





# CosinorAge: Unified Python and Web Platform for Biological Age Estimation from Wearable- and Smartwatch-based Activity Rhythms

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## Software

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## Summary

Every day, millions of people track their steps, sleep, and activity rhythms using smartwatches and fitness trackers. These continuous data streams offer an opportunity to transform routine self-tracking into meaningful health insights that inform biological aging. However, most wearable data tools remain fragmented, proprietary, and inaccessible, limiting translation into actionable knowledge.

CosinorAge is an open-source framework that estimates biological age from wearable-derived circadian, physical activity, and sleep metrics. It provides a unified, reproducible Python pipeline for data preprocessing, feature computation, and biological age estimation, with trained model parameters from large-scale datasets such as the UK Biobank. Its companion CosinorAge Calculator offers identical functionality via a Web interface. Together, they enable transparent, scalable, and personalized health monitoring while bridging digital health and biological aging research.

## Statement of Need

Circadian rhythms play a critical role in maintaining key regulatory systems, including metabolic, immune, and endocrine pathways, and tightly govern rest–activity cycles encompassing sleep and physical activity, both essential to healthy aging. Disruptions in these daily rhythms, such as reduced amplitude, irregular activity timing, low activity levels, or poor sleep regularity, have been consistently linked to increased risk of chronic diseases, mortality, systemic inflammation, and accelerated biological aging (Shim et al., 2024, 2025). Given these associations, there is an urgent need for continuous high-resolution monitoring of daily rest–activity patterns to characterize individualized rhythmicity and guide timely targeted interventions to optimize healthspan.

Wearable devices and smartwatches enable a scalable, non-invasive, and cost-efficient method for deriving digital biomarkers of circadian rhythms, physical activity, and sleep at both individual and population levels. However, most analytic tools focus on isolated metrics or rely on proprietary algorithms, limiting transparency, reproducibility, and their linkage to health outcomes such as biological age. To address this gap, we developed CosinorAge (Shim et al., 2024), a digital biomarker framework that estimates biological age and healthspan from circadian rest–activity rhythms using wearable data.

## State of the Field

Existing software packages for wearable-derived activity analysis typically focus on specific methodological components rather than providing an end-to-end framework that links behavioral rhythms to clinically interpretable aging outcomes. Tools such as pyActigraphy (Hammad et al., 2021), actipy (Papazoglou & contributors, 2021), CosinorPy (Moškon, 2020), and scikit-digital-health (Adamowicz et al., 2022) analyze specific domains of wearable data, while GGIR (van Hees et al., 2025) lacks a native Python implementation and functionality to link derived metrics to health-related outcomes.

CosinorAge was developed to address these limitations by integrating circadian rhythm analysis, physical activity, and sleep metrics into a single, reproducible pipeline that directly estimates biological age. Extending existing tools was insufficient to support harmonized preprocessing across heterogeneous devices, joint modeling across behavioral domains, and the application of openly available biological age model coefficients. As a result, a new framework was required to enable consistent, transparent application across cohorts and study contexts.

## Software Design

CosinorAge was designed as a modular framework that balances flexibility, reproducibility, and accessibility across diverse wearable data sources. Core analytical logic is implemented in a reusable Python package and exposed through a Web interface with identical functionality, enabling both rigorous research workflows and no-code usage without diverging outcomes.

### CosinorAge Python Package

The **CosinorAge Python package** is structured into three core modules, each representing a key stage in the pipeline for analyzing accelerometer data and predicting biological age, CosinorAge. Its modular architecture allows components to be used independently or integrated into a streamlined workflow. Figure 2 illustrates the modular design and high-level data flow between components.

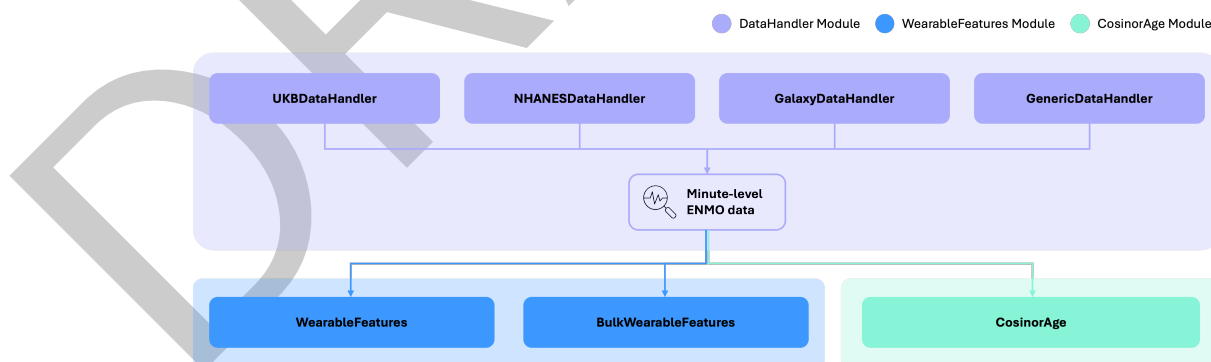


Figure 1: Package scheme.

### DataHandler Module

The package provides a total of four DataHandler subclasses to support accelerometer data from multiple sources including UK Biobank (UKB), NHANES, Samsung Galaxy Smartwatches (Galaxy), and Bring-Your-Own-Data (BYOD). UKBDataHandler, NHANESDataHandler, and GalaxyDataHandler perform source-specific filtering, preprocessing, and scaling to produce standardized, minute-level ENMO time series. Detailed data preprocessing for each DataHandler can be found on GitHub. For greater flexibility, a GenericDataHandler is also provided, allowing

71 users to process any compatible CSV file formatted according to a defined specification through  
72 a BYOD approach. The resulting ENMO data can then be passed to the feature extraction  
73 and modeling modules for downstream analysis.

#### 74 **WearableFeatures Module**

75 The WearableFeatures module includes two classes: WearableFeatures and BulkWearableFeatures.  
76 Designed for individual-level analysis, the WearableFeatures class computes a comprehensive  
77 set of metrics from minute-level ENMO data, covering physical activity, sleep behavior, and  
78 both parametric and non-parametric circadian rhythm features. For cohort-level studies, the  
79 BulkWearableFeatures class supports batch processing of multiple individuals, enabling users  
80 to analyze feature distributions and explore inter-feature correlations across the population.  
81 The list of features computed from this module is summarized below:

Domain	Metrics
Circadian Rhythm Analysis	MESOR, cosinor amplitude, acrophase, M10, L5, interdaily stability (IS), intradaily variability (IV), relative amplitude (RA)
Physical Activity Analysis	Light physical activity (LPA), Moderate physical activity (MPA), vigorous physical activity (VPA), sedentary duration
Sleep Analysis	Total sleep time (TST), wake after sleep onset (WASO), percent time asleep (PTA), number of waking bouts (NWB), sleep onset latency (SOL)

#### 82 **CosinorAge Module**

83 The CosinorAge module represents the final stage of the pipeline and contains a single class  
84 responsible for predicting the CosinorAge biomarker. It takes minute-level ENMO data as  
85 input and applies a pre-trained proportional hazards model to estimate biological age (Shim  
86 et al., 2024). The model supports three sets of coefficients - unisex, female-specific, and  
87 male-specific. If available, sex can be included as an optional input to improve prediction  
88 accuracy. The underlying model coefficients were estimated from large-scale cohorts such as  
89 UK Biobank and are openly available. This open-weight design enables researchers to apply the  
90 same model across diverse datasets with clear and accessible parameters, thereby facilitating  
91 reproducibility and offering a transparent alternative to proprietary algorithms.

#### 92 **CosinorAge Calculator: Web User Interface**

93 To enhance the accessibility of the **CosinorAge Python package**, we developed a Web interface  
94 that allows researchers and users to analyze their own data without requiring any installation  
95 or programming expertise ([www.cosinorage.app](http://www.cosinorage.app)). Users can simply upload their data, which  
96 is processed by the **CosinorAge package** in the backend. Results are presented in a clear,  
97 report-style format that includes visualizations to aid interpretation. A multi-user mode is  
98 also available, enabling researchers to upload and analyze data from multiple individuals  
99 simultaneously, allowing for the exploration of feature distributions and correlations across  
100 cohorts.

101 The Web interface is organized into several sections:

- 102     ▪ The Home tab provides an overview of the CosinorAge framework, its purpose, key  
103       features, and demo video.
- 104     ▪ The Documentation tab offers comprehensive API and interface documentation.

- The Calculator tab hosts the core analysis workspace with interactive tools for uploading wearable data, running activity rhythm analyses and biological age estimation, and viewing results in real time.
- The About tab presents information about the research group and contributing members.

The Calculator tab offers a user-friendly interface, as illustrated in Figure 3. **CosinorAge Calculator** supports BYOD via batch CSV uploads from either single or multiple individuals, with automatic file structure preview for validation (subject to file size limits). Users can configure device type, timestamp format, time zone, and select parameters for analysis. When multi-individual mode is selected, the summary dashboard presents descriptive statistics for all extracted features, a feature correlation matrix, and visual summaries of each metric at the population level.

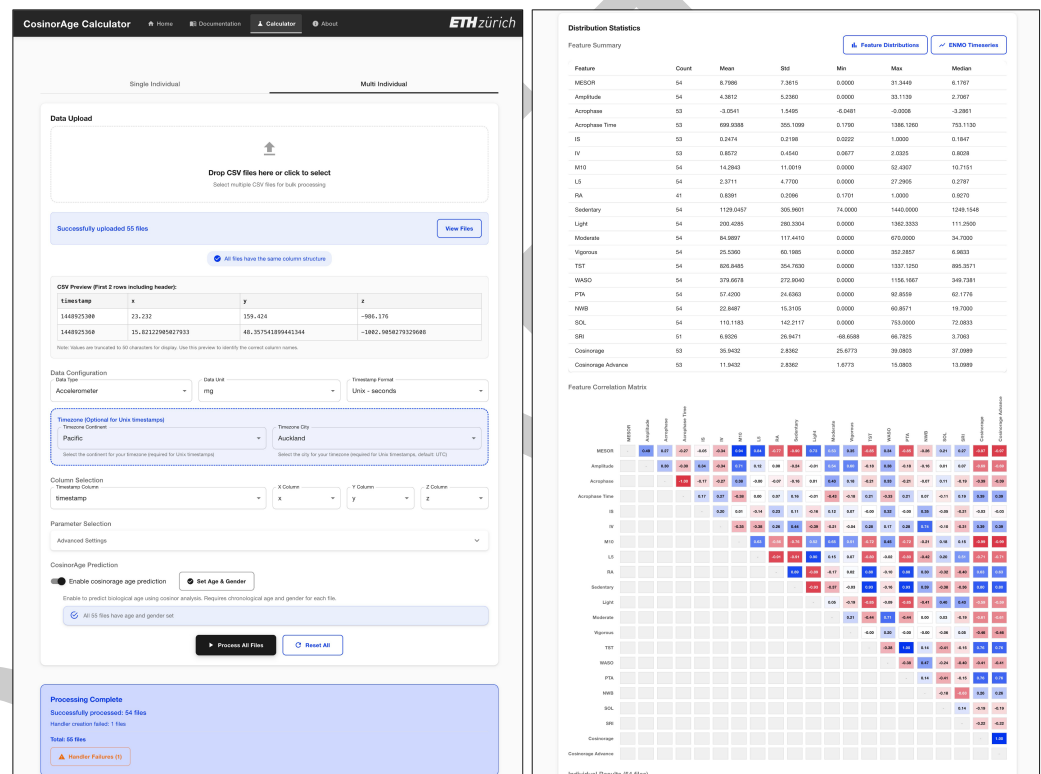


Figure 2: Data upload interface & summary dashboard.

## Research Impact Statement

CosinorAge operationalizes prior peer-reviewed work demonstrating that circadian rest-activity rhythms are strongly associated with mortality risk and biological aging (Shim et al., 2024, 2025). By releasing openly available model coefficients derived from large-scale population datasets such as UK Biobank, the framework enables reproducible biological age estimation without retraining and supports comparability across independent cohorts.

The software supports research-grade actigraphy, large epidemiological datasets (e.g., UK Biobank and NHANES), and consumer smartwatch data, facilitating cross-device and cross-study analyses. Recent validation work has demonstrated comparability between research-grade accelerometers and consumer smartwatches for circadian rhythm assessment (Wu et al., 2025), highlighting the translational potential of the platform. By combining open-source implementation, standardized preprocessing, and biological age estimation, CosinorAge

provides a reusable research tool for studying aging trajectories, intervention effects, and digital biomarkers across diverse populations.

Minute-level activity data collected using a Samsung Galaxy smartwatch from a 45-year-old female over 7 days was analyzed using the CosinorAge Python package. The blue lines display ENMO activity intensity, while the red curve indicates the cosinor model fit. Based on the recorded activity pattern, the predicted biological age is 49.0 years.

**Figure 3:** Minute-level activity data collected using a Samsung Galaxy smartwatch from a 45-year-old female over 7 days was analyzed using the CosinorAge Python package. The blue lines display ENMO activity intensity, while the red curve indicates the cosinor model fit. Based on the recorded activity pattern, the predicted biological age is 49.0 years.

## AI Usage Disclosure

Generative AI tools were used in a limited capacity to support code development and language editing during manuscript preparation. All software, analyses, and text were critically reviewed, validated, and finalized by the authors.

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