# Estimating Submaximal $\dot{V}O_2$ max Using Wrist-worn Wearable Technology: A Solution for Accessibility, Convenience and Accuracy

Bohan Shi, Natalie W.C. Lam, Kum Yin Loke, Entong Zhou, Jocelin Wong, Joel Chin, and Marcus Soo

***Abstract*— $\dot{V}O_2$ max is a key metric for cardio-respiratory fitness, serving as a motivator for exercise and an indicator of health risk for those with lower-than-average values. However, existing $\dot{V}O_2$ max measurement methods have significant limitations in accessibility and feasibility, making it challenging for certain populations, such as the elderly or physically infirm individuals, to obtain accurate VO2 max assessments. Most commercial wearables only measure $\dot{V}O_2$ max during running exercise, and the gold standard requires intense exercise in a lab setting, which can be challenging for some individuals. Despite this, determining their $\dot{V}O_2$ max is still crucial for their health and well-being.**

**This article presents a solution for the absence of $\dot{V}O_2$ max measurement in the general population by exploring a method to estimate it through wearable technology. Data from 50 volunteers (38 male, 22 female) was used to train a regression model that predicts $\dot{V}O_2$ max from heart rate data. A cross-sectional study measured a mean absolute error of 1.38 and 1.20 for the walk and the run model prediction, respectively. The study also measured a small positive mean error (run $-0.102 \pm 1.6$, walk $-2.9 \times 10^{-5} \pm 1.7$). A second study aimed at performing a longitudinal assessment was conducted as well ($n = 10$) and the study measured a negligible positive mean error for the predicted $\dot{V}O_2$ max (run $0.744 \pm 2.4$, walk $0.740 \pm 2.2$) in the model. The mean absolute error measured is 1.54 and 1.69 for the walk and run predictions respectively. The results show good agreement between the predicted $\dot{V}O_2$ max and ground truth, providing a reliable estimate of $\dot{V}O_2$ max.**

***Index Terms*— Connected GPS, Heart Rate, Statistical Modeling, Submaximal $\dot{V}O_2$ max estimation, Photoplethysmography, and Wrist-worn Consumer Wearable.**

## I. INTRODUCTION

The COVID-19 pandemic has disrupted daily life, making it difficult to maintain physical fitness due to closed gyms and limited team sports. However, maintaining fitness is crucial in combating the stress of isolation and reducing the risk of severe viral infection [1]. A useful metric for tracking fitness is $\dot{V}O_2$ max, or maximal oxygen uptake. It is widely accepted as the gold standard for measuring cardio-respiratory fitness (CRF) and is recognised by the World Health Organisation.

$\dot{V}O_2$ max is calculated as the millilitres of oxygen uptake per kilogram of body weight per minute ($mL/kg/min$) during maximal intensity exercise (e.g. running or cycling) [2, 3]. With greater oxygen consumption, an individual is able to unleash more energy to support aerobic exertions. However, it varies based on factors like gender, age, and personal fitness [2]. Studies have linked higher $\dot{V}O_2$ max values to a lower risk of developing certain types of cancer and a higher likelihood of survival [4]. Thus, measuring CRF through $\dot{V}O_2$ max provides a benchmark for individuals to adjust their exercise regimen and lower their risk of illnesses.

Besides serving as a goal for individuals to strive for, $\dot{V}O_2$ max is also a predictor of health and mortality. Fung et al. showed that there is a clear correlation between $\dot{V}O_2$ max and ten-year mortality [4], with those having a higher $\dot{V}O_2$ max having a more significant chance of living. Studies have also shown that individuals with a higher level of CRF have a lower risk of developing certain types of cancer, such as breast cancer and lung cancer [5, 6]. Thus, measuring CRF through $\dot{V}O_2$ max provides a benchmark for individuals to adjust their exercise regimen and lower their risk of illnesses.

Traditional methods of measuring $\dot{V}O_2$ max involve high-intensity exercise and the use of metabolic gas analyzers, making it inaccessible to many individuals, including the elderly and recovering patients [2, 3, 7]. These methods are also physically and financially demanding, adding further barriers to obtaining a $\dot{V}O_2$ max measurement. To make $\dot{V}O_2$ max more accessible, a simpler and more convenient method of estimation is necessary.

One of these methods is submaximal $\dot{V}O_2$ max estimation. It is a class of methods used to estimate the $\dot{V}O_2$ max values of an individual without requiring the participant to perform strenuous physical exercise and reach peak oxygen utilisation. The submaximal estimation approach reduces the demands on the participant and makes it more accessible to a greater proportion of the population. Grant et al. conducted a study to compare the submaximal $\dot{V}O_2$ max estimations against the maximal $\dot{V}O_2$ max measurements [7]. In their study,

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they recruited twenty-two young, healthy male volunteers to undergo a cycling ergometer test, multistage progressive shuttle run test, and Cooper 12-minute walk/run test and measured the air they expired during the test using a gas analyser. The collected data was then used to predict the $\dot{V}O_2$ max through extrapolation with the maximum heart rate [7]. Jones et al. conducted another study with 6 minutes stepper test as a physical activity while measuring the heart rate and exhaled gases and showed that even though the test was not too physically demanding, the $\dot{V}O_2$ max predicted was still acceptable [8]. These studies illustrated the viability of predicting the $\dot{V}O_2$ max based on activities that have not necessarily reached maximum intensity.

Although previous studies have shown that measuring $\dot{V}O_2$ max does not require the participant to exert themselves to exhaustion, they all require participants to possess a gas analyser to determine the amount of oxygen consumed in the expired gases. The $\dot{V}O_2$ max can also be indirectly estimated from heart rate measurements. Weyand et al. [9] managed to successfully predict $\dot{V}O_2$ max with less than 10% error by measuring a combination of heart rate and foot ground contact time measured with a device attached to the shoe. Plasqui and Westerterp [10] used heart rate data and accelerometry data from a sensor strapped to the trunk of the body to predict $\dot{V}O_2$ max. Beltrame et al. [11] utilised machine learning technique to the data collected to predict $\dot{V}O_2$ max. Finally, Sudin et al. [12] used photoplethysmography (PPG) sensors embedded in the gloves of cyclists to measure their heart rates. PPG is able to monitor the flow of blood through the blood vessels by measuring either the reflection or absorption of light incidents on human skin. With this data, Sudin et al. were able to estimate the $\dot{V}O_2$ max of the cyclists.

Since wearables, such as watches, belts and gloves, along with sensors, are able to gather sufficient data to predict the $\dot{V}O_2$ max of the individual, it is much more convenient for individuals to determine their $\dot{V}O_2$ max without having to go through the cumbersome process of measuring their maximal $\dot{V}O_2$ max, it has become more accessible, even for non-professionals to measure their CRF. This white paper introduced our in-house method of estimating $\dot{V}O_2$ max value from the PPG and connected Global Positioning System (GPS) data. The PPG data was acquired from the commercial wearable Actxa Spark+ series 2 sensor, and the GPS information was collected through the smartphone's built-in GPS. By applying various data mining and signal processing techniques, our solution can effectively identify the type of workout (e.g. running or brisk walking) and select the best segments of data for $\dot{V}O_2$ max prediction. Using the reliable segments of heart rate and GPS data as input, we have trained multiple supervised regression models, and the most robust regression model was deployed in the server to predict the $\dot{V}O_2$ max value of the participant.

Since $\dot{V}O_2$ max measures the cardio-respiratory fitness, performing such measurements typically requires some form of physical activity, though it is possible for some non-exercise methods to obtain a relatively acceptable estimate for the general population through a questionnaire [13]. There are many reliable physical tests established by past research, such as the Rockport fitness walking test [14], Cooper test [15] and the stepper test [16]. For the Rockport test, subjects are required to walk 1 mile while data is collected and it was designed for a wide range of ages (from 30 to 60) [14]. The Cooper test involves a 12-minute run for subjects while $\dot{V}O_2$ max is measured [15]. Finally, the stepper test is conducted on a stepper and is suitable for patients with chronic lung disease [16].

| | Rockport | Cooper |
|---|---|---|
| Advantages | Minimal equipment required | |
| | Can be self-administered | |
| | Wider range of population studied | Customised pace depending on individual's fitness levels |
| | Suitable for unfit individuals | |
| | Accessible for individuals with chronic illnesses | |
| Disadvantages | Results dependent on individual's personal motivation | More accurate at faster pace |

TABLE I: Comparison of advantages and disadvantages of Rockport and Cooper tests [22-25]

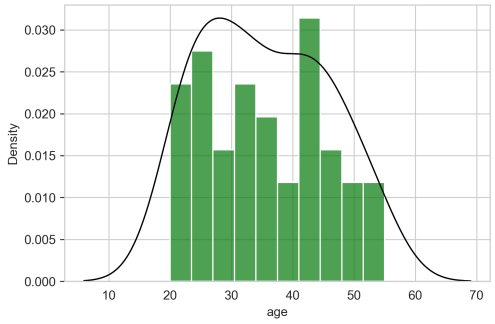
The choice of activity when measuring $\dot{V}O_2$ max is vital since different tests can yield different results. For example for the average person, the maximal $\dot{V}O_2$ max measured from a cycle ergometer is typically lower than that obtained by running on a treadmill [17-20]. To complicate matters, professional cyclists can attain higher values of $\dot{V}O_2$ max measurements when cycling compared to running due to the extensive professional cycle training [21]. As a result, careful consideration is required for the selection of the physical activity used in measuring the $\dot{V}O_2$ max and the $\dot{V}O_2$ max measured from different activities might not be directly comparable.

## II. METHODS

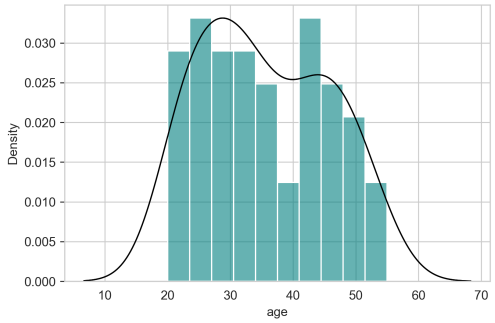
### A. Data Acquisition

Two independent data collection sessions were conducted between April 2021 to Feb 2022. The first was the cross-sectional study designed to measure samples from a relatively larger population at a single point in time, while the second was the longitudinal study designed to observe the time evolution of $\dot{V}O_2$ max predicted by the model and verify the long-term consistency and reliability of the model. For both of the data collection sessions, the procedure and instruments for data collection are the same. The heart rate measurements were collected with a consumer-grade wrist-worn wearable hereafter referred to as a tracker as well as the H10 Polar chest strap ECG device. The tracker is the primary collection device with a PPG sampling frequency of 50 Hz, and it supplies the heart rate measurement at a rate of 25 Hz. The polar ECG was used as a reference device to verify the HR data collected by the tracker and has a sampling frequency of 1000 Hz. The ground truth $\dot{V}O_2$ max measurements were obtained using a Garmin smartwatch (Forerunner 945), which is a utilization of the industry leader Firstbeat's $\dot{V}O_2$ max algorithm.

Location data was acquired with smartphones' built-in GPS module and the sophisticated background location-tracking

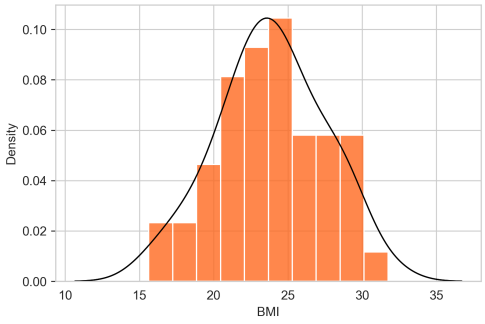



(a) Run age distribution

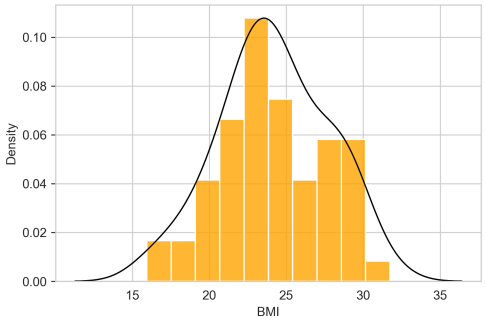



(b) Walk age distribution

Fig. 1: Age distribution among volunteers.




(a) Run BMI distribution




(b) Walk BMI distribution

Fig. 2: BMI distribution among volunteers.

and geofencing API ( React Native Background Geolocation API v4.4.4). Since the average GPS accuracy in open areas with good weather conditions is within 4.88 meters (16 feet) [26]. However, the GPS reception will be unavailable due to insufficient visible satellites or obstacles. The API will provide alternative location services using WiFi or cellular networks to maximise the accuracy of the location data collected.

*1) Cross-sectional Study:* Subjects involved in this study are healthy adult volunteers consisting of both males ($n = 38$) and females ($n = 22$) aged between 20 to 55 years. All participants have consented and signed a Personal Data Protection Act (PDPA) agreement to release the data collected for use in the study. The distribution of ages and BMI of volunteers who participated in the study are shown in Figures Figure 1 and Figure 2.

Two sets of data were collected from volunteers - the walk and the run heart rate. For the walk data, volunteers were instructed to walk at a brisk pace for 1.6 km while wearing the Polar H10 chest ECG and the wearable to collect two sets of heart rate data. Following the walk, they were given at least 30 minutes of rest before continuing for a 1.6 km run. During both instances, they wore a Garmin watch to measure their $\dot{V}O_2$ max for that session. Prior to each workout session, the Garmin watch was factory reset to input the participant's basic profile data.

The aggregated data was processed and statistically analysed through robust regression to create a model that predicts the $\dot{V}O_2$ max of an individual from their heart rate data measured from the wearable. Robust regression allows the model to reduce the impact of outliers compared to simpler models such as ordinary least squares regression.

*2) Longitudinal Study:* As part of the longitudinal study conducted to explore the long-term consistency of the model derived above. In the study, volunteers ($n = 10$) representing different age groups were invited to return for 4 additional rounds of data collection as outlined in Section Figure II-A.1. The first two sessions were conducted within a single week while the subsequent two were conducted with at least seven days intervals between them. Since the $\dot{V}O_2$ max of an individual should not change within a short period of time, this, as well as the adherence between the model prediction and Garmin prediction were taken into consideration.

## B. Data Pre-processing

It is not surprising that there is predominantly a positive correlation between heart rate and movement speed (See Figure 3) while running at a higher speed is associated with a higher heart rate (proportional to the individual's maximum heart rate). However, in real-world scenarios, an outdoor workout session might be disrupted by external factors, such as traffic conditions. Occasionally, the physically inactive user will find it challenging to maintain the same exercise intensity and might reduce the running and walking speed or stop during a walkout. The instantaneous change in movement will not be immediately reflected by a corresponding change in heart rate, and this will cause the $\dot{V}O_2$ max prediction to be wrongly estimated. Other factors also impact the tracker's HR measurement quality. For example, data might become

unstable when water or sweat passes under the watch and affect the optical sensor's reading. Lighting conditions, skin tones, and the wrist-worn tracker's fit and placement will significantly impact the HR measurements through the PPG signals.

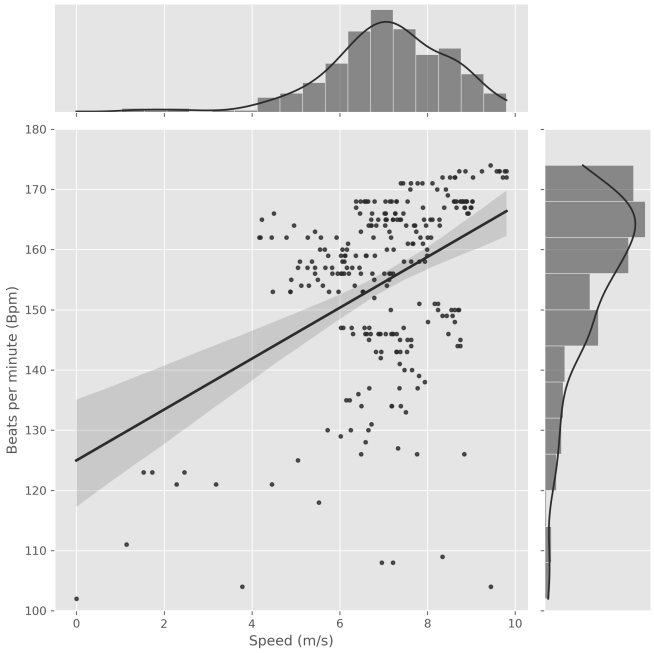



Fig. 3: The movement speed obtained from GPS has a linear relationship with heart rate.

The quality of GPS data was another challenge when the speed data from GPS could be inaccessible when the satellite signal is interfered with by buildings or clouds.

Therefore, extensive data preparation is required before feeding the data into the prediction model. Figure 4 summarised the overview of the data preparation operations.

### C. Statistical Modelling

*1) Ordinary Least Squares (OLS):* Ordinary Least Squares (OLS) is a form of linear regression that is used in estimating the relationship between a dependent variable and several observed independent variables [27, 28]. When applied in predicting $\dot{V}O_2$ max, the dependent variable is the $\dot{V}O_2$ max of the subjects while the independent variables are the data measured from the subject. OLS works by attempting to fit a linear equation to the independent variables while minimising the sum of squared errors. While common, OLS is susceptible to outliers which can adversely affect the accuracy of the resultant model.

*2) Robust Regression (RE):* Robust Regression (RE) is another form of linear regression that is less sensitive to the presence of outliers [29, 30]. Therefore, RE is more likely to fit a better model with noisy data. Due to the nature of the data collection, the subjects are required to undergo intense physical activity which introduces motion artefacts and noise, especially for the heart rate measurements. RE can therefore be used to minimise the effect of these outliers on the trained model from the noisy data, thus improving the model performance.

## III. RESULTS

Using the methods introduced in the previous chapter and the data collected from the cross-sectional study, a model that could predict the $\dot{V}O_2$ max from the anthropometric data, workout data and GPS data (speed and distance travelled) was trained. The model was then further evaluated based on its performance based on the data collected from the cross-sectional study and the longitudinal study.

### A. Cross-sectional Study Result

The model was trained on data obtained from the cross-sectional study. Only a single measurement from each subject is included in the training data set. The subsequent measurements were used to validate the performance of the model once it has been trained. Using the heart rate data as well as the physical parameters of the volunteers, the model estimates the $\dot{V}O_2$ max of each volunteer for each of their walk and run sessions. This prediction is compared against the $\dot{V}O_2$ max values measured by the Garmin watch measuring the error. The distribution of the prediction errors is shown in Figure 5 for the validation data. Both the walk and run predictions have a small negative mean error (run $-0.102 \pm 1.6$, walk $-2.9 \times 10^{-5} \pm 1.7$). Overall, the model performs well with a mean absolute error of $1.20$ and $1.38$ for the run and walk predictions respectively.

Figure 6a displays the Bland Altman plot of the walk data while Figure 6b shows the plot for the run data. The Bland Altman plot accesses the agreement between the Garmin measurements and the model predictions for both the walk and run data taken from the cross-sectional study. The figures also show the negative biases of the model predictions with the walk error very close to 0.

### B. Longitudinal Study

The longitudinal study was conducted to determine the performance of the model trained with data in the cross-sectional study. It was conducted in the same manner as the cross-sectional study, except that there were fewer subjects while the number of measurements per subject increased. Using the model trained in the cross-sectional study, the model prediction of the $\dot{V}O_2$ max values from the measured data is compared with the $\dot{V}O_2$ max values measured by the Garmin watch. The distribution of the errors is shown in Figure 7. Both the walk and run predictions have a small positive mean error (run $0.744 \pm 2.4$, walk $0.740 \pm 2.2$). The $\dot{V}O_2$ max of the model thus has a mean absolute error of $1.54$ and $1.69$ for the walk and run predictions respectively.

## IV. DISCUSSION AND CONCLUSIONS

In this article, we presented a complete solution to predict submaximal $\dot{V}O_2$ max. Figure 8 illustrates the workflow of our $\dot{V}O_2$ max solution. A sophisticated pre-processing module will convert the user's profile and workout data into the pre-defined

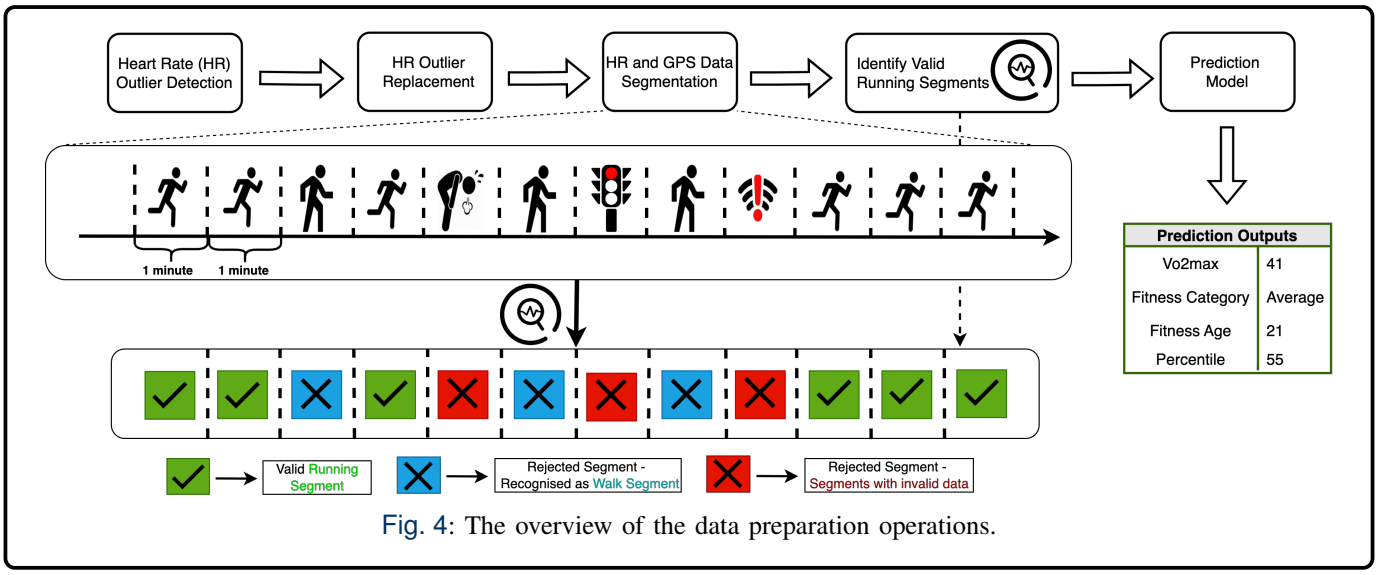



Fig. 4: The overview of the data preparation operations.

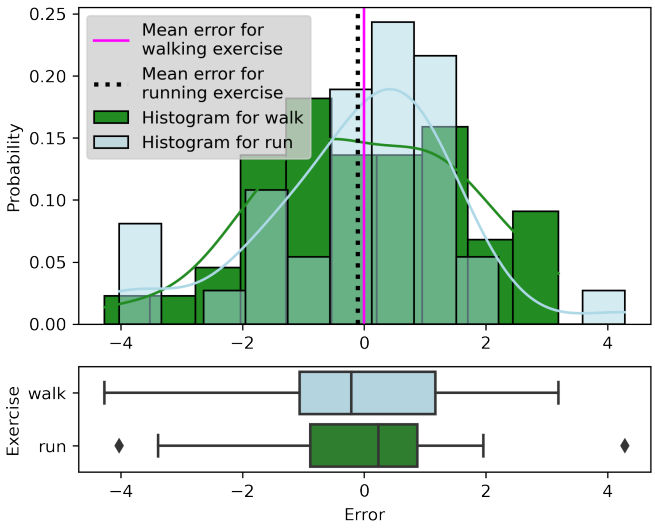
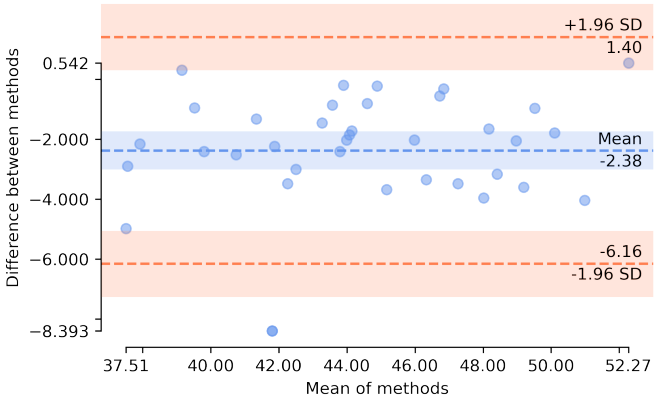
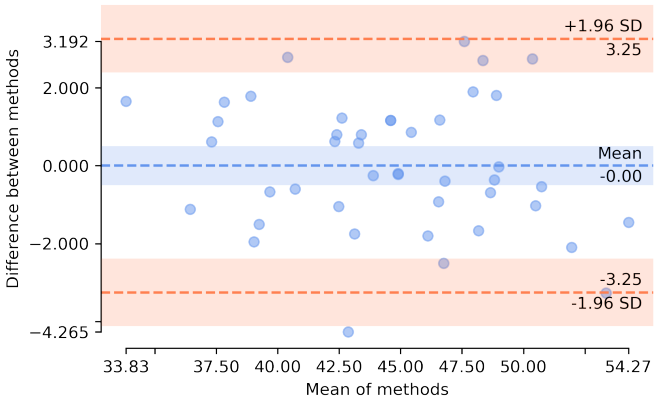



Fig. 5: Cross-sectional study differences between $\dot{V}O_2$ max predictions and Garmin measurements for walk and run.




(a) Bland Altman plot for running




(b) Bland Altman plot for walking

Fig. 6: Bland Altman plot of cross-sectional study data comparing the model prediction with Garmin measurements.

data structure and select only the quality data to feed into the prediction model. The ML prediction module will determine the type of workout and select the optimal formula to predict the $\dot{V}O_2$ max, and the prediction outcome will be stored in the server to allow the users to review the change in $\dot{V}O_2$ max. The prediction model for both types of workouts achieved similar performance with negligible prediction bias as well as a tight grouping compared to the actual $\dot{V}O_2$ max reading.

The prediction model will be further validated through a clinical validation study with laboratory measurements of maximal $\dot{V}O_2$ max, the gold standard for $\dot{V}O_2$ max measurements. This new study will require the cooperation of laboratories with dedicated equipment as well as volunteers of sufficient fitness to withstand the rigours of exercising to their peak physical performance. This study will provide gold-standard measurement data for the fitter proportion of the population.

Besides the physically fit population, the model should also be validated for the less physically fit population. Therefore, another study has to be conducted to validate the prediction model on the elderly and the physically infirm. Since these

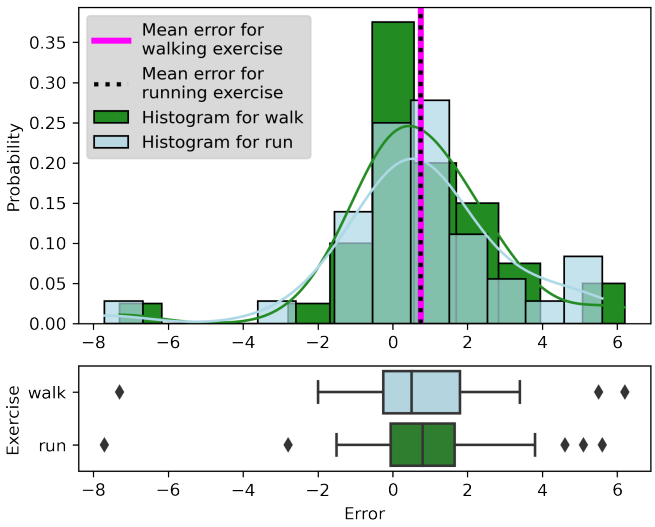



Fig. 7: Longitudinal study differences between $\dot{V}O_2$ max predictions and Garmin measurements for walk and run.

sections of the population are unlikely to be able to withstand the rigours of maximal $\dot{V}O_2$ max measurements, a device that can estimate their cardio-respiratory fitness is very welcome. Ensuring that the prediction model performs well for these segments of the population or establishing the limitations of the model will be the aim of this study.

Overall, in this article, the prediction model was trained to estimate $\dot{V}O_2$ max from heart rate data as well as exercise statistics. The model was then evaluated using data measured from volunteers during the two studies, and the result validated the model to be a good predictor for the $\dot{V}O_2$ max. Our solution has a great potential to benefit and impact individuals with different fitness levels and even the elderly with underlying health conditions.

## References


[1] R. J. Simpson and E. Katsanis, "The immunological case for staying active during the covid-19 pandemic," *Brain, behavior, and immunity*, vol. 87, p. 6, 2020.

[2] B. Strasser and M. Burtscher, "Survival of the fittest: Vo2max, a key predictor of longevity," *Front Biosci (Landmark Ed)*, vol. 23, no. 23, pp. 1505–1516, 2018.

[3] D. C. Poole and A. M. Jones, "Measurement of the maximum oxygen uptake vo2max: Vo2peak is no longer acceptable," *Journal of applied physiology*, vol. 122, no. 4, pp. 997–1002, 2017.

[4] E. Fung, L. Ting Lui, F. Gustafsson, F. C. Yau, J. C. Leung, P. Wiklund, M.-R. Järvelin, P. S. Macdonald, and J. Woo, "Predicting 10-year mortality in older adults using vo2max, oxygen uptake efficiency slope and frailty class," *European journal of preventive cardiology*, vol. 28, no. 10, pp. 1148–1151, 2021.

[5] J. B. Peel, X. Sui, S. A. Adams, J. R. Hébert, J. W. Hardin, and S. N. Blair, "A prospective study of cardiorespiratory fitness and breast cancer mortality," *Medicine and science in sports and exercise*, vol. 41, no. 4, p. 742, 2009.

[6] X. Sui, D.-c. Lee, C. E. Matthews, S. A. Adams, J. R. Hébert, T. S. Church, C.-D. Lee, and S. N. Blair, "The influence of cardiorespiratory fitness on lung cancer mortality," *Medicine and science in sports and exercise*, vol. 42, no. 5, p. 872, 2010.

[7] S. Grant, K. Corbett, A. Amjad, J. Wilson, and T. Aitchison, "A comparison of methods of predicting maximum oxygen uptake." *British journal of sports medicine*, vol. 29, no. 3, pp. 147–152, 1995.

[8] S. Jones, T. Tillin, S. Williams, E. Coady, N. Chaturvedi, and A. D. Hughes, "Assessment of exercise capacity and oxygen consumption using a 6 min stepper test in older adults," *Frontiers in physiology*, vol. 8, p. 408, 2017.

[9] P. G. Weyand, M. Kelly, T. Blackadar, J. C. Darley, S. R. Oliver, N. E. Ohlenbusch, S. W. Joffe, and R. W. Hoyt, "Ambulatory estimates of maximal aerobic power from foot-ground contact times and heart rates in running humans," *Journal of Applied Physiology*, vol. 91, no. 1, pp. 451–458, 2001.

[10] G. Plasqui and K. R. Westerterp, "Accelerometry and heart rate as a measure of physical fitness: proof of concept." *Medicine and science in sports and exercise*, vol. 37, no. 5, pp. 872–876, 2005.

[11] T. Beltrame, R. Amelard, A. Wong, and R. L. Hughson, "Prediction of oxygen uptake dynamics by machine learning analysis of wearable sensors during activities of daily living," *Scientific reports*, vol. 7, no. 1, pp. 1–8, 2017.

[12] S. Sudin, A. Shakaff, A. Zakaria, A. Salleh, F. Saad, and A. Abdullah, "Cyclist performance classification system based on submaximal fitness test," *Journal of Telecommunication, Electronic and Computer Engineering (JTEC)*, vol. 10, no. 1-13, pp. 73–78, 2018.

[13] S. M. Schembre and D. A. Riebe, "Non-exercise estimation of vo2max using the international physical activity questionnaire," *Measurement in physical education and exercise science*, vol. 15, no. 3, pp. 168–181, 2011.

[14] F. A. Dolgener, L. D. Hensley, J. J. Marsh, and J. K. Fjelstul, "Validation of the rockport fitness walking test in college males and females," *Research quarterly for exercise and sport*, vol. 65, no. 2, pp. 152–158, 1994.

[15] B. Das, "Estimation of maximum oxygen uptake by evaluating cooper 12-min run test in female students of west bengal, india," *Journal of Human Sport and Exercise*, vol. 8, no. 4, pp. 1008–1014, 2013.

[16] J. Grosbois, C. Riquier, B. Chehere, J. Coquart, H. Béhal, F. Bart, B. Wallaert, and C. Chenivesse, "Six-minute stepper test: a valid clinical exercise tolerance test for copd patients," *International journal of chronic obstructive pulmonary disease*, vol. 11, p. 657, 2016.

[17] G. Keren, A. Magazanik, and Y. Epstein, "A comparison of various methods for the determination of vo2max," *European journal of applied physiology and occupational physiology*, vol. 45, no. 2, pp. 117–124, 1980.

[18] P.-O. Åstrand, "Quantification of exercise capability and evaluation of physical capacity in man," *Progress in cardiovascular diseases*, vol. 19, no. 1, pp. 51–67, 1976.

[19] L. Hermansen and B. Saltin, "Oxygen uptake during maximal treadmill and bicycle exercise." *Journal of applied physiology*, vol. 26, no. 1, pp. 31–37, 1969.

[20] E. Kamon and K. B. Pandolf, "Maximal aerobic power during laddermill climbing, uphill running, and cycling." *Journal of Applied Physiology*, vol. 32, no. 4, pp. 467–473, 1972.

[21] J. M. Hagberg, M. Giese, and R. Schneider, "Comparison of the three procedures for measuring $\dot{V}O_2$ max in competitive cyclists," *European Journal of Applied Physiology and Occupational Physiology*, vol. 39, no. 1, pp. 47–52, 1978.

[22] C. Kline, J. P. Porcari, R. Hintermeister, P. S. Freedson, A. Ward, R. F. McCarron, J. Ross, and J. Rippe, "Estimation of from a one-mile track walk, gender, age and body weight," *Med. Sports Exerc*, vol. 19, pp. 253–259, 1987.

[23] S. M. Teo-Koh, "Relationship between peak vo2 and performance on the rockport fitness walking test of adolescent males with mental retardation," 1994.

[24] K. H. Cooper, "A means of assessing maximal oxygen intake: correlation between field and treadmill testing," *Jama*, vol. 203, no. 3, pp. 201–204, 1968.

[25] V. Noonan and E. Dean, "Submaximal exercise testing: clinical application and interpretation," *Physical therapy*, vol. 80, no. 8, pp. 782–807, 2000.

[26] F. Van Diggelen and P. Enge, "The world's first gps mooc and worldwide laboratory using smartphones," in *Proceedings of the 28th international technical meeting of the satellite division of the institute of navigation (ION GNSS+ 2015)*, 2015, pp. 361–369.

[27] D. Montgomery and E. Peck, "Introduction to linear regression analysis., 2nd edn.(john wiley & sons: New york.)," 1992.

[28] R. Davidson, J. G. MacKinnon *et al.*, *Econometric theory and methods*. Oxford University Press New York, 2004, vol. 5.

[29] W. N. Venables and B. D. Ripley, *Modern applied statistics with S-PLUS*. Springer Science & Business Media, 2013.

[30] P. J. Huber and E. M. Ronchetti, "Robust statistics john wiley & sons," *New York*, vol. 1, no. 1, 1981.

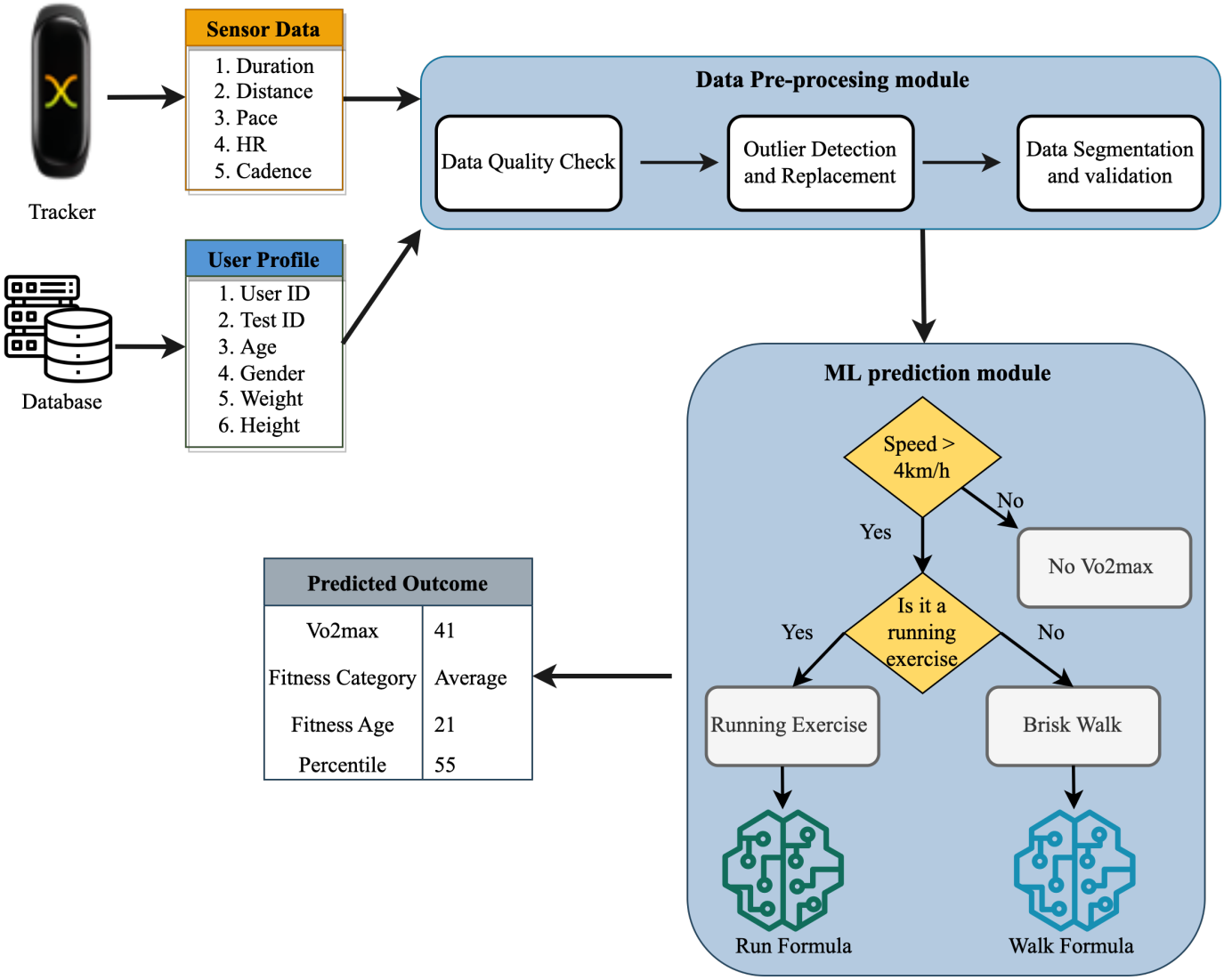



Fig. 8: The workflow of $\dot{V}O_2$ max solution.