Using Apple Watch to measure heart rate, calorimetry, and activity

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Overview

This paper highlights the methodologies, research studies, and variables that Apple evaluates and uses when developing Apple Watch heart rate and calorimetric capabilities, along with their associated algorithms. It also provides guidance on best practices to follow to ensure optimal performance.

The paper reviews the underlying hardware and software technologies of Apple Watch that measure heart rate, estimate calories burned, and serve as the basis for associated heart health and fitness features. It begins by detailing the development and validation of the optical heart sensor. It then discusses how Apple Watch uses sensor fusion and machine learning (ML) models to provide heart rate monitoring throughout the day. The paper explores the methodology for calorie measurement on Apple Watch, covering best practices in estimating calories burned during the day. It explains how combining ML-based models for activity classification, combined with workout context, heart rate, acceleration, rotation, elevation, and geolocation signals can augment calorimetry models. Next, the paper evaluates the development and validation of calorimetry estimates across different workout types and details the approach to sensor fusion and how it prioritizes information depending on the workout type. In addition, it examines various health and fitness features informed by heart rate and calorimetry data. Finally, the paper outlines several options for accessing the data and features provided by Apple Watch.

Data collection for the development and validation of heart rate and calorimetry measurements across multiple studies was approved by an internal review board, additional approval was obtained from an institutional review board (IRB) as needed, with participants consenting to the collection and use of their data for this purpose.

Measuring heart rate

Introduction

Heart rate and its response to activity are important indicators of health and fitness. If the heart beats too quickly or too slowly, or if it beats with an irregular rhythm, it may be a sign of a significant change in health and fitness. Apple Watch enables users to monitor their heart rate and gain insights into their cardiovascular health using two sensor modalities: an optical heart sensor and an electrical heart sensor.

All Apple Watch models are equipped with an optical heart sensor, capable of measuring heart rate during user-initiated activities such as those in the Heart Rate app, Workout app, and Mindfulness app. It also performs background measurements throughout the day, without requiring users to interact with their watch. From these readings, Apple Watch provides additional insights and notifications, including resting heart rate, walking heart rate average, cardio recovery, high and low heart rate notifications, irregular rhythm notifications, AFib History, calorimetry, and cardio fitness.

This section reviews the development, validation, and performance of the optical heart sensor and the foundational heart rate algorithms on Apple Watch. It also discusses how Apple Watch uses the optical heart rate monitoring capability to inform heart rate features.

For detailed information regarding the development, validation, and performance of the electrical heart sensor, please visit Using Apple Watch for Arrhythmia Detection.

Optical heart sensor

Principles of operation

All Apple Watch models include an optical heart sensor located on the back of the watch. This sensor uses infrared and green LEDs, paired with light-sensitive photodiodes, to measure heart rate at the wrist via photoplethysmography (PPG). When the heart beats, the volume of blood in the wrist increases, leading to increased light absorption. Between beats, blood volume and light absorption decrease. Apple Watch records heart rate based on the fluctuation in light absorption by rapidly flashing its LEDs and using the photodiodes to measure the returned light. The infrared LEDs monitor heart rate in the background throughout the day, invisible to the user. During user-initiated workouts, Apple Watch uses the green LEDs to better accommodate heart rate measurements in challenging motion scenarios. Operating the sensor with the green LEDs consumes more battery than when using the infrared LEDs.

Figure 1 on the following page shows the sensor layout on Apple Watch Series 6, representative of Apple Watch Series 6 and later and Apple Watch Ultra 1 and later.

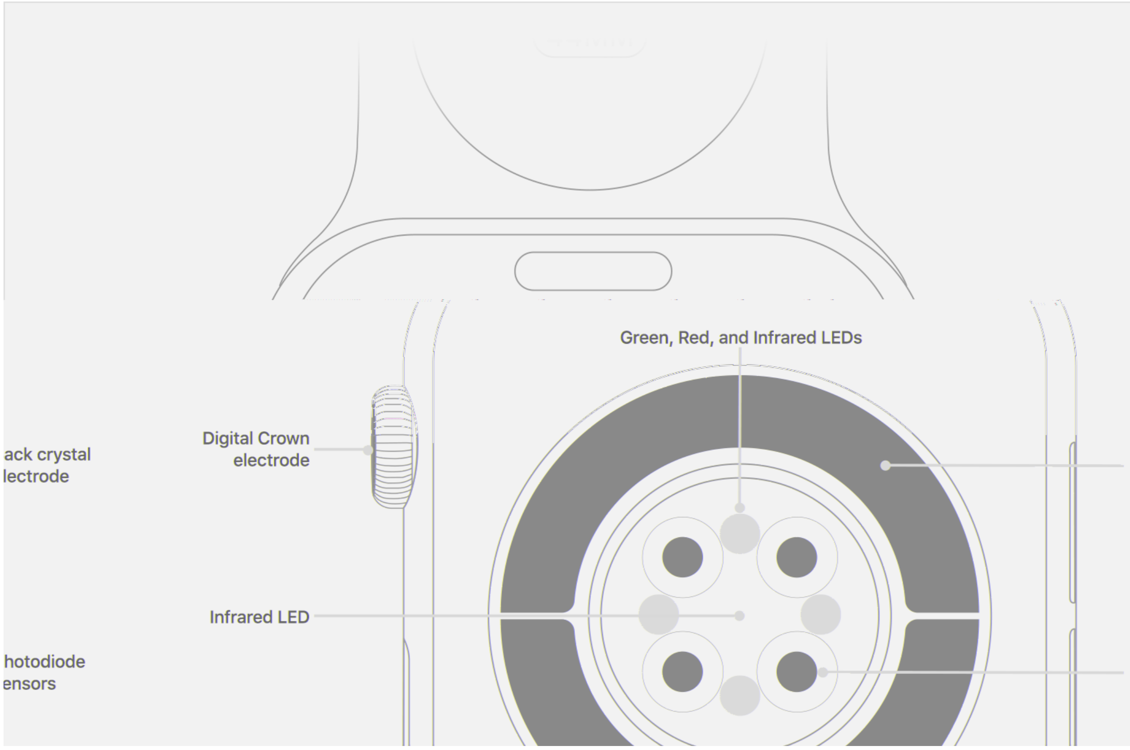

Figure 1. Apple Watch Series 6 sensor layout.

Development

Understanding the structures present in wrist tissue was crucial in developing the optical heart sensor for Apple Watch. Arteries contain the desired heartbeat signal but constitute only approximately 30 percent of the tissue's blood. The remaining blood is found in veins, is nonpulsatile, and is highly influenced by user motion. A sensor that samples deeper vessels can interrogate more tissue and may have a stronger heartbeat signal, but it also samples wider vessels, which are more prone to motion artifacts caused by blood inertia during motion. It may also be more sensitive to motion artifacts from muscles and tendons. In contrast, sensors sampling shallower vessels may produce signals too weak to reliably measure some users' heartbeats.

Motion artifacts are one of the most important factors influencing the optimal sensor design. Many properties of the sensor can affect its motion tolerance, including:

- LED-photodiode separation distance
- Shape of the optical illumination profile
- Number of individual sensor locations on the skin (when sensors are used simultaneously, algorithms can focus on areas of skin with better signal or fewer motion artifacts)
- Light wavelength
- Back crystal shape
- Back crystal material
- Watch band tightness

In addition to physiological sensitivities, hardware susceptibility to aggressors (confounding sources of error) must also be minimized. This includes rejecting ambient light from the signal — for example, sunlight or flickering indoor light sources such as LED lighting — and ensuring that the sensor can coexist without interference from a variety of other electrical and optical signals in a small form factor. To develop a sensor that meets all these requirements, Apple employed the following techniques:

- Conducting research studies with motion, which required building research hardware and testing across many cohorts and activity types
- Performing optical modeling of sensor hardware and tissue properties
- Validating and refining optical models across a diverse cohort of users
- Collecting data across activities and cohorts from regions throughout the world to develop algorithms and refine hardware

Figure 2 shows an example of a research study conducted during the development of the Apple Watch optical sensor. The study used a custom optical fiber-based sensor to explore multiple potential design concepts simultaneously without needing to switch devices on the arm, including various wavelengths and source-receiver separations during motion. It yielded valuable information about how to make the best possible sensor across a range of conditions and users.

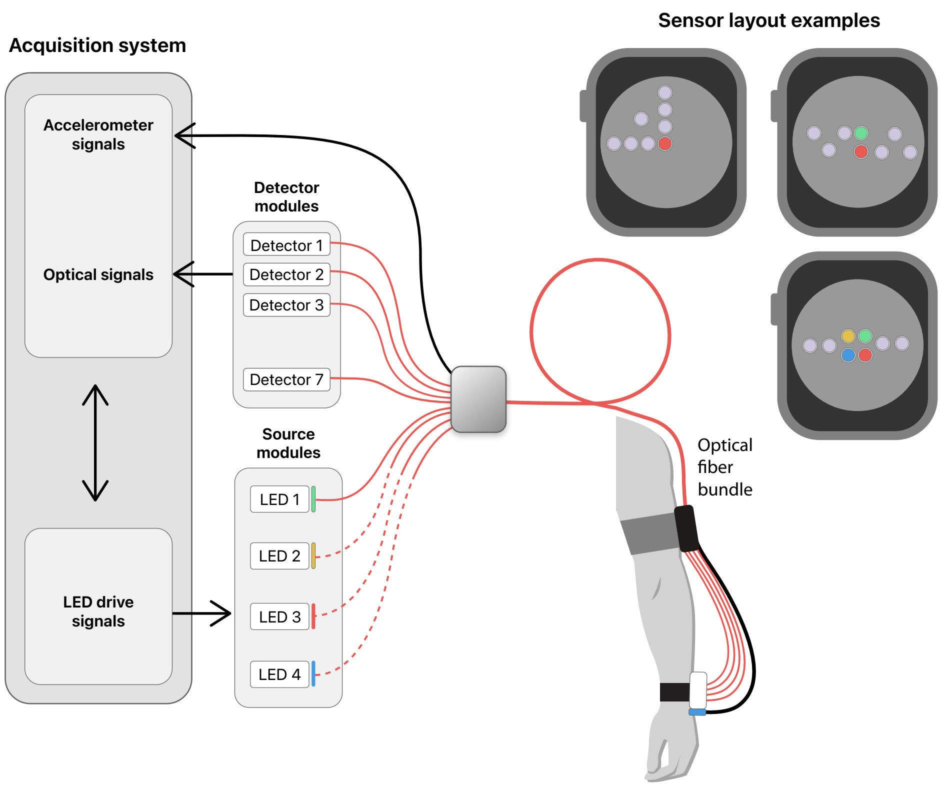

Figure 2. The setup of an optical fiber-based system that was used to develop the Apple Watch optical sensor. This system, which could be worn during a variety of activities, allowed the testing of various combinations of optical sources, with separate optical fiber bundles placed in unique locations to receive light that had passed through the skin before exiting at a different location.

Validation

The performance of heart rate measurements on Apple Watch has been validated across a broad range of physiological and environmental factors that can impact signal quality, including skin variability, skin perfusion, watch band fit, and motion. With each update to Apple Watch hardware and software, sensor performance is revalidated to ensure continued high-quality results.

Skin variability

Making sure that Apple Watch performs well for all users, across the full global range of skin types and tones, significantly influenced hardware design and validation. Melanin strongly absorbs light at the wavelengths used by the Apple Watch optical sensor — particularly in the green part of the spectrum — potentially making PPG measurements more challenging for users with darker skin tones. To account for this, the Apple Watch sensing platform automatically adjusts the LED current (and hence the light output), photodiode gain (sensitivity to light), and sampling rate to achieve adequate signal resolution across the full global range of human skin tones. Permanent or temporary changes to skin, such as tattoos, can impact heart sensor performance. The ink, pattern, and saturation of some tattoos can block light from the sensor, making it difficult to get reliable readings.

Skin perfusion

Skin perfusion — the amount of blood flow present in the tissue — is another major factor in the optical heart sensor's measurement efficacy. Perfusion varies significantly from person to person due to physiological differences, such as skin composition, body mass index (BMI), and body temperature, and can also be impacted by the user's environment. For example, when users exercise in the cold or swim in a pool, blood vessels may undergo vasoconstriction, especially in a user's extremities. This may cause skin perfusion in the wrist to be too low for the heart sensor to obtain a high-quality measurement.

Watch band usage

For best results, Apple Watch should be worn snugly but comfortably. To obtain optimal measurements, the back of Apple Watch needs continuous skin contact with the optical heart sensor. Watch band material may affect how tightly a user chooses to wear their watch, but it doesn't impact heart rate measurements after accounting for band tightness. Please visit the Wearing your Apple Watch page to learn more about achieving a good fit and potential skin sensitivities.

User activity

The optical heart sensor has been developed to optimize performance across a wide range of activities and ambient conditions. Heart rate algorithms use accelerometer signals to suppress motion-induced noise from PPG signals, and they withhold measurements if the PPG signal is corrupted by motion. Rhythmic movements, such as running or cycling, are easier to track and provide more reliable measurements compared with irregular movements like tennis or boxing. Activities that involve significant finger or wrist movements are also challenging due to additional artifacts introduced by muscle and tendon motion. Measuring heart rate during activities such as swimming can be difficult due to water disrupting the interface between the sensor and skin, as well as cold water causing vasoconstriction, which reduces blood perfusion in the skin. Apple Watch maintains robust performance in features such as calorimetry — regardless of heart rate availability — with other sensor signals. This is discussed in more detail in the Calorimetry algorithms section.

Hardware validation studies

When developing and validating a new generation of the Apple Watch optical sensor, multiple types of studies are conducted:

- **Stationary signal studies** assess the strength of the received signal across a diverse range of participants in stationary settings.
- **Ambient light rejection studies** collect data in various indoor and outdoor environments to validate measurements in different lighting scenarios.
- **Cold chamber studies** capture data in cold environments to validate performance when skin perfusion and PPG signal quality are low.
- **Motion studie**s collect data during a variety of exercises to optimize hardware design and validate performance across diverse ambient conditions.
- **Fine motion studies** gather data during stationary use cases to determine the quality of beat-to-beat measurements in the presence of small motions, during which the watch remains stationary — such as when tapping fingers while the wrist rests on a surface.
- **Everyday use studies** check product performance during real-world use

Key variable studied	Stationary signal study	Ambient light rejection study	Cold chamber study	Motion study	Fine motion study	Everyday use study
Optical model validation	✓	✓				
Skin tone	✓	✓	✓	✓	✓	✓
Skin perfusion	✓		✓	✓	✓	✓
BMI	✓					✓
Age	✓					✓
Skin site variability	✓		✓	✓		✓
Band tightness	✓	✓		✓	✓	✓
Exercise type			✓	✓		✓
Small hand motion			✓		✓	✓
Climate	✓		✓	✓	✓	✓
Ambient lighting	✓	✓		✓		✓
Uncontrolled environment	✓					✓

Table 1. Summary of the study types used to validate the key variables.

Heart rate algorithms

Apple Watch uses three heart rate algorithms to support heart rate monitoring across a diverse range of use cases. The foreground heart rate algorithm optimizes performance for a variety of common activities and is primarily used to support user-initiated measurement, regardless of whether the user is active or still. It attempts to provide one heart rate measurement in beats per minute (bpm) every five seconds. The background algorithm monitors heart rate throughout the day but reports measurements only when the user is still. It attempts to report one heart rate in bpm every 5 minutes. The tachogram algorithm measures pulse-to-pulse intervals in milliseconds to inform Heart Rate Variability (HRV) and irregular rhythm detection. Together, these algorithms support heart rate measurement in a range of 30 to 210 bpm.

The latest versions of these three foundational heart rate algorithms use ML models trained on large and diverse research studies to fuse information from multiple PPG sensors and accelerometers, extracting reliable heart rate information across a variety of activities and ambient conditions. The two key types of metrics for evaluating the heart rate performance of these algorithms are accuracy (relative to ground truth heart rate) and availability (the fraction of time that heart rate measurements are available). The heart rate algorithms on Apple Watch prioritize accuracy over availability, withholding measurements when they determine that sensor signals are inadequate to support reliable heart rate readings. This section of the paper details the development and validation of the three foundational heart rate algorithms and their performance, including accuracy and availability.

Later sections — including Heart rate features, Measuring calories, and Additional fitness features — explore how Apple Watch uses the heart rate monitoring capability provided by the three foundational algorithms to enable additional downstream health and fitness features. The paper also describes how Apple Watch maintains robust performance — regardless of heart rate availability — for features such as calorimetry.

Foreground heart rate algorithm

The foreground heart rate algorithm consumes green PPG and accelerometer signals. It's primarily used to measure heart rate when users open the Heart Rate app or start a workout session in the Workout app. In every non-overlapping five seconds window, the algorithm chooses one heart rate measurement with the highest quality to display and publish to HealthKit.

The algorithm was developed and validated using Apple Watch sensor data and reference heart rate data collected from over one hundred thousand indoor and outdoor workout sessions, covering various workout types such as walking, running, cycling, and high-intensity interval training (HIIT). The studies recruited participants across diverse demographics, including sex, BMI, race, ethnicity, and skin tone. Some studies were conducted in Apple laboratories and global field study sites, where participants followed step-by-step instructions for indoor or outdoor activities at different exertion levels. Other studies involved real-world wear of Apple Watch over extended periods, with participants recording workouts in their chosen environments and at their preferred exertion levels. All sessions collected ground truth heart rate data using chest strap heart rate monitors or ECG monitors simultaneously.

Table 2 on the following page summarizes the performance of the foreground heart rate algorithm across a variety of common activities during a subset of sessions from subjects not used for ML model training or hyperparameter tuning.

	Average foreground heart rate performance			
Activity	**Measurements within 5 bpm of truth (%)**	**Measurements within 10 bpm of truth (%)**	**Availability (%)**	**Test data†**
Sedentary activity	98	99.7	99	410 sessions, 60 hours
Walking (all terrain / conditions)	87	95	91	6,770 sessions, 3,060 hours
Walking (treadmill, lab conditions)	96	99	99	630 sessions, 180 hours
Running (all terrain / conditions)	88	94	88	2,420 sessions, 1,260 hours
Running (treadmill, lab conditions)	96	98	97	370 sessions, 160 hours
Cycling (all terrain / conditions)	96	99	97	1,480 sessions, 1,010 hours
Cycling (stationary bike, lab conditions)	99	99.8	99	100 sessions, 30 hours
HIIT	91	97	95	630 sessions, 440 hours
Yoga	92	98	96	1,010 sessions, 660 hours
Other	89	96	93	8,270 sessions, 5,160 hours

Table 2. Performance is measured with a five-second reporting cadence across all activity sessions. Accuracy is defined as the fraction of published measurements within 5 or 10 bpm of the truth from a chest strap reference. Availability represents the fraction of time when heart rate is reported. Activity type is determined based on study protocol (for example, the sedentary protocol in the table required no movement during data collection) or the type of workout recorded by the study participant. The majority of walking, running, and cycling sessions were conducted under natural usage, spanning a broad range of terrain, environmental conditions and participant behavior. Additionally, a small subset of sessions were collected in Apple laboratories under controlled conditions using treadmills and stationary exercise equipment. These laboratory-based exercise sessions tend to yield significantly higher accuracy and availability. †Test data excludes all sessions from subjects used in ML model training and hyperparameter tuning.

Background heart rate algorithm

The background heart rate algorithm consumes infrared PPG and accelerometer signals to measure heart rate throughout the day without requiring users to interact with their watch. Because infrared PPG is sensitive to motion artifacts, all background heart measurements are limited to times when the user is still (that is, acceleration in any direction is below a minimal threshold). In every non-overlapping five minutes window, Apple Watch attempts to publish one background heart rate to HealthKit, with availability subject to signal quality and user motion.

The algorithm was developed using Apple Watch sensor data and ECG or chest strap reference heart rate data collected during tens of thousands of hours of real-world wear, with a diverse range of activity levels and environments (for example, home, workplace, indoor, outdoor, and typical daily use). Participants with high or low heart rates were included in the studies to cover the full range of heart rates supported by Apple Watch.

Apple Watch SE, Apple Watch Series 4, and Apple Watch Series 5 use version 1 of the background heart rate algorithm. Apple Watch Series 6 and later and all Apple Watch Ultra models use the updated version 2 of the algorithm to measure heart rate. Version 2 is an ML model that provides improved accuracy, developed and validated using Apple Watch sensor data and reference ground truth spanning over 50,000 hours from more than 1,000 subjects. Table 3 summarizes the algorithm's performance on a real-world data set of 21,000 hours of daily living from 480 subjects not used for ML model training or hyperparameter tuning.

	Average background heart rate performance			
Algorithm version	**Measurements within 5 bpm of truth (%)**	**Measurements within 10 bpm of truth (%)**	**Average reports per hour**	**Test data†**
V1 (available on Apple Watch SE, Apple Watch Series 4, and Apple Watch Series 5)	72	85	12	480 subjects, 21,000 hours
V2 (available on Apple Watch Series 6 and later and Apple Watch Ultra)	89	97	12	

Table 3. Algorithm performance is presented for measurements made in the background during daily living when the user is still at a five-minute cadence for the average user in the data set. Accuracy is defined as the fraction of published measurements within 5 or 10 bpm of the truth from a chest strap reference. Availability represents the average number of published measurements per hour. The analysis compares both versions of the algorithm applied to the same PPG data. Results demonstrate the improvement in performance achieved using ML techniques in V2. †Test data excludes all sessions from subjects used in ML model training and hyperparameter tuning.

Tachogram algorithm

The tachogram algorithm consumes green PPG and accelerometer signals to produce a tachogram — a list of the time between heartbeats — while the user is still. It captures tachograms opportunistically in the background throughout the day. Based on these background recordings, Apple Watch provides HRV measurements, irregular rhythm detection, and AFib History monitoring. The algorithm also measures tachograms during a user-initiated Breathe session in the Mindfulness app, which asks users to remain still.

The tachogram algorithm was developed using Apple Watch sensor data and ECG reference data collected during various conditions and user behaviors, such as daytime and overnight wear, fine motion, hand tremors, reduced wrist perfusion, rapid ventricular response in arrhythmias like AFib, riding in a car, and deep breathing. For more information on the development and validation of the tachogram algorithm, please review Using Apple Watch for Arrhythmia Detection.

Table 4 summarizes the performance of the tachogram algorithm on a subset of subjects not used for ML model training or hyperparameter tuning. This algorithm is primarily used by irregular rhythm notifications version 2,[1] AFib History, and Breathe, as well as to compute HRV. Users can verify their version of the irregular rhythm notification feature by visiting Find your version of the irregular rhythm notification feature.

	Average tachogram performance			
Rhythm type or activity	**Instantaneous pulse rates within 5 bpm of truth (%)**	**Coverage (%)**	**Availability (%)**	**Test data†**
Normal sinus rhythm	99.6	92	98	240 subjects, 266,000 tachograms
Permanent or persistent AFib	97	88	96	70 subjects, 86,000 tachograms
Paroxysmal AFib	99	92	98	100 subjects, 117,000 tachograms
Other arrhythmias	95	90	96	56 subjects, 69,000 tachograms
Deep breathing	99.7	90	99	400 subjects, 2,000 tachograms

Table 4. Performance is measured across all tachograms collected passively throughout the day and published to HealthKit. Accuracy is defined as the fraction of instantaneous pulse rates accurate within 5 bpm of the reference heart rate measured by ECG. Coverage indicates the fraction of the tachogram duration when instantaneous pulse rate is reported in a tachogram. Availability represents the fraction of tachograms successfully measured and reported to HealthKit (containing at least 10 consecutive pulses). Arrhythmia categories in the table are determined based on reference data collected from a reference ambulatory ECG patch. The "other arrhythmias" category includes premature atrial contractions (PACs), premature ventricular contractions (PVCs), bundle branch block (BBB), atrial tachycardia, heart block, junctional rhythms, and supraventricular tachycardia (SVT). †Test data excludes all sessions from subjects used in ML model training and hyperparameter tuning.

[1] At the time of publication, irregular rhythm notification feature version 2 is not available in all markets.

Heart rate features

The optical heart sensor and heart rate algorithms on Apple Watch enable many heart rate features. Users can measure their heart rate any time when using the Heart Rate app, during exercise with the Workout app, or during a Reflect session in the Mindfulness app — regardless of whether they're active or still. Apple Watch also measures heart rate and tachograms in the background when the user is still or during a user-initiated Breathe session in the Mindfulness app. Every measurement is published to HealthKit along with its time stamp. Apple Watch then aggregates longitudinal heart rate data to produce additional heart health and fitness insights and notifications, such as resting heart rate, walking heart rate average, cardio recovery, high and low heart rate notifications, irregular rhythm notifications, AFib History, calorimetry, and cardio fitness.

This section discusses how Apple Watch uses the three foundational heart rate algorithms to enable heart rate features.

Heart Rate app, Workout app, and cardio recovery

When using the Heart Rate app or Workout app including Fitness+ sessions, Apple Watch attempts to report one heart rate every five seconds using the foreground heart rate algorithm, with availability subject to signal quality. While in extended workout mode, the watch duty cycles the green LEDs to reduce power and support longer workouts. Based on signal quality and use of extended workout mode, the time between published measurements can vary.

After a user-initiated workout ends, Apple Watch continues to use the foreground heart rate algorithm to monitor heart rate for three minutes to estimate cardio recovery. This measure is a prediction of a user's 60-second heart rate recovery after submaximal exercise at 85 percent of the predicted heart rate maximum. Reported cardio recovery has an upper bound of 55 bpm and is designed to be robust to differences in exertion across a user's workouts. Higher cardio recovery values can indicate better cardiovascular health.

Mindfulness app

In the Mindfulness app, the user may initiate a Breathe or Reflect session. During a Breathe session, the user is guided through a deep breathing exercise while remaining still for one minute or more. Apple Watch measures heartbeats using the tachogram algorithm, then displays one heart rate every minute, reflecting the average heart rate during the guided breathing cycle. Along with these heart rates, estimated HRV and a tachogram are published to HealthKit. (The Breathe session tachograms aren't used to determine if irregular rhythm notifications should be sent, nor do they contribute to AFib History measurements). Users can view their heart rate and HRV after completing a Breathe session and use the data for biofeedback retrospectively.

During a Reflect session, the user is presented with a thought-provoking theme to focus on for one minute or more. Unlike a Breathe session, Reflect doesn't ask the user to be still. Apple Watch measures heart rate during a Reflect session using the foreground heart rate algorithm and displays the average heart rate at the end of the session.

Apple Fitness+ subscribers can listen to guided meditations with their Apple Watch, which measures heart rate using the foreground heart rate algorithm. As the meditation plays, the elapsed time and heart rate are displayed on Apple Watch.

Background heart rate, resting heart rate, and walking heart rate

The background heart rate algorithm monitors heart rate in the background throughout the day when the user is still. Every five minutes, it attempts to publish a heart rate to HealthKit, with availability subject to signal quality and user motion.

When sufficient background heart rate measurements are available, a subset from the most inactive parts of the day — except those recorded during Sleep Focus, scheduled Bedtime, or time of sleep— is used to estimate resting heart rate. This is an estimation of the user's lowest heart rate during periods of rest while awake and is updated periodically throughout the day, with a single daily resting heart rate published to HealthKit at the end of the day. These daily estimates can be reviewed longitudinally in the Health app. A lower resting heart rate typically indicates better heart health and cardiovascular fitness.

Apple Watch occasionally activates the foreground heart rate algorithm in the background when it senses that the user is performing certain activities. For example, the foreground heart rate algorithm is triggered for up to one minute for spot checks when the user appears to be walking, without the user needing to interact with their watch. If signal quality is adequate, a spot-checked walking heart rate is published to HealthKit. The user also receives one average walking heart rate daily. Walking heart rate can be used as a baseline for light exercise to measure how the user's heart responds to activity.

High and low heart rate notifications

Apple Watch checks for unusually high or low heart rates in the background, which could be signs of a serious underlying condition. The default threshold is 120 bpm for high heart rate notifications and 40 bpm for low heart rate notifications.

Apple Watch monitors background heart rate using the background heart rate algorithm. If a user's heart rate exceeds the high threshold or drops below the low threshold while they appear to have been inactive for 10 minutes and multiple additional conditions are met, Apple Watch activates the tachogram algorithm for up to one minute. If the results from the two algorithms are consistent, Apple Watch sends the user a notification. The user can view and set their high and low thresholds for notifications in the Apple Watch app or the Health app on iPhone.

Irregular rhythm notifications, and AFib History, and heart rate variability

Apple Watch attempts to measure tachograms in the background using the tachogram algorithm. Tachograms are collected and analyzed only if the user remains still enough to obtain a measurement. The default tachogram measurement cadence is every four hours, increasing to two hours or 15 minutes when a user enables irregular rhythm notifications or AFib History, respectively. Apple Watch calculates HRV using the standard deviation of normal-to-normal measurements (SDNN) and attempts to reject ectopic (non-normal) beats before publishing tachograms for SDNN calculation. In cases of high ectopic burden (or AFib arrhythmia), SDNN may be influenced by non-normal beats that couldn't be rejected. Within HealthKit, SDNN is stored alongside the sequence of individual beat-to-beat measurements, used to calculate other HRV metrics.

The irregular rhythm notification feature, intended for adult users without a prior AFib diagnosis, monitors tachograms in the background for irregular rhythms suggestive of AFib and notifies users upon detection (a positive tachogram classification followed by a positive confirmation cycle). For more information on the development, validation, and performance of the irregular rhythm notification feature, please refer to the validation summary Using Apple Watch for Arrhythmia Detection.

The AFib History feature is intended for adult users with a diagnosis of AFib to help them understand their AFib burden over time as well as the relationship between their AFib burden and lifestyle over time. AFib burden is defined as the proportion of time the user is in AFib during a monitoring period, expressed as an estimated percentage of time their heart showed signs of AFib during the previous week of watch wear.

The lowest percentage reported is “2% or less.” Due to sampling, AFib History cannot determine a complete absence of AFib. The user receives notifications every Monday with a retrospective estimate of the average AFib burden measured compared with the previous week. Users must wear their Apple Watch at least 12 hours a day for five days a week to consistently receive estimates. AFib History also shows users the day of week and time of day that their heart is most frequently showing signs of AFib, called *highlights*. AFib History highlights are available to view after six weeks of wearing Apple Watch. The AFib History feature is compatible with Apple Watch Series 4 or later and all Apple Watch Ultra models, paired with an iPhone 8 or later. To learn how to set up AFib History and log life factors that impact AFib, please visit Track your AFib History with Apple Watch.

Measuring calories

Introduction

In addition to being a robust heart rate measurement tool, Apple Watch offers an accurate and consistent way to track calories burned. Apple Watch uses heart rate and calorimetry data to inform various health and fitness features, including those in the Workout, Activity, Fitness, and Health apps, which are highlighted later in this section.

Tracking calorie expenditure can help users maintain an active and healthy lifestyle. On Apple Watch, calories are an estimate of energy burned. Active Calories, represented by the red Move ring, are the calories burned above basal (resting) calories. Total calories are a combination of active and basal calories. Monitoring calories burned can help users stay active throughout the day, track workout expenditures, and make informed refueling choices.

Apple Watch is also a useful device for researchers who want to measure calorimetric data during specific activities or longer-term remote monitoring, inside or outside a laboratory, for both small and large-scale studies.

Current laboratory standards, including indirect calorimetry, pressure-sensitive mats for gait estimation, and courses with distance verified via measuring wheel, each requiring proctors, a dedicated laboratory space, and resources — are accepted as accurate but are not feasible for all study types or larger populations. And they can be carried out on only an infrequent basis due to resource and facility constraints, as well as participant availability. Apple Watch removes these barriers by providing a more accessible way to collect data, enabling rich data sets across a diverse population in a variety of everyday settings.

Many elements go into estimating calorie expenditure: hardware sensors, software algorithms, and user health data. This section describes the process for detecting and reporting calorimetry on Apple Watch — starting with the sensors, followed by the motion coprocessor and the system on chip (SoC) for signal processing, ML-based activity classification, and algorithm calculations — that fuse together information from the various sensors, complemented by user metrics to produce an individualized calorie count. The section also details best practices for obtaining reliable signals.

Calorimetric hardware

Several key sensors support calorimetry algorithms on Apple Watch, in addition to a motion coprocessor and an Apple Watch SoC that process sensor data and calculate algorithms.

Optical Heart Sensor

The optical heart sensor in Apple Watch uses green PPG and accelerometer signals with the foreground heart rate algorithm to measure heart rate during potentially challenging motion scenarios in workouts. Heart rate, measured in bpm, is one of the signals Apple Watch uses to inform activity intensity for calorimetry. For more information, see in the Optical heart sensor section earlier in this paper.

Accelerometer

An accelerometer is a sensor that measures change in velocity. Apple Watch has a three-axis accelerometer that delivers acceleration values in each of three orthogonal directions. The values reported by the accelerometer are measured in increments of the gravitational acceleration, with the value 1.0 representing an acceleration of 9.8 meters per second squared in the given direction. Acceleration values may be positive or negative depending on the direction of the acceleration. In Figure 3, the X, Y, and Z arrows show the direction of positive acceleration in the three orthogonal directions. The accelerometer is used to inform motion-based features such as steps.

Figure 3. Apple Watch labeled with the three orthogonal directions for sensing accelerations and rotations using the built-in accelerometer and gyroscope, respectively.

Gyroscope

A gyroscope measures the rate at which a device rotates around a spatial axis. Apple Watch is equipped with a three-axis gyroscope, which delivers rotation values around each of three orthogonal axes. Rotation values are measured in radians per second around the given axis. Rotation values may be positive or negative depending on the direction of the rotation. In Figure 3, the curved arrows show the direction of positive rotation around the X, Y, and Z directional axes. The gyroscope is used to inform motion-based features with a lot of rotation, such as the number and intensity of freestyle swimming strokes.

Barometer

A barometer measures atmospheric pressure, detecting varying values at different elevations. Apple Watch is equipped with a barometer that combined with user motion, measures elevation changes, detects terrain grade, and helps estimate the number of flights of stairs climbed and associated increases in calorie expenditure.

Geolocation receiver

A geolocation receiver estimates its location based on signals from systems such as Global Navigation Satellite Systems (GNSS), which includes the Global Positioning System (GPS). Multiple data samples can be used to detect distance traveled over time. Distance and steps are used in stride calibration, which estimates a more accurate step-based distance traveled throughout the day.

Motion coprocessor and system on chip

The motion coprocessor runs low-power algorithms and sensor processing that produce all-day calorie estimates. The primary motivation for integrating the coprocessor is to provide basic sensor processing facilities for all-day features — such as step counting — to decrease the wake-up frequency of the entire Apple Watch SoC and reduce battery consumption. During workout sessions, the SoC is active, running robust algorithms and sensor processing to inform features such as workout-specific calorimetry.

Calorimetry algorithms

Calorimetry best practices

Best practices must be understood and followed to obtain accurate energy expenditure values. For targeted activities, users (including researchers) should employ additional methods to optimize calorie measurements. These methods are discussed in the Calorimetry in workouts section. To get optimal all-day measurements from Apple Watch, these guidelines should be followed:

Understand the values

When collecting and reporting data, users need to understand the values and report the desired metrics. For example, Apple Watch reports basal and active calories. These two values should be combined to report total calorie expenditure. A framework such as ResearchKit can be used to build study-specific apps and can be helpful for data collection.

Keep personal information up to date

Apple Watch uses personal information — such as weight, height, age, sex, and wheelchair status — to help inform health and fitness features, including how many calories the user burns. To improve the accuracy of these features, users can update their personal information in the My Watch tab of the Apple Watch app on iPhone. To learn how, read Get the most accurate measurements using your Apple Watch.

Calibrate Apple Watch

During outdoor pedestrian activity, Apple Watch opportunistically attempts automatic calibration to learn the user's cardiorespiratory fitness (CRF or VO_2 max) level and stride length. In calorimetry, a user's VO_2 max can inform the relative intensity of exertion. An individualized value for stride length improves distance and pace accuracy when geolocation information is limited or unavailable. This personalized calibration on Apple Watch enhances the accuracy of calorie, distance, and pace measurements.

Those who want to accelerate the calibration process — for example, researchers performing short-term targeted data collection, where devices may be used to collect data from participants with different fitness levels and stride lengths — can improve the accuracy of measurements using calibration steps. For more details, visit Calibrate your Apple Watch for improved Workout and Activity accuracy.

Check Settings

For Apple Watch to access the information needed to measure calories, users should turn on Location Services and Motion Calibration & Distance in Privacy & Security settings on their paired iPhone. For details, see Calibrate your Apple Watch for improved Workout and Activity accuracy.

In the Apple Watch app on iPhone, Wrist Detection must be on to ensure that background heart rate readings (like resting and walking rates) are measured. For instructions on how to turn on Wrist Detection, see Get the most accurate measurements using your Apple Watch.

Check the fit

Apple Watch should be worn snugly but comfortably so that the sensors can obtain the most accurate readings. For guidance, see the Watch band usage part of this paper and visit Wearing your Apple Watch.

Activity classification and calorie calculation

This section focuses on the general methodology for classifying activities and calculating calories during and outside of workout sessions. Later in this paper, the Calorimetry in workouts section details the additional sensor signals and models available in workout sessions.

Machine learning–based models for activity classification

Activity classification is fundamental to ensuring that the correct calorimetry algorithms are running on Apple Watch. ML-based models trained on thousands of hours of data identify movement patterns associated with different activities (for example, swimming, cycling, or running). Apple Watch uses this activity context in various ways, including calorimetry algorithm selection, workout pause/resume and start/end reminders, and automatic progression through Multisport workouts.

Calculating calories

Apple Watch runs algorithms that continuously calculate metrics to inform calorie expenditure, including activity classification, step counting, wheelchair push counting, and activity intensity.

Activity classification informs which metabolic equivalents (METs) models to use in calorie estimates. These METs models fuse together specific information generated from the sensor signals, and they take individual physiological metrics into account. The basal model is used to estimate the amount of energy required for the user's body to function while at rest. Basal METs are computed from the user's demographics (weight, height, age, sex, wheelchair status) and current activity. The basal model will produce an estimate that varies slightly depending on current activity. The activity models estimate the amount of energy the user expends while active, in addition to the basal levels.

Finally, the user's weight and the duration of time at a given level of exertion is used to convert METs to calories. Total calories represent the combination of basal and active calorie values. Figure 4 illustrates the flow of data from activity models and calorie conversion to the active calorie calculation.

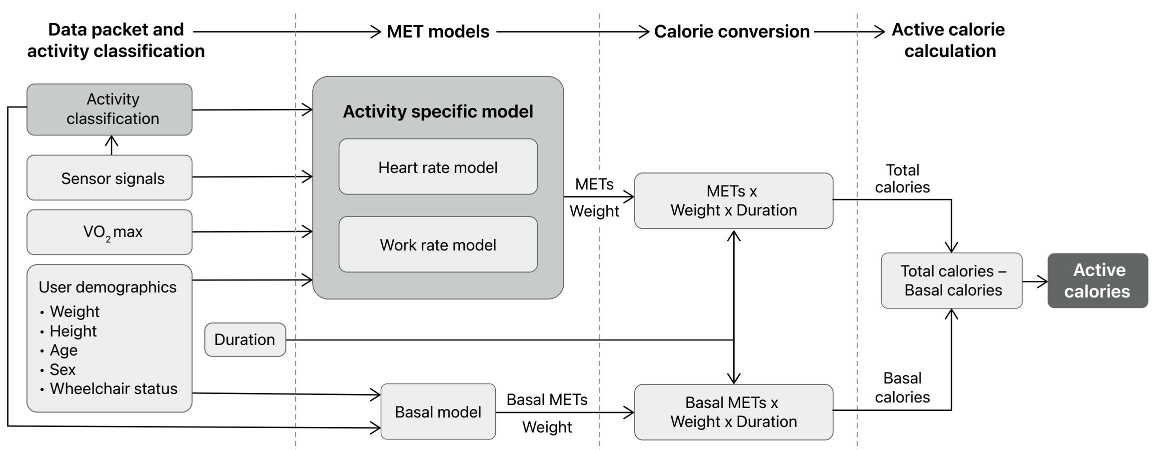

Figure 4. Flow diagram representing the process of calculating total and active calories from input data packets, activity classification, and activity specific models.

For users 13 years and younger, a unique ML model was developed for activity classification. Instead of active calories, Apple Watch calculates Move minutes, indicating how many minutes the user has spent actively moving. This model was specifically designed to capture the movement patterns of younger users and is based on hundreds of hours of targeted data collection.

Calorimetry in workouts

Measuring workout calories

In addition to the all-day signals discussed previously, more sensor information and processing is available during workouts, including PPG heart rate and geolocation information. Using a method similar to the one described in the last section — Activity classification and calorie calculation — algorithms combine this information to estimate METs. Different from all-day measurements, these algorithms are workout-specific with richer information, and their resulting calorimetry estimates are more robust. Apple conducted studies and collected design and validation data sets, including the gold standard reference Metabolic Cart (MET-Cart), to ensure that calories estimated by Apple Watch are as accurate as possible. These efforts are discussed in the following section, Calorimetry estimates: Design, validation, and maintenance. In a research context, workout sessions are useful for collecting the most robust and accurate data for a given activity. Calorimetry best practices detailed earlier in this paper should be followed to obtain optimal results.

Depending on the workout type started and the ML model-based activity classification, Apple Watch selects the sensor data inputs deemed most appropriate to calculate calories for that activity. Heart rate is just one of the many factors that Apple Watch uses to measure activity and exercise. Other important signals are acceleration, rotation, elevation, and geolocation. For example, when the user is running indoors, Apple Watch uses the accelerometer. To obtain the most accurate calorie and activity data, the user should choose the appropriate workout session on Apple Watch for the activity. When starting Fitness+ workout sessions, the corresponding workout type will automatically be selected.

By leveraging an activity classification ML model to detect specific user movement patterns, Apple Watch can automatically start some workouts if the user forgets to initiate the workout on their own. In this case, the user will receive a notification after a certain amount of time spent doing the activity, asking if they want to record their workout. If they confirm, the user receives workout credit beginning from the time they started exercising. The time it takes for the notification to surface will vary depending on the workout type. For the best user experience, the time was chosen to align with likely workout behavior compared with everyday activity. Apple Watch can provide workout start reminders for the Indoor Walk, Outdoor Walk, Indoor Run, Outdoor Run, Outdoor Cycle, Elliptical, Indoor Rowing, Pool Swim, and Open Water Swim workouts.

Workout models

For each of the workout models, specific sensors and features are used as inputs. Table 5 details which primary sensor and feature inputs support the different types of workout models. These workout models are represented in the Activity specific model box in Figure 4 of the Activity classification and calorie calculation section. The specific workout model types listed in Table 5 have validated calorimetry models, with performance detailed in the next section. Note that for other outdoor workouts where walking or running is the predominant form of movement, calories are estimated using a combination of the pedestrian and heart rate models. For all other models, the user will earn at least the credit equivalent of a brisk walk while moving, with the potential for additional credit based on sensor data and activity classification.

	Model inputs							
Workout model type	**Heart rate**	**Motion**	**Grade**	**Geolocation-based speed**	**Stride length calibration**	**Steps**	**Pushes**	**VO_2 max, user metrics**
Outdoor pedestrian • Walking • Running • Hiking	✓	✓	✓	✓	✓	✓		✓
Indoor pedestrian • Walking • Running	✓	✓			✓	✓		✓
Outdoor wheelchair • Walking pace • Running pace		✓	✓	✓			✓	✓
Outdoor cycling	✓	✓	✓	✓				✓
Swimming		✓		✓				✓
Rowing		✓						✓
Additional heart rate and motion fused • Elliptical • Stair stepper • Dance • Kickboxing	✓	✓						✓
Heart rate predominant • Indoor cycling • High-intensity interval training • Cross country skiing • Functional strength training • Core training • Pilates • Yoga • Cooldown • Tai chi	✓	✓						✓
Other workouts	✓	✓			✓	✓		✓

Table 5. Different types of workout models and key inputs. Motion input includes signals from sensors such as accelerometer and gyroscope, and features derived from those signals. Heart rate predominant models refer to calorimetry models that more heavily rely on the heart rate sensor signals.

Calorimetry estimates: Design, validation, and maintenance

To validate calorimetry, Apple conducted studies to collect separate design and validation data sets. A gold standard is used for the source of reference truth for step metrics and calorimetry models. For step metrics, the reference truth is a wheeled distance and a proctor tallied step-count. For the steady-state aerobic calorimetry models, the reference truth is indirect calorimetry from a calibrated MET-Cart, which produces measurements of VO_2 consumed.

The flow of product feature conception, collection of data sets, development, implementation, validation, and maintenance are illustrated in Figure 5 below.

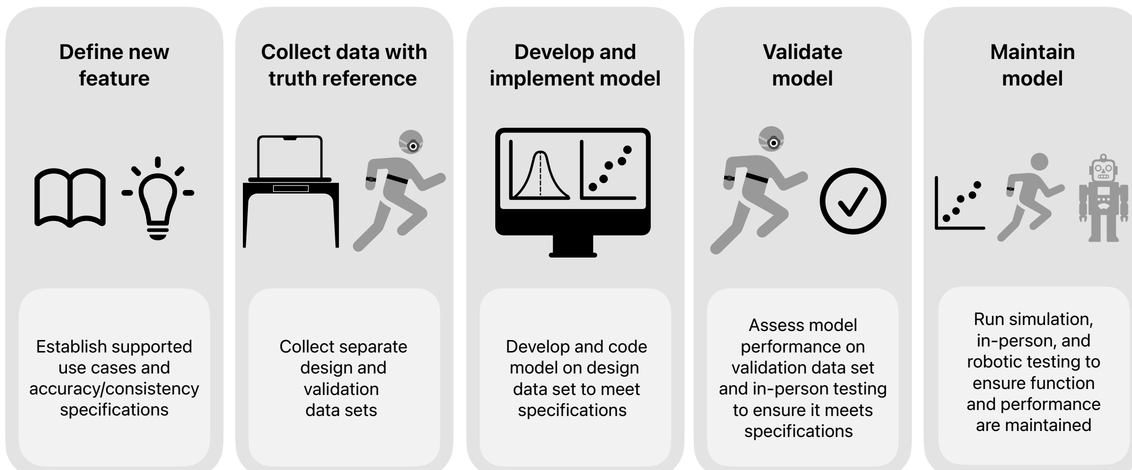

Figure 5. Apple's process for calorimetry model conception, data collection, development, implementation, validation, and maintenance.

In general, calorimetry estimates are based on activity context. In all-day calorimetry, when exertions are below walking effort, estimates of sit, stand, and sedentary (at rest) behavior inform accuracy. Table 6 on the following page details the calorimetry accuracy for aerobic activities when best practices are followed. The calorimetry design and validation studies included hundreds of data sets, powered based on the complexity of the model.

Algorithm performance is evaluated and maintained across new hardware releases and software updates using simulation, in-person, and robotic testing. It is important that the best practices highlighted in the Calorimetry algorithms section are followed to obtain the most accurate energy expenditure values.

Model type	N (validation)	% Error calories relative to reference (mean ± SD)
Outdoor/Indoor pedestrian • Walking • Running • Hiking	130	0 ± 9
Outdoor wheelchair • Walking pace • Running pace	130	-1 ± 16
Outdoor cycling	298	5 ± 13
Swimming	151	5 ± 20
Rowing	100	-2 ± 15
Additional indoor machines • Elliptical • Stair stepper	75	0 ± 15
Dance • Cardio styles (3)	243	0 ± 14
Kickboxing	145	3 ± 15
Heart rate predominant (higher intensity) • Indoor cycling • High-intensity interval training • Cross country skiing	218	-2 ± 14
Heart rate predominant (moderate intensity) • Functional strength training • Core training • Pilates	53	2 ± 17
Heart rate predominant (lower to moderate intensity) • Yoga • Cooldown • Tai chi	43	3 ± 20

Table 6. Accuracy represented by mean and standard deviation (SD) of error of aerobic calorimetry models relative to reference when best practices are followed. The errors in the table represent performance from ongoing validation data collections, across a typical range of exertion and fitness levels. Errors may be higher in scenarios where devices are not calibrated, or atypical environments for activities where the user may experience prolonged anaerobic calorie expenditure such as extended periods of steep incline during pedestrian activities or extreme water temperature during swimming. Heart rate predominant models refer to calorimetry models that more heavily rely on the heart rate sensor signal.

Additional fitness features

The models discussed in this paper inform numerous features and data streams, including the Activity, Workout app experiences on Apple Watch, plus the Fitness app experience and Health app features on iPhone.

Cardiorespiratory fitness

Apple Watch estimates a user's cardio fitness level as measured by VO_2 max, the maximum volume of oxygen that an individual can extract from inhaled air. Users can view how their cardio fitness level is classified based on their age group and sex in the Health app on iPhone and iPad, and they can receive a notification if it falls within the low range. Learn more by reading Using Apple Watch to Estimate Cardio Fitness with VO2 max, Track your cardio fitness levels, and Cardio fitness notifications are available today on Apple Watch.

Activity app

The Activity app experience includes setting personal Activity goals, tracking progress throughout the day with Activity rings (red Move ring, green Exercise ring, and blue Stand or Roll ring), observing trends over time on a paired iPhone, and even competing with friends. The Activity app tracks how often the user stands or rolls, the calories burned from movement, and the minutes of brisk activity (exercise) completed. The three differently colored rings summarize the user's progress. The objective is to sit less, move more, and get some exercise by completing each ring every day.

Activity goals

Activity goals help the user track how their activity is adding up over the day. The user can customize goals to align with their activity objectives for each day of the week. The Move ring encourages the user to match or exceed their daily active calorie burn goal to ensure they stay as active as they intend throughout the day. The Exercise ring measures how many total minutes of active calories burned were brisk enough to reach an intensity that can make a positive impact on the user's heart health. The Stand ring is designed to measure how many hours per day the user stood up or moved for at least one minute, helping reduce long sedentary periods. Apple Watch notifies the user when goals are reached and offers suggestions and encouragement to help them close their rings.

When Activity goals are met, they're represented by a closed Activity ring, and the user earns an award. Workouts completed in the Workout app, as well as those from third-party apps or user-entered workouts written to the Health app, count toward ring totals. At midnight each day, the ring totals reset, giving the user a new opportunity to meet daily goals. If the user wants to take a break from activity tracking, they can pause the ring experience for 1 to 90 days while retaining their award streak. The Activity goals experience provides summaries of activity and aims to keep users engaged with their fitness and health goals in both the short and long term. Researchers carrying out activity studies with Apple Watch will benefit from comprehensive and robust data sets from engaged participants. Learn more at Track daily activity with Apple Watch.

Move ring

The Move ring provides a cumulative estimate of how many active calories a user has burned in a day. Active calories, explained in more detail in the Calculating calories portion of this paper, are burned through activities such as standing or moving around, in addition to resting (basal) calories.

For users 13 years and younger, the Move ring shows how many minutes the user has spent actively moving around. For help earning Move credit, visit Get the most accurate measurements using your Apple Watch.

Exercise ring

Users can complete the default daily Exercise goal by exercising for at least 30 minutes each day, or they can customize it to any amount of time between 5 and 90 minutes. Every full minute of movement that equals or exceeds the intensity of a brisk walk counts toward daily Exercise goals on Apple Watch, including activity outside of a workout session. The intensity threshold equivalent to a brisk walk is adjusted based on personal information, such as Apple Watch–detected cardiorespiratory fitness (VO_2 max). This personalization creates a balanced Exercise ring experience for users of all cardiorespiratory fitness levels (see Cardiorespiratory fitness on the previous page). In workout sessions, the user can also earn exercise minutes for sustained exertions at a personalized moderate intensity.

For wheelchair users, brisk activity is measured in brisk pushes. Any activity below this level counts only toward the daily Move goal.

For users 13 years and younger, the Exercise ring focuses on minutes of brisk activity, such as running, jumping, and playing. (For more information, refer to See activity and health reports for family members.) Learn how to meet the Exercise goal at Get the most accurate measurements using your Apple Watch.

Stand or Roll ring

Users can complete the default daily Stand goal by standing up and moving around for at least one minute during 12 different hours of the day, or they can customize the goal to any number of hours between 6 and 16. Apple Watch awards Stand credit when it detects a standing pose. Users can also earn credit through movements such as swaying, twisting, shifting, fidgeting, and walking.

If the user specifies that they use a wheelchair, the Stand ring switches to the Roll ring. Roll shows hours in which the user pushed around in a wheelchair for at least one minute.

Stand or Roll minutes

Stand minutes are the number of minutes throughout the day that a user is standing and moving. Apple Watch automatically tracks and logs these minutes in Health. Reviewing Stand minutes over time can help the user understand how active or sedentary they are. Earning at least one Stand minute each hour also earns an hour in the user's Stand ring.

If the user specifies that they use a wheelchair, Apple Watch will track Roll minutes, similar to the Stand and Roll rings. Roll minutes represent the number of minutes throughout the day that they have spent pushing around in a wheelchair. They will also earn the hour in their Roll ring for each hour in which they earn at least one Roll minute.

Fitness trends

Trends in the Fitness app on iPhone give users a brief overview of their progress in Move, Exercise, Stand or Roll goals, as well as other key metrics compared with past performance. This view allows users to easily determine if they are on track or identify areas that need more attention.

Trends are based on how metrics have developed over the last 90 days compared with the last 365 days. (Estimates might change due to updates in how they are calculated.) If the Trend arrow for a particular metric points up, the user is maintaining or improving fitness levels. If an arrow points down, the user's 90-day average for that metric has declined.

Fitness+ Burn Bar

The Burn Bar leverages crowd-sourced data to create an interactive experience within Fitness+ workouts. Weight-normalized calories — calculated as METs multiplied by duration — are tracked throughout each workout for the community of users. This feature enables users to continuously compare their energy expenditure during the workout with that of others who have completed the same session. To learn more about Apple Fitness+ and the Burn Bar, see How to Use Apple Fitness+.

GymKit

Apple Watch can pair and sync data with compatible cardio equipment such as treadmills, indoor bikes, ellipticals, and stair steppers, which provide the user with more personalized and accurate information about their workout. The user can use connected gym equipment to start and stop Apple Watch workouts and exchange workout data, such as distance and heart rate. To learn more, see Use gym equipment with Apple Watch.

Multisport

The Multisport workout type automatically progresses between any sequence of swimming, cycling, and running workouts by leveraging activity classification from an ML model. To learn how to set up a Multisport workout, see Combine multiple workouts on Apple Watch.

Functional threshold power and Power Zones

Algorithms combining sensor data from Apple Watch and connected power meters can estimate functional threshold power (FTP), the highest level of cycling intensity a rider could theoretically maintain for an hour. Using FTP, Apple Watch calculates personalized Power Zones, allowing users to easily see the current zone they are working in and track how much time they spend in each zone. FTP is an important metric because it provides cyclists with a helpful way to measure conditioning progress over a period of time and forms the foundation for Power Zones. For more information see: Go cycling with Apple Watch.

Effort estimates to inform training load

Workout Effort is a notion of workout session intensity. Effort multiplied by workout duration informs the training load experience in the Activity and Fitness apps. Training load compares the user's training over the last seven days with the previous 28 days, helping the user make informed decisions about upcoming workouts. To learn about how to set up and view training load, see Track your training load on Apple Watch.

Apple Watch supports automatic Effort estimation for most cardio-focused workouts. This estimation leverages an ML model trained on approximately 70,000 workout sessions from the Apple Heart and Movement Study. The model's features are generated from a combination of user information — such as age and VO_2 max — and data used in calorimetry, including heart rate. Users can manually adjust the Effort estimate or enter a value in sessions where an estimate is not provided. To learn more, see End and view a summary of your workout on Apple Watch.

How to access data

Users have several options for accessing the data and features discussed in this paper. The best choice will depend on the requirements of each use case.

ResearchKit

ResearchKit is an open source framework introduced by Apple that enables researchers and developers to create powerful apps for medical research. Developers can easily create visual consent flows, real-time dynamic active tasks, and surveys using a variety of customizable modules to build on and share with the community. ResearchKit was designed to easily interface with HealthKit, so researchers can access — with user consent — highly relevant data for their studies, like daily step counts, calorie use, and heart rate. To learn more, visit Apple's Research & Care page.

HealthKit

HealthKit is a central repository for health and fitness data on iPhone, iPad, and Apple Watch. With user consent, apps communicate with the HealthKit store to access and share this data. Creating a complete, personalized health and fitness experience involves the following tasks:

- Collecting and storing health and fitness data
- Analyzing and visualizing the data
- Enabling social interactions

HealthKit apps take a collaborative approach to building this experience. Developers can focus their apps on a subset of tasks that interest them most. To learn more, visit the HealthKit Documentation page.

SensorKit

As the system gathers information using various sensors on a device, SensorKit enables an app, with user consent, to access select raw data or metrics processes from a sensor, such as:

- Steps information
- Accelerometer or rotation-rate data
- Optical and electrical heart sensor data
- The configuration of a watch on the user's wrist
- Ambient light in the physical environment
- Details about a user's routine commute or travel

SensorKit is a private entitlement; thus apps require Apple approval. Use cases are limited to health research, and access to the data types also requires user permission. To learn more, see SensorKit Documentation.

Apple Watch and iPhone

Users can view many features and data types directly on Apple Watch and iPhone, including in the Heart Rate, Health, Activity, and Fitness apps. They can track a range of signals, such as their heart rate, cardio fitness, and how much they move, exercise, and stand day-to-day. For many features, users can check their daily progress on their Apple Watch or review their entire history in the Fitness and Health apps on iPhone. To learn more, visit Track daily activity with Apple Watch and Use the Health app on your iPhone or iPad.

Conclusion

Apple Watch accurately measures and reports heart rate and calories burned, and it creates an engaging health and fitness experience for all users. This paper highlights the methodologies, research studies, and variables that Apple evaluates and uses when developing heart rate and calorimetric capabilities along with their associated algorithms. It also provides guidance on best practices to follow to ensure optimal performance.