

¹ 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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⁹ Summary

¹⁰ 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 ¹¹ wearable data tools remain fragmented, proprietary, and inaccessible, limiting translation into ¹² actionable knowledge.

¹⁵ 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 ¹⁶ trained model parameters from large-scale datasets such as the UK Biobank. Its companion ¹⁷ CosinorAge Calculator offers identical functionality via a Web interface. Together, they ¹⁸ enable transparent, scalable, and personalized health monitoring while bridging digital health ¹⁹ and biological aging research.

²² Statement of Need

²³ Circadian rhythms play a critical role in maintaining key regulatory systems, including metabolic, ²⁴ immune, and endocrine pathways, and tightly govern rest–activity cycles encompassing sleep ²⁵ and physical activity, both essential to healthy aging. Disruptions in these daily rhythms, such ²⁶ as reduced amplitude, irregular activity timing, low activity levels, or poor sleep regularity, have ²⁷ been consistently linked to increased risk of chronic diseases, mortality, systemic inflammation, ²⁸ and accelerated biological aging (Shim et al., 2024, 2025). Given these associations, there ²⁹ is an urgent need for continuous high-resolution monitoring of daily rest–activity patterns to ³⁰ characterize individualized rhythmicity and guide timely targeted interventions to optimize ³¹ healthspan.

³² Wearable devices and smartwatches enable a scalable, non-invasive, and cost-efficient method ³³ for deriving digital biomarkers of circadian rhythms, physical activity, and sleep at both ³⁴ individual and population levels. However, most analytic tools focus on isolated metrics or rely ³⁵ on proprietary algorithms, limiting transparency, reproducibility, and their linkage to health ³⁶ outcomes such as biological age. To address this gap, we developed CosinorAge (Shim et ³⁷ al., 2024), a digital biomarker framework that estimates biological age and healthspan from ³⁸ circadian rest–activity rhythms using wearable data.

39 State of the Field

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

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

53 Software Design

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

58 CosinorAge Python Package

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

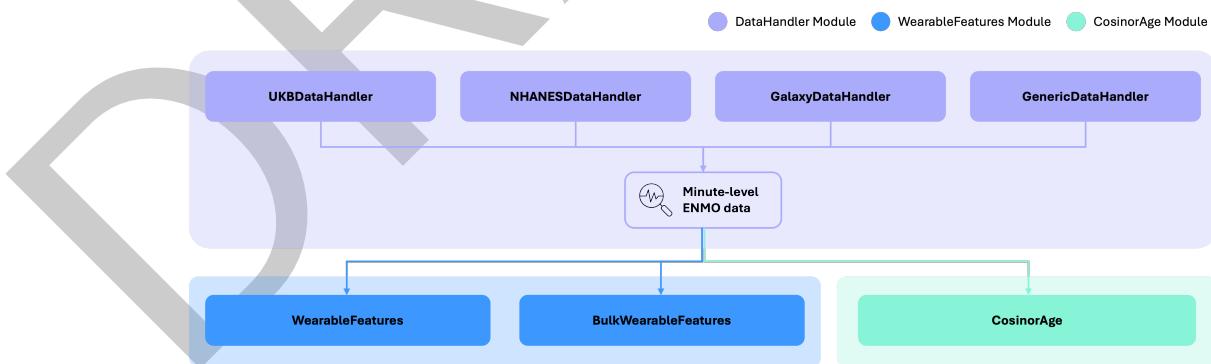


Figure 1: Package scheme.

64 DataHandler Module

65 The package provides a total of four DataHandler subclasses to support accelerometer data
 66 from multiple sources including UK Biobank (UKB), NHANES, Samsung Galaxy Smartwatches
 67 (Galaxy), and Bring-Your-Own-Data (BYOD). UKBDataHandler, NHANESDataHandler, and
 68 GalaxyDataHandler perform source-specific filtering, preprocessing, and scaling to produce
 69 standardized, minute-level ENMO time series. Detailed data preprocessing for each DataHandler
 70 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 et al., 2024](#)).
⁸⁶ 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). 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:

- ¹⁰² ¹⁰³ ▪ The Home tab provides an overview of the CosinorAge framework, its purpose, key features, and demo video.
- ¹⁰⁴
- ¹⁰⁵ ▪ The Documentation tab offers comprehensive API and interface documentation.

- 107 ▪ The Calculator tab hosts the core analysis workspace with interactive tools for uploading
- 108 wearable data, running activity rhythm analyses and biological age estimation, and
- 109 viewing results in real time.
- 110
- 111 ▪ The About tab presents information about the research group and contributing members.
- 112 The Calculator tab offers a user-friendly interface, as illustrated in Figure 3. **CosinorAge**
- 113 **Calculator** supports BYOD via batch CSV uploads from either single or multiple individuals,
- 114 with automatic file structure preview for validation (subject to file size limits). Users can
- 115 configure device type, timestamp format, time zone, and select parameters for analysis. When
- 116 multi-individual mode is selected, the summary dashboard presents descriptive statistics for all
- 117 extracted features, a feature correlation matrix, and visual summaries of each metric at the
- 118 population level.

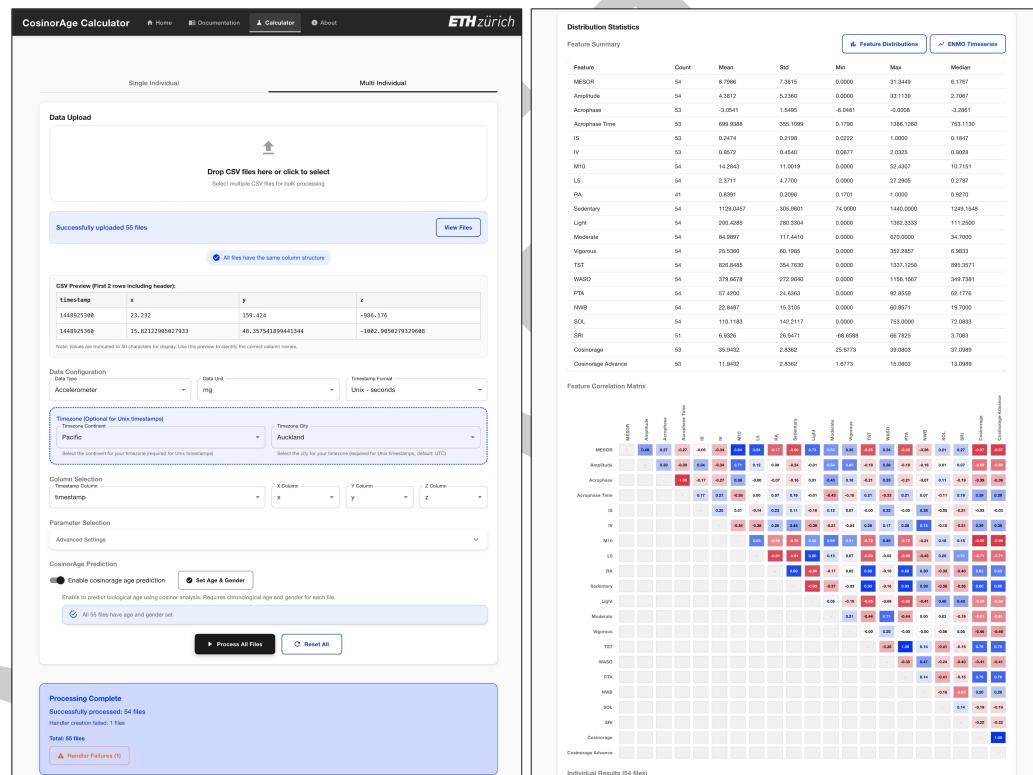


Figure 2: Data upload interface & summary dashboard.

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

¹³¹ provides a reusable research tool for studying aging trajectories, intervention effects, and digital
¹³² 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.

¹³³ AI Usage Disclosure

¹³⁴ Generative AI tools were used in a limited capacity to support code development and language
¹³⁵ editing during manuscript preparation. All software, analyses, and text were critically reviewed,
¹³⁶ validated, and finalized by the authors.

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