, Height, Weight, Gender, BMT10, YRS10, HrsXC, HrsSP, HrsOther, HrsTot, RaceComp, Wave
Model 144	Age, Height, Weight, Gender, BMT10, YRS10, HrsXC, HrsSP, HrsOther, HrsTot, RacePlnd, Wave
Model 145	Age, Height, Weight, Gender, BMT10, YRS10, HrsXC, HrsSP, HrsOther, RaceComp, RacePlnd, Wave
Model 146	Age, Height, Weight, Gender, BMT10, YRS10, HrsXC, HrsSP, HrsTot, RaceComp, RacePlnd, Wave
Model 147	Age, Height, Weight, Gender, BMT10, YRS10, HrsXC, HrsOther, HrsTot, RaceComp, RacePlnd, Wave
Model 148	Age, Height, Weight, Gender, BMT10, YRS10, HrsSP, HrsOther, HrsTot, RaceComp, RacePlnd, Wave
Model 149,	Age, Height, Weight, Gender, BMT10, YRSALL, HrsXC, HrsSP, HrsOther, HrsTot, RaceComp, RacePlnd
Model 150	Age, Height, Weight, Gender, BMT10, YRSALL, HrsXC,HrsSP, HrsOther, HrsTot, RaceComp, Wave
Model 151	Age, Height, Weight, Gender, BMT10, YRSALL, HrsXC, HrsSP, HrsOther, HrsTot, RacePlnd, Wave
Model 152	Age, Height, Weight, Gender,B MT10, YRSALL, HrsXC, HrsSP, HrsOther, RaceComp, RacePlnd, Wave
Model 153	Age, Height, Weight, Gender, BMT10, YRSALL, HrsXC, HrsSP, HrsTot, RaceComp, RacePlnd, Wave

Table A.3.187. Overview of race time models along with octuple combinations of the predictor variables

Models	Predictor Variables
Model 154	Age, Height, Weight, Gender, BMT10, YRSALL, HrsXC, HrsOther, HrsTot, RaceComp, RacePlnd, Wave
Model 155	Age, Height, Weight, Gender, BMT10, YRSALL, HrsSP, HrsOther, HrsTot, RaceComp, RacePlnd, Wave
Model 156	Age, Height, Weight, Gender, BMT10, HrsXC,HrsSP, HrsOther, HrsTot, RaceComp, RacePlnd, Wave
Model 157	Age, Height,Weight, Gender,YRS10, YRSALL, HrsXC,HrsSP, HrsOther, HrsTot, RaceComp, RacePlnd
Model 158	Age, Height,Weight, Gender,YRS10, YRSALL, HrsXC,HrsSP, HrsOther, HrsTot,RaceComp, Wave
Model 159	Age, Height,Weight, Gender,YRS10, YRSALL, HrsXC,HrsSP, HrsOther, HrsTot, RacePlnd, Wave
Model 160	Age, Height,Weight, Gender,YRS10, YRSALL, HrsXC,HrsSP, HrsOther, RaceComp, RacePlnd, Wave
Model 161	Age, Height, Weight, Gender,YRS10, YRSALL, HrsXC,HrsSP, HrsTot, RaceComp, RacePlnd, Wave
Model 162	Age, Height, Weight, Gender,YRS10, YRSALL,HrsXC, HrsOther, HrsTot, RaceComp, RacePlnd, Wave
Model 163	Age, Height,Weight, Gender,YRS10, YRSALL,HrsSP, HrsOther, HrsTot, RaceComp, RacePlnd, Wave
Model 164	Age, Height, Weight, Gender, YRS10, HrsXC,HrsSP, HrsOther, HrsTot, RaceComp, RacePlnd, Wave
Model 165	Age, Height, Weight, Gender, YRSALL, HrsXC,HrsSP, HrsOther, HrsTot, RaceComp, RacePlnd, Wave

A.9. Prediction Models Created using nonuple combinations

By using nonuple combinations of the predictor variables, a total of 55 prediction models have been formed, respectively

Table A.3.188. Overview of race time models along with nonuple combinations of the predictor variables

Models	Predictor Variables
Model 1	Age, Height, Weight, Gender, BMT5, BMT10, YRS10, YRSALL, HrsXC, HrsSP, HrsOther, HrsTot, RaceComp
Model 2	Age, Height, Weight, Gender, BMT5, BMT10, YRS10, YRSALL, HrsXC, HrsSP, HrsOther, HrsTot, RacePlnd
Model 3	Age, Height, Weight, Gender, BMT5, BMT10, YRS10, YRSALL, HrsXC, HrsSP, HrsOther, HrsTot, Wave
Model 4	Age, Height, Weight, Gender, BMT5, BMT10, YRS10, YRSALL, HrsXC, HrsSP, HrsOther, RaceComp, RacePlnd
Model 5	Age, Height, Weight, Gender, BMT5, BMT10, YRS10, YRSALL, HrsXC, HrsSP, HrsOther, RaceComp, Wave
Model 6	Age, Height, Weight, Gender, BMT5, BMT10, YRS10, YRSALL, HrsXC, HrsSP, HrsOther, RacePlnd, Wave
Model 7	Age, Height, Weight, Gender, BMT5, BMT10, YRS10, YRSALL, HrsXC, HrsSP, HrsTot, RaceComp, RacePlnd
Model 8	Age, Height, Weight, Gender, BMT5, BMT10, YRS10, YRSALL, HrsXC, HrsSP, HrsTot, RaceComp, Wave
Model 9	Age, Height,Weight, Gender, BMT5, BMT10,YRS10, YRSALL, HrsXC, HrsSP, HrsTot,RacePlnd, Wave
Model 10	Age, Height, Weight, Gender, BMT5, BMT10, YRS10, YRSALL, HrsXC, HrsSP, RaceComp, RacePlnd, Wave
Model 11	Age, Height, Weight, Gender, BMT5, BMT10, YRS10, YRSALL, HrsXC, HrsOther, HrsTot, RaceComp, RacePlnd

Table A.3.189. Overview of race time models along with nonuple combinations of the predictor variables

Models	**Predictor Variables**
Model 12	Age, Height,Weight, Gender, BMT5, BMT10,YRS10, YRSALL,HrsXC, HrsOther, HrsTot,RaceComp, Wave
Model 13	Age, Height,Weight, Gender, BMT5, BMT10,YRS10, YRSALL,HrsXC, HrsOther, HrsTot,RacePlnd, Wave
Model 14	Age, Height,Weight, Gender, BMT5, BMT10,YRS10, YRSALL,HrsXC, HrsOther, RaceComp,RacePlnd, Wave
Model 15	Age, Height,Weight, Gender, BMT5, BMT10,YRS10, YRSALL, HrsXC, HrsTot, RaceComp,RacePlnd, Wave
Model 16	Age, Height,Weight, Gender, BMT5, BMT10,YRS10, YRSALL,HrsSP, HrsOther, HrsTot, RaceComp, RacePlnd
Model 17	Age, Height,Weight, Gender, BMT5, BMT10,YRS10, YRSALL,HrsSP, HrsOther, HrsTot,RaceComp, Wave
Model 18	Age, Height,Weight, Gender, BMT5, BMT10,YRS10, YRSALL,HrsSP, HrsOther, HrsTot,RacePlnd, Wave
Model 19	Age, Height, Weight, Gender, BMT5, BMT10, YRS10, YRSALL, HrsSP, HrsOther, RaceComp, RacePlnd, Wave
Model 20	Age, Height, Weight, Gender, BMT5, BMT10, YRS10, YRSALL, HrsSP, HrsTot, RaceComp, RacePlnd, Wave
Model 21	Age, Height, Weight, Gender, BMT5, BMT10, YRS10, YRSALL, HrsOther, HrsTot, RaceComp, RacePlnd, Wave
Model 22	Age, Height, Weight, Gender, BMT5, BMT10, YRS10, HrsXC, HrsSP, HrsOther, HrsTot, RaceComp, RacePlnd

Table A.3.190. Overview of race time models along with nonuple combinations of the predictor variables

Models	Predictor Variables
Model 23	Age, Height, Weight, Gender, BMT5, BMT10, YRS10, HrsXC, HrsSP, HrsOther, HrsTot, RaceComp, Wave
Model 24	Age, Height, Weight, Gender, BMT5, BMT10, YRS10, HrsXC, HrsSP, HrsOther, HrsTot, RacePlnd, Wave
Model 25	Age, Height, Weight, Gender, BMT5, BMT10, YRS10, HrsXC, HrsSP, HrsOther, RaceComp, RacePlnd, Wave
Model 26	Age, Height, Weight, Gender, BMT5, BMT10, YRS10, HrsXC, HrsSP, HrsTot, RaceComp, RacePlnd, Wave
Model 27	Age, Height,Weight, Gender, BMT5, BMT10, YRS10,HrsXC, HrsOther, HrsTot, RaceComp,RacePlnd, Wave
Model 28	Age, Height, Weight, Gender, BMT5, BMT10, YRS10, HrsSP, HrsOther, HrsTot, RaceComp, RacePlnd, Wave
Model 29	Age, Height, Weight, Gender, BMT5, BMT10, YRSALL, HrsXC, HrsSP, HrsOther, HrsTot, RaceComp, RacePlnd
Model 30	Age, Height,Weight, Gender, BMT5, BMT10, YRSALL, HrsXC,HrsSP, HrsOther, HrsTot,RaceComp, Wave
Model 31	Age, Height, Weight, Gender, BMT5, BMT10, YRSALL, HrsXC, HrsSP, HrsOther, HrsTot, RacePlnd, Wave
Model 32	Age, Height, Weight, Gender, BMT5, BMT10, YRSALL, HrsXC, HrsSP, HrsOther, RaceComp, RacePlnd, Wave
Model 33	Age, Height,Weight, Gender, BMT5, BMT10, YRSALL, HrsXC, HrsSP, HrsOther, RaceComp, RacePlnd, Wave

Table A.3.191. Overview of race time models along with nonuple combinations of the predictor variables

Models	Predictor Variables
Model 34	Age, Height, Weight, Gender, BMT5, BMT10, YRSALL, HrsXC, HrsOther, HrsTot, RaceComp, RacePlnd, Wave
Model 35	Age, Height,Weight, Gender, BMT5, BMT10, YRSALL,HrsSP, HrsOther, HrsTot, RaceComp,RacePlnd, Wave
Model 36	Age, Height,Weight, Gender, BMT5, BMT10, HrsXC,HrsSP, HrsOther, HrsTot, RaceComp,RacePlnd, Wave
Model 37	Age, Height,Weight, Gender, BMT5, YRS10, YRSALL, HrsXC, HrsSP, HrsOther, HrsTot, RaceComp, RacePlnd
Model 38	Age, Height, Weight, Gender, BMT5,YRS10, YRSALL, HrsXC, HrsSP, HrsOther, HrsTot, RaceComp, Wave
Model 39	Age, Height, Weight, Gender, BMT5, YRS10, YRSALL, HrsXC, HrsSP, HrsOther, HrsTot, RacePlnd, Wave
Model 40	Age, Height,Weight, Gender, BMT5,YRS10, YRSALL, HrsXC, HrsSP, HrsOther, RaceComp, RacePlnd, Wave
Model 41	Age, Height, Weight, Gender, BMT5, YRS10, YRSALL, HrsXC, HrsSP, HrsTot, RaceComp, RacePlnd, Wave
Model 42	Age, Height, Weight, Gender, BMT5, YRS10, YRSALL, HrsXC, HrsOther, HrsTot, RaceComp, RacePlnd, Wave
Model 43	Age, Height,Weight, Gender, BMT5,YRS10, YRSALL,HrsSP, HrsOther, HrsTot, RaceComp,RacePlnd, Wave
Model 44	Age, Height,Weight, Gender, BMT5, YRS10, HrsXC, HrsSP, HrsOther, HrsTot, RaceComp, RacePlnd, Wave
Model 45	Age, Height, Weight, Gender, BMT5, YRSALL, HrsXC, HrsSP, HrsOther, HrsTot, RaceComp, RacePlnd, Wave

Table A.3.192. Overview of race time models along with nonuple combinations of the predictor variables

Models	**Predictor Variables**
Model 46	Age, Height, Weight, Gender, BMT10, YRS10, YRSALL, HrsXC, HrsSP, HrsOther, HrsTot, RaceComp, RacePlnd
Model 47	Age, Height, Weight,Gender, BMT10,YRS10, YRSALL, HrsXC,HrsSP, HrsOther, HrsTot,RaceComp, Wave
Model 48	Age, Height, Weight, Gender, BMT10, YRS10, YRSALL, HrsXC, HrsSP, HrsOther, HrsTot, RacePlnd, Wave
Model 49	Age, Height, Weight,Gender, BMT10,YRS10, YRSALL, HrsXC,HrsSP, HrsOther, RaceComp,RacePlnd, Wave
Model 50	Age, Height, Weight, Gender, BMT10, YRS10, YRSALL, HrsXC, HrsSP, HrsTot, RaceComp, RacePlnd, Wave
Model 51	Age, Height, Weight,Gender, BMT10,YRS10, YRSALL,HrsXC, HrsOther, HrsTot, RaceComp,RacePlnd, Wave
Model 52	Age, Height, Weight, Gender, BMT10, YRS10, YRSALL, HrsSP, HrsOther, HrsTot, RaceComp, RacePlnd, Wave
Model 53	Age, Height, Weight, Gender, BMT10, YRS10, HrsXC, HrsSP, HrsOther, HrsTot, RaceComp, RacePlnd, Wave
Model 54	Age, Height,Weight, Gender, BMT10, YRSALL, HrsXC, HrsSP, HrsOther, HrsTot, RaceComp,RacePlnd, Wave
Model 55	Age, Height, Weight, Gender, YRS10, YRSALL, HrsXC, HrsSP, HrsOther, HrsTot, RaceComp, RacePlnd

A.10. Prediction Models Created using decuple combinations

By using decuple combinations of the predictor variables, a total of 11 prediction models have been formed, respectively

Table A.3.193. Overview of race time models along with decuple combinations of the predictor variables

Models	Predictor Variables
Model 1	Age, Height, Weight, Gender, BMT5, BMT10, YRS10, YRSALL, HrsXC, HrsSP, HrsOther, HrsTot, RaceComp, RacePlnd
Model 2	Age, Height, Weight, Gender, BMT5, BMT10, YRS10, YRSALL, HrsXC, HrsSP, HrsOther, HrsTot, RaceComp, Wave
Model 3	Age, Height, Weight, Gender, BMT5, BMT10, YRS10, YRSALL, HrsXC, HrsSP, HrsOther, HrsTot, RacePlnd, Wave
Model 4	Age, Height,Weight, Gender, BMT5, BMT10,YRS10, YRSALL, HrsXC, HrsSP, HrsOther, RaceComp,RacePlnd, Wave
Model 5	Age, Height, Weight, Gender, BMT5, BMT10, YRS10, YRSALL, HrsXC, HrsSP, HrsTot, RaceComp, RacePlnd, Wave
Model 6	Age, Height, Weight, Gender, BMT5, BMT10, YRS10, YRSALL, HrsXC, HrsOther, HrsTot, RaceComp, RacePlnd, Wave
Model 7	Age, Height,Weight, Gender, BMT5, BMT10,YRS10, YRSALL, HrsSP, HrsOther, HrsTot, RaceComp,RacePlnd, Wave
Model 8	Age, Height, Weight, Gender, BMT5, BMT10, YRS10, HrsXC, HrsSP, HrsOther, HrsTot, RaceComp, RacePlnd, Wave
Model 9	Age, Height, Weight, Gender, BMT5, BMT10, YRSALL, HrsXC, HrsSP, HrsOther, HrsTot, RaceComp, RacePlnd, Wave
Model 10	Age, Height, Weight, Gender, BMT5, YRS10, YRSALL, HrsXC, HrsSP, HrsOther, HrsTot, RaceComp, RacePlnd, Wave
Model 11	Age, Height, Weight, Gender, BMT10, YRS10, YRSALL, HrsXC, HrsSP, HrsOther HrsTot, RaceComp, RacePlnd, Wave

A.11. Prediction Models Created using undecuple combinations

By using undecuple combinations of the predictor variables, a total of 1 prediction models have been formed, respectively

Table A.3.194. Overview of race time models along with undecuple combinations of the predictor variables

Models	Predictor Variables
Model1	Age, Height, Weight, Gender, BMT5, BMT10, YRS10, YRSALL, HrsXC, HrsSP, HrsOther, HrsTot, RaceComp, RacePlnd, Wave

A.12. Feature Selection Based Prediction Models

Table A.3.195. Overview of racing time prediction models for racing-time-set-(1)

Models	Predictor Variables
Model 1	Age, Weight, HrsSP, HrsTot, Height, YRSALL, HrsXC, HrsOther, Sex, YRS10, RacePlnd, BMT5, BMT10, RaceComp
Model 2	Age, Weight, HrsSP, HrsTot, Height, YRSALL, HrsXC, HrsOther, Sex, YRS10, RacePlnd, BMT5, BMT10
Model 3	Age, Weight, HrsSP, HrsTot, Height, YRSALL, HrsXC, HrsOther, Sex, YRS10, RacePlnd, BMT5
Model 4	Age, Weight, HrsSP, HrsTot, Height, YRSALL, HrsXC, HrsOther, Sex, YRS10, RacePlnd
Model 5	Age, Weight, HrsSP, HrsTot, Height, YRSALL, HrsXC, HrsOther, Sex, YRS10
Model 6	Age, Weight, HrsSP, HrsTot, Height, YRSALL, HrsXC, HrsOther, Sex
Model 7	Age, Weight, HrsSP, HrsTot, Height, YRSALL, HrsXC, HrsOther
Model 8	Age, Weight, HrsSP, HrsTot, Height, YRSALL, HrsXC
Model 9	Age, Weight, HrsSP, HrsTot, Height, YRSALL
Model 10	Age, Weight, HrsSP, HrsTot, Height
Model 11	Age, Weight, HrsSP, HrsTot
Model 12	Age, Weight, HrsSP
Model 13	Age, Weight
Model 14	Age

Table A.3.196. Overview of racing time prediction models for racing-time-set-(2)

Models	Predictor Variables
Model 15	Wave, Age, Weight, HrsSP, Height, Sex, HrsTot, HrsOther, YRS10, HrsXC, RacePlnd, YRSALL, BMT5, RaceComp, BMT10
Model 16	Wave, Age, Weight, HrsSP, Height, Sex, HrsTot, HrsOther, YRS10, HrsXC, RacePlnd, YRSALL, BMT5, RaceComp
Model 17	Wave, Age, Weight, HrsSP, Height, Sex, HrsTot, HrsOther, YRS10, HrsXC, RacePlnd, YRSALL, BMT5
Model 18	Wave, Age, Weight, HrsSP, Height, Sex, HrsTot, HrsOther, YRS10, HrsXC, RacePlnd, YRSALL
Model 19	Wave, Age, Weight, HrsSP, Height, Sex, HrsTot, HrsOther, YRS10, HrsXC, RacePlnd
Model 20	Wave, Age, Weight, HrsSP, Height, Sex, HrsTot, HrsOther, YRS10, HrsXC,
Model 21	Wave, Age, Weight, HrsSP, Height, Sex, HrsTot, HrsOther, YRS10
Model 22	Wave, Age, Weight, HrsSP, Height, Sex, HrsTot, HrsOther
Model 23	Wave, Age, Weight, HrsSP, Height, Sex, HrsTot
Model 24	Wave, Age, Weight, HrsSP, Height, Sex
Model 25	Wave, Age, Weight, HrsSP, Height
Model 26	Wave, Age, Weight, HrsSP
Model 27	Wave, Age, Weight
Model 28	Wave, Age
Model 29	Wave