ORIGINAL PAPER

JMS Journal of Medical Science

Healthy Young POLes – HYPOL database with synchronised beat-to-beat heart rate and blood pressure signals

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Keywords: data sharing, cardiovascular time series, RR intervals, blood pressure, interbeat intervals, healthy young people

Received: 2023-10-20
Accepted: 2023-11-12
Published: 2023-11-13

How to Cite: Guzik P, Krauze T, Wykrętowicz A, Piskorski J. Healthy Young POLes – HYPOL database with synchronised beat-to-beat heart rate and blood pressure signals: HYPOL – Cardiovascular Time Series Database. JMS. 2023 Nov. 13;92(4):e941. doi:10.20883/medical.e941

DOI: https://doi.org/10.20883/medical.e941

ABSTRACT

Data sharing in medical research entails making research data available to other researchers for review, reuse, and collaboration. This paper seeks to describe the HYPOL (Healthy Young POLes) database, which has been prepared for sharing. This database houses the clinical characteristics and beat-to-beat cardiovascular time series of 278 individuals of Polish descent, all aged between 19 and 30 years. The data were collected from healthy volunteers who participated in multiple projects at the Department of Cardiology-Intensive Therapy research laboratory, Poznan University of Medical Sciences, Poznan, Poland. The cardiovascular time series data was obtained from non-invasive continuous finger blood pressure and ECG recordings, with sessions lasting up to 45 minutes. The HYPOL database includes an xls file detailing the main clinical characteristics and text files that capture ECG-derived RR intervals, finger systolic, diastolic, and mean blood pressure values, as well as the duration of interbeat intervals.

The data is from 149 women (53.6% of the total) and 129 men. The median age of all participants studied was 24 years, their BMI was <24 kg/m^2, pulse rate and blood pressure were average. The median duration of the recordings was almost 30 minutes. In addition, we summarise selected parameters of heart rate variability (HRV) and heart rate asymmetry (HRA).

The HYPOL database is available at hypol.ump.edu.pl. The download of data is free after simple registration. Researchers and engineers can use the database to test various mathematical algorithms for HRV, HRA, blood pressure variability and asymmetry, and baroreflex function, except for selling it.

Introduction

Data is the primary driving force behind science, offering evidence to support scientific claims and hypotheses. The discovery of new phenomena, development of innovative technologies, testing of theories, and generation of knowledge would only be possible with data. Data can be sourced through experiments, observations, surveys, or simulations. It can be analysed through diverse methods such as statistics, machine learning, or visualisation. When shared, data can be repurposed and reused [1-4].

Data sharing in medical research involves making research data available to other researchers for reuse, review and collaboration. It has received increasing attention and support from many international and national agencies, including the Organisation for Economic Co-operation and Development, the European Commission, the National Institutes of Health (NIH) and the G8 Science Ministers [1,4].

The basic idea of data sharing is that publicly funded research data is a public good that should be openly accessible with minimal restrictions, in line with transparency, reproducibility, efficiency and collaboration [1-4]. Sharing clinical and physiological research data is strongly encouraged, as it is essential for evidence-based medicine and public health policy development. Scientific, economic and ethical reasons support data sharing. Reusing and sharing data from clinical trials has also earned its recommendations and principles.

Scientifically, data sharing allows comparisons, meta-analyses and hypothesis testing, thereby increasing the validity of the data and allowing replication, which is necessary to detect falsifications and errors in the findings of other authors. It can reduce the need for redundant studies. Research funders and governmental agencies support the optimisation of resource use through the economical reuse of data. Ethically, data sharing respects the contributions of trial participants and is consistent with the idea that access to data to improve health is a fundamental right [1-4].

Data reuse saves time, accelerates progress, intensifies medical research and improves local, national and international collaboration. Data sharing also promotes scientific openness, transparency and efficiency.

Many sources provide free access to a range of clinical and physiological data. Some provide data from intensive care units, such as MIMIC-III and the eICU Collaborative Research Database, with detailed information on critically ill patients [5,6]. Other sources include cohort studies of cardiovascular health and disease, such as the Sleep Heart Health Study and the Cardiovascular Health Study with electrocardiograms (ECGs), the BIDMC Congestive Heart Failure Database, or the Apnea ECG Database [7–9].

A classic example of a multi-signal database is PhysioNet. It is a web-based resource established in 1999 under the auspices of the National Institutes of Health. PhysioNet supports and promotes complex physiological and clinical data research by providing high-quality datasets, software tools and educational materials for researchers, teachers, academics, students and clinicians [10–15].

Many of the datasets available on Physionet are examples of cardiovascular time series. In general, time series are sequences of values that change over time. Cardiovascular time series are sequences of different measures that reflect the function of the cardiovascular system, which changes with each heartbeat [16–33]. Classic examples of such series (see **Figure 1**) include:

- the duration of each cardiac cycle, measured as the distance between two consecutive R waves of the QRS complex on the ECG, is called the RR interval [16,19];
- the inter-beat interval, measured as the distance between the two systolic peaks of the pressure or pulse oxygenation waveform, is called the IBI [20];
- systolic blood pressure (SBP) and diastolic blood pressure (DBP) reflect the maximum and minimum values of the arterial pressure waveform, respectively [18,24].

Some other examples of cardiovascular time series whose values change with each heartbeat are:

- mean blood pressure (MBP) is the height of the pulse pressure time integral, calculated as the area under the pressure waveform divided by the duration of the cardiac cycle [18,21,22,24];
- pulse pressure, which is the difference between SBP and DBP [24–28];

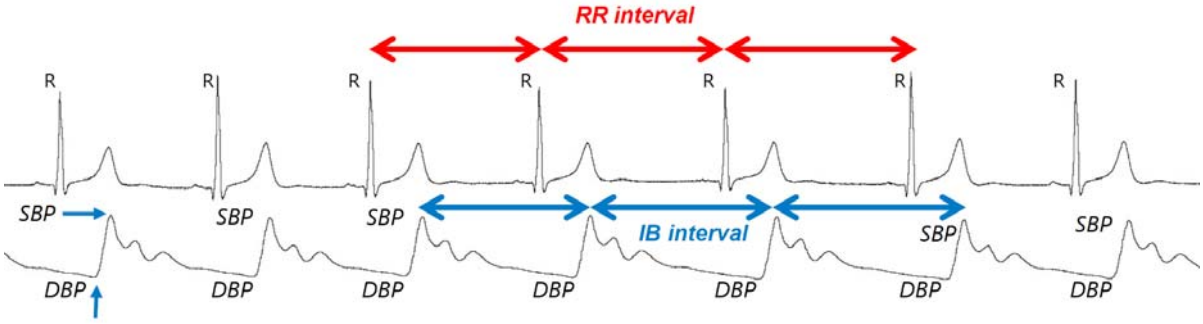

Figure 1. Example of a simultaneously recorded ECG and finger arterial pressure waveform from a healthy male. R indicates the R-waves in the QRS complex, and the distances between successive R-waves are called RR intervals. The local maxima on a pressure waveform are SBP, and the minima are DBP. The distances between the maxima of consecutive SBP waveforms are termed interbeat (IB) intervals. The pressure waveform was recorded by photoplethysmography using Portapres 2.

- pulse wave velocity, which is the rate at which pressure waves move forward in the arterial tree [29,30];
- stroke volume, which is the amount of blood ejected into the aorta by the left ventricle during a contraction [21,22];
- central venous pressure, which is the blood pressure in the venae cavae near the right atrium of the heart [31];
- vascular resistance, which is the resistance to blood flow created by the arteries and veins [21,22];
- QT interval, which is the distance between the beginning of the Q wave and the end of the T wave of the ECG [32];
- AV interval, which is the distance between the A and V peaks in the intracardiac electrograms, corresponding to atrioventricular conduction [33,34].

Cardiovascular time series can be described by mathematical parameters such as mean, standard deviation, and coefficient of variation [16, 18]. The RR intervals from the ECG are the easiest to measure and, therefore, study [16, 17]. Several mathematical methods and parameters describe the RR interval time series; this field of research is known as Heart Rate Variability (HRV). Nearly 60,000 papers have been published on heart rate variability in the last 50 years, and their abstracts are available on PubMed (**Figure 2**). In 2021, the number of published abstracts with this term was almost 4 thousand. HRV has been widely investigated in clinical, physiological, psychological, and sports studies [16,17,35-40]. Specific recommendations have been proposed for HRV [16,17].

While studying RR intervals and developing novel mathematical approaches to HRV, our

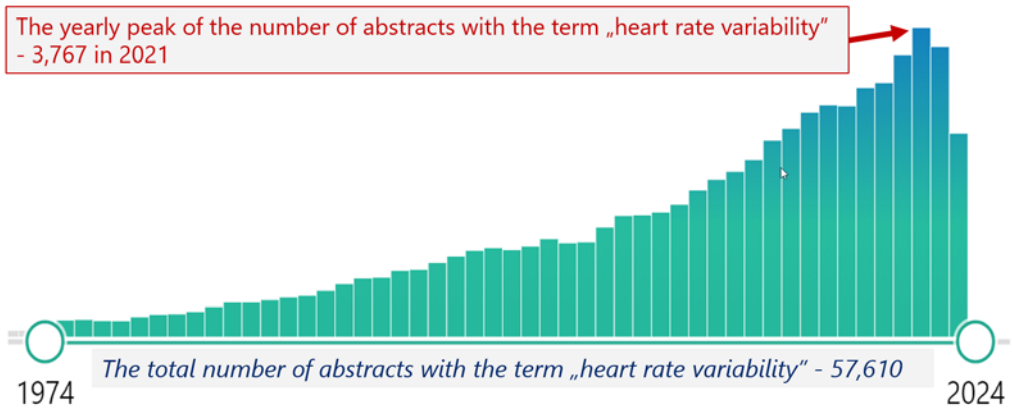

Figure 2. Trends in the number of papers with abstracts on heart rate variability in the last 50 years – data come from the PUBMED database and have been automatically generated by this service.

group discovered and described the phenomenon of Heart Rate Asymmetry (HRA). HRA is related to the unequal contributions of heart rate accelerations and decelerations to RR interval variance, structure, complexity, and trends [41-49]. We have also reported the existence of the phenomenon of HRA compensation [49]. HRA compensation is evident when heart rate accelerations contribute more to long-term HRV than heart rate decelerations do to short-term HRV.

Another example of a commonly studied cardiovascular time series is blood pressure variability (BPV) [18]. The definition of BPV is much broader than that of HRV, and repeated measures of blood pressure other than beat-to-beat are also accepted, e.g., minute-to-minute, measurement-to-measurement, or visit-to-visit [18].

Beat-to-beat blood SPB, DPB, or MBP measurements are more complicated than RR intervals from the ECG. Continuous blood pressure is monitored invasively using special catheters placed in the arteries of patients in intensive care units during some operations or cardiac wards. It is a standard procedure. However, the variability of these measurements is rarely studied. An alternative approach is to use non-invasive, usually photoplethysmography, measurements of finger SBP and diastolic blood pressure with specialised devices, e.g., Portapres, Finapres, Finometer, and TaskForce Monitor [18].

BPV has also been used in various studies and has earned its clinical recommendations [18]. In addition, we have shown that BPV also has asymmetric characteristics. SBP increases have a more significant contribution to short-term BPV than SBP decreases, which means there is another phenomenon of blood pressure asymmetry (BPA) [51].

Changes in blood pressure modify heart rate, i.e., the duration of RR intervals, via baroreceptors located in the arterial walls, mainly in the aortic arch and both bulbs of the carotid arteries [51-53]. Baroreceptors are pressure-sensitive nerve endings that detect changes in blood pressure and send reflex signals to slow or accelerate heart rate and reduce or increase vascular tone. Baroreflex function can be measured using parameters such as baroreflex sensitivity (BRS) and its delay or effectiveness (BRE) at rest during various physiological manoeuvres or pharmacological interventions [23,51-57].

Recently, we proposed a new method to study baroreflex function (ppBR) using combined Poincare plots of concordant SBP and RR intervals [56,57]. This method has shown that spontaneous short, long, and total BRS have asymmetric characteristics. Increases in SBP have stronger short-term but weaker long-term and overall effects on heart rate decelerations than on accelerations. In addition, the BRS is weaker for the interactions between SBP increases and heart rate decelerations than for the interactions between SBP decreases and heart rate accelerations. Furthermore, increases in SBP prolonged RR intervals in the short-term BPV more than decreases in SBP shortened RR intervals. In the long term, this effect is reversed: SBP decreases shortened RR intervals more than SBP increases them. The reversed effects of SBP increases vs. decreases on short- and long-term BRS demonstrated the existence of compensatory mechanisms within the baroreflex function.

Many scientists study HRV, HRA, BPV, BPA, or baroreflex function. Despite years of research, hundreds of analytical methods, and generated parameters, reference values still need to be improved. In addition, direct comparisons of different methods for HRV, HRA, BPV, BPA, or baroreflex function are rare or lacking, most likely because common reference data are not available to other scientists. In addition, some issues, such as gender differences or the effect of supine resting time, have not been fully resolved in the cardiovascular time series.

Our team has been monitoring and analysing cardiovascular time series for over 25 years, conducting dozens of studies on healthy people and heart disease patients. During this time, we have successfully collected data from thousands of individuals.

In autumn 2022, the Board of the European Study Group on Cardiovascular Oscillations and its President, Professor Alberto Porta, decided to announce a new scientific competition for 2024, "ESGCO 2024": Characterisation of sex differences in heart rate and blood pressure time series" (https://www.esgco.org/challenges). For this challenge, we have decided to share data containing different cardiovascular time series recorded at rest in healthy young men and women.

This paper aims to characterise the population studied and the data to be shared. We have,

therefore, selected a set of identically recorded ECGs and finger pressure waveforms to share with other scientists.

Study population and materials

We carefully selected baseline clinical characteristics and beat-to-beat data from several cardiovascular time series from seven projects conducted in our laboratory at the Department of Cardiology-Intensive Therapy, Poznan University of Medical Sciences, Poznan, Poland. The local bioethics committee approved all projects with the following decision numbers and issue dates:

- 1144/05 of 08 September 2005,
- 1251/05 of 08 September 2005,
- 89/09 of 05 February 2009,
- 538/10 of 17 June 2010,
- 975/15 of 05 November 2015,
- 708/18 of 14 June 2018,
- 953/19 of 03 October 2019.

Most of the studies have been completed, and the last is ongoing.

All data are from healthy volunteers who agreed to participate in specific projects, gave written informed consent before participating in the study, and were informed that they could withdraw at any time. All projects were conducted following the Declaration of Helsinki [58].

Candidates were asked to abstain from alcohol for at least 24 hours and from tobacco, coffee, and energy drinks for at least 12 hours before the study. They were also asked to come to the laboratory fasting or postprandial, but at least two hours after their last meal (at the participant's choice).

The participants' health status was assessed by obtaining information on current signs and symptoms, family history, and environmental data. The history focused on chronic diseases, previous surgery and invasive procedures, acute infections, pharmacological agents and dietary supplements, drug or alcohol use and dependence, and sports training and competition participation. We excluded people with:

- known chronic illness or previous myocardial infarction, stroke, neoplasm, atrial fibrillation or flutter or after pulmonary vein electrophysiological ablation, with intracardiac occlusion, pulmonary embolism, epilepsy;
- acute infection or invasive procedure in the last three months;
- signs and symptoms of acute illness;
- chronic medication use, except oral hormonal contraception in women of reproductive age;
- pregnancy or breastfeeding in the last three months;
- drug or alcohol dependence;
- current professional endurance or resistance athletes.

Occasional use of non-steroidal anti-inflammatory drugs for pain relief (e.g., headache) was allowed, except for 48 hours before signal recording. During the routine physical examination, we always:

- took basic anthropometric measurements of body weight and height;
- obtained a standard 12-lead resting ECG;
- measured resting brachial blood pressure in the sitting position after a 10-minute rest using an oscillometric method (one of Omron's blood pressure monitors in the years 2005–2020, with two recent models Omron M5 and Omron M7 Intelli IT, Omron, Kyoto, Japan).

We excluded participants with:

- resting sinus rhythm <40 or at least 100 beats/minute, non-sinus rhythm, PQ <120 ms with features of preexcitation, channelopathies, left or right ventricular hypertrophy, QRS duration at least 120 ms, ST-segment depression or negative T waves in leads other than aVR, III and V1;
- SBP 140 mmHg or more and/or DBP 90 mmHg or more;
- body mass index <15 or at least 30 kg/m^2.

Non-invasive continuous finger blood pressure and ECG recording

All participants rested in the supine position during signal acquisition. An A/D converter—either Porti 5 with a sampling frequency of 1600 Hz or Porti 17 with a sampling frequency of 2048 Hz-recorded three channels of a bipolar chest lead ECG. TMSI (Oldenzaal, The Netherlands) produced both devices.

A non-invasive beat-to-beat finger arterial blood pressure signal was simultaneously recorded using a volume-clamp photoplethysmographic method and transferred to the A/D converter. The finger arterial pressure waveforms

were recorded using either the Portapres 2 or the Finapres Nova, both from FMS (Amsterdam, The Netherlands). Signals were recorded for at least 15 minutes, depending on the protocol and project. For the HYPOL database, we have selected signals up to 45 minutes.

Signal processing and export of cardiovascular time series

Preliminary automated analysis of the recordings was performed using the libRASCH/RASCHlab software from the libRASCH project (v. 0.6.1; http://www.librasch.org, Munich, Germany) [59]. If necessary, a visual examination of all beats and manual correction came next. ECG-derived RR intervals for each cardiac cycle with appropriate beat type annotation (regular = 0, ventricular = 1, supraventricular = 2, technical artefact = 3) and photoplethysmography-derived finger SBP, DBP, MBP, and interbeat intervals were retrieved from stored recordings. These values form the HYPOL database and can be used to calculate HRV, HRA, BPV, BPA, baroreflex function, and other analyses of cardiovascular time series.

HYPOL database

The database will be called HYPOL because it represents Healthy Young POLes, i.e., individuals of Polish ethnicity, representing the wider European ethnic group in the narrow age range between 19 and 30 years. No participant names or other sensitive data are provided; all individuals remain anonymous. The database consists of two files:

1. HYPOL DATABASE.zip, containing 278 tab-separated text files with the extension.rea. Each.rea file is from a different individual in the HYPOL population. These files contain seven columns with the following labels and data:
   - time[min] – time track expressed in minutes and synchronised beat-to-beat values of:
   - rri[ms] – duration of RR intervals in milliseconds;
   - rr-flags[] – annotation about the beat type with codes 0 for the beat of sinus origin, 1 for ventricular depolarisation, 2 for supraventricular depolarisation, and 3 for technical artefact;
   - rr-systolic[mmHg] – finger pressure SBP in mmHg;
   - rr-diastolic[mmHg] – finger pressure DBP in mmHg;
   - rr-mean[mmHg] – finger pressure MBP in mmHg;
   - ibi[ms] – duration of inter-beat interval in ms;

   Table 1 displays an example of the initial rows of the file.
2. HYPOL clinical characteristics.xls is a single Excel file with baseline clinical characteristics and file names of each individual. The columns in this file are as follows:
   - file name – the name of each record corresponding to the file names in the zipped database;
   - sex [nominal codes: "1" woman; "2" man] – with codes 1 for a woman; 2 for a man;
   - age [years] – age in years;

Table 1. A sample of 12 first beat-to-beat values from a file ag19.rea from a 26-year-old healthy woman from the HYPOL database.

time[min]	rri[ms]	rr-flags[]	rr-systolic[mmHg]	rr-diastolic[mmHg]	rr-mean[mmHg]	ibi[ms]
0.0143333333333	860.0	0	89.315797	47.274514	61.53427	899.375
0.0285416666667	852.5	0	86.846042	47.295679	62.534981	838.125
0.04321875	880.625	0	91.539302	52.472703	63.188214	1006.25
0.0601145833333	1013.75	0	91.539732	47.603983	59.600983	1186.875
0.0789479166667	1130.0	0	85.107737	43.821491	58.331134	960.0
0.0958645833333	1015.0	0	88.080992	45.398066	57.477056	1071.875
0.113645833333	1066.875	0	84.611382	41.475861	53.912648	1073.75
0.13121875	1054.375	0	79.921412	38.595414	53.739337	883.75
0.14628125	903.75	0	84.617817	41.585544	55.961219	925.625
0.16171875	926.25	0	85.355127	41.490876	64.19002	904.375
0.17728125	933.75	0	86.473242	42.82278	55.28799	1001.25
0.191322916667	842.5	0	87.400954	43.441398	54.951375	1039.0625

- BMI [kg/m^2] – body mass index in kg/m^2;
- body Height [cm] – body height in centimetres;
- body WEIGHT [kg] – body weight in kilograms;
- pulse rate [bpm] – pulse rate in beats/minute measured at the peripheral artery at the same time as brachial blood pressure;
- brachial SBP [mmHg] – brachial SBP in mmHg;
- brachial DBP [mmHg] – brachial DBP in mmHg;
- brachial MBP [mmHg] – brachial MBP in mmHg;
- brachial PP [mmHg] – brachial pulse pressure in mmHg;
- FPP – fractional pulse pressure, i.e. the ratio of PP to MBP.

Preliminary data analysis

To demonstrate the capabilities of the database, we will compute selected parameters of HRV and HRA for all participants. HRV and HRA parameters were computed using publicly available, open-source software (HRAexplorer.com). For the computation, we applied the following filters:

› only for RR intervals of sinus (normal) origin;
› the minimal accepted RR interval was 500 ms, which corresponds to the 120 beats/minute momentary heart rate of;
› the maximal accepted RR interval was 1500 ms, corresponding to the 40 beats/minute momentary heart rate.

Details on the computation and definitions of HRV and HRA parameters can be found elsewhere [15–17,23,41–43,47–49,61–67].

For HRV, we will present the following parameters [15–17,23,47,48,61–66]:

› mean RR – mean duration of all RR intervals;
› SD1 – the square root of the short-term RR intervals variance;
› SD2 – the square root of the long-term RR intervals variance;
› SD2/SD1 – the ratio of SD1 to SD2;
› SDNN – the square root of the total RR intervals variance;
› pNN50 – the percentage of successive RR intervals that differ by more than 50 ms;
› CS – the contribution of the short-term variance to the total HRV;
› CV – the coefficient of variation of RR intervals, i.e., the SDNN to Mean RR ratio.

For the spectral analysis, we applied the method of Lomb-Scargle periodograms. We used the ranges suggested by the Task Force of the European Society of Cardiology and the North American Society of Pacing Electrophysiology [16,62–66]:

› TP – the total power in the whole frequency range (0.00–0.4 Hz) of all RR intervals;
› VLF – the power of very low frequency (0.00–0.04 Hz) of RR intervals;
› LF – the power of low frequency (0.04–0.15 Hz) of RR intervals;
› HF – the power of high frequency (0.15–0.4 Hz) of RR intervals;
› LF/HF – the ratio of the powers of LF to HF.

For HRA, we will show the following parameters [41–43,47,49,67]:

› SD1a – the square root of the short-term RR intervals variance derived from accelerations;
› SD1d – the square root of the short-term RR intervals variance derived from decelerations;
› SD2a – the square root of the long-term RR intervals variance derived from accelerations;
› SD2d – the square root of the long-term RR intervals variance derived from decelerations;
› SDNNa – the square root of the total RR intervals variance derived from accelerations;
› SDNNd – the square root of the total RR intervals variance derived from decelerations;
› C1d – the contribution of HR decelerations to the short-term HRV;
› C2d – the contribution of HR decelerations in long-term HRV;
› CTd – the contribution of HR decelerations in total HRV;
› Nd, also known as the Porta index – the contribution of the number of HR decelerations to the total number of changing heartbeats, i.e. heart rate accelerations and decelerations [47,48,67];
› CLa – the contribution of the long-term variance to the total HRV derived from HR accelerations;
› CLd – the contribution of the long-term variance to the total HRV derived from HR decelerations;
› CSa – the contribution of the short-term variance to the total HRV derived from HR accelerations;

- CSd – the contribution of the short-term variance to the total HRV derived from HR decelerations;
- HRA1 – the presence of short-term HRA that is present if C1d >0.5;
- HRA2 – the presence of long-term HRA that is present if C2d <0.5;
- HRAT – the presence of total HRA that is present if C1d >0.5;
- HRAN – the presence of HRA based on the analysis of the number of heart rate decelerations and accelerations, which is present if Nd <0.5;
- HRA compensation – the simultaneous presence of HRA1 and HRA2, i.e. if C1d >0.5 is accompanied by C2d <0.5.

Statistical Analysis

Graphical analysis of data distribution (histograms and Q-Q plots) and the D'Agostino-Pearson test showed that some data had normal distribution while others did not [68]. For this reason, all continuous data will be presented as Mean, standard deviation (SD), median, 25th percentile and 75th percentile. Binomial tests were used to study the presence of specific asymmetric features. Statistical analyses were performed using PQStat Software (PQStat v.1.8.4.138, PQStat Software, Poznan, Poland).

Results

There were 149 women (53.6% of all) and 129 (46.4%) men; no significant difference in sex distribution was found (p = 0.2303). The median age of all studied participants was 24 years; their BMI was <24 kg/m^2. Pulse rate and brachial SBP and DBP were regular. The duration of the recordings was nearly 30 minutes, and the mean quality showed that over 96% of all RR intervals were of sinus origin.

Table 2 (see next page) summarises continuous data for clinical characteristics and measured HRV and HRA parameters.

Table 3 provides a list of the rates for different types of HRA. All forms of HRA and the HRA compensation were present in most analysed recordings.

Table 3. The rate of various forms of HRA in the HYPOL group.

HRA form	N	%	P value
HRA1	227	81.66%	<0.0001
HRA2	223	80.22%	<0.0001
HRAT	220	79.14%	<0.0001
HRAN	184	66.19%	<0.0001
HRA compensation	208	74.84%	<0.0001

Abbreviations: HRA – heart rate asymmetry; HRA1 – the presence of short-term HRA; HRA2 – the presence of long-term HRA; HRAN – the presence of HRA based on the analysis of the number of heart rate decelerations and accelerations; HRAT – the presence of total HRA.

Discussion

We provide the HYPOL database with data from healthy young adult Poles aged between 18 and 30 years who were enrolled in several previous studies conducted in our department. HYPOL database contains essential information on clinical characteristics and hundreds of files containing cardiovascular time series values, namely RR intervals from ECG and SBP, DBP, MBP and interbeat intervals measured from finger pressure waveforms. We also provide a summary of selected parameters describing HRV and HRA. These parameters have been calculated using specific filters, i.e. only RR intervals of sinus origin between 500 and 1500 ms.

As mentioned earlier, data sharing is a powerful tool that can be used to accelerate progress in medical research. By making data more available, accessible and reusable, data sharing can help researchers compare data or findings, explore problems and make discoveries. The HYPOL database allows such comparisons to be made with other databases.

The cardiovascular time series files we provide also contain different information about the duration of cardiac cycles. Although the RR intervals from the ECG and the interbeat intervals from photoplethysmography are assumed to represent the duration of the cardiac cycle, each characterises different features of cardiovascular system activity. In comparison, RR intervals reflect the distances between two peaks of ventricular electrical depolarisation, while IB intervals are the distances between two peaks of pressure waveforms. These waveforms are recorded using dis-

Table 2. Summary of continuous clinical data and selected HRV and HRA parameters from the HYPOL database. Exclusively, RR intervals of sinus origin ranging from 500 to 1500 ms were used for HRV and HRA analyses.

Analysed variables	Mean	SD	Median	25th percentile	75th percentile
Age (years)	23.75	2.58	24.00	22.00	25.00
Body height (cm)	173.35	9.04	172.00	167.00	180.00
Body weight (kg)	66.49	12.33	65.00	57.00	75.00
BMI (kg/m^2)	21.98	2.66	21.79	19.99	23.80
Pulse rate (bpm)	66.67	9.23	66.00	61.00	72.00
Brachial SBP (mmHg)	111.55	10.29	112.00	104.00	118.00
Brachial DBP (mmHg)	66.64	7.12	67.00	62.00	71.00
Brachial MBP (mmHg)	80.41	7.44	80.00	75.00	86.00
Brachial PP [mmHg]	44.94	8.48	44.00	38.00	51.00
Fractional pulse pressure	0.56	0.11	0.56	0.47	0.64
Duration of the recording (min)	29.29	3.19	29.99	29.99	30.00
Sinus origin of RR intervals [%]*	96.97	1.43	96.86	96.15	97.21
Mean RR interval (ms)	893.23	113.51	893.73	807.46	961.13
SDNN (ms)	72.39	28.34	64.77	53.21	85.06
SD1 (ms)	42.54	25.82	34.94	26.12	52.67
SD2 (ms)	92.42	32.70	85.21	69.82	108.73
SD2/SD1	2.46	0.72	2.37	1.94	2.81
CS	0.17	0.08	0.15	0.11	0.21
CV	0.08	0.03	0.07	0.06	0.09
pNN50 (%)	28.88	18.76	25.63	14.16	43.71
SDNNd (ms)	49.79	18.75	45.31	37.10	58.36
SDNNa (ms)	52.51	21.35	46.36	38.26	63.58
SD1d (ms)	31.89	19.81	26.01	18.47	39.71
SD1a (ms)	28.04	16.74	23.50	18.24	34.49
SD2d (ms)	62.04	20.05	58.46	48.27	71.72
SD2a (ms)	68.35	26.23	61.56	50.55	82.72
Nd	0.49	0.03	0.49	0.47	0.51
C1d	0.55	0.06	0.55	0.51	0.58
C2d	0.46	0.05	0.47	0.44	0.49
CTd	0.48	0.03	0.48	0.46	0.50
CSd	0.09	0.05	0.08	0.06	0.12
CSa	0.07	0.04	0.07	0.05	0.09
CLd	0.39	0.06	0.39	0.35	0.43
CLa	0.45	0.04	0.45	0.42	0.48
TP [ms^2]	6322.80	6049.42	4405.63	2876.26	7484.11
VLF [ms^2]	2597.28	2387.04	1952.62	1219.79	3078.41
LF [ms^2]	1807.45	1768.45	1202.62	759.69	2201.29
HF [ms^2]	1918.08	2622.67	1035.27	573.77	2190.65
LF/HF	1.35	0.82	1.17	0.80	1.73

* The percentage of RR intervals originating from the sinus node and with a duration between 500 and 1500 ms.
Abbreviations: BMI – body mass index; C1d – the contribution of HR decelerations to the short-term HRV; C2d – the contribution of HR decelerations in long-term HRV; CLa – the contribution of the long-term variance to the total HRV derived from HR accelerations; CLd – the contribution of the long-term variance to the total HRV derived from HR decelerations; CS – the contribution of the short-term variance to the total HRV; CSa – the contribution of the short-term variance to the total HRV derived from HR accelerations; CSd – the contribution of the short-term variance to the total HRV derived from HR decelerations; CTd – the contribution of HR decelerations in total HRV; CV – the coefficient of variation of RR intervals; HF – the power of the high frequency of RR intervals; LF – the power of the low frequency of RR intervals; LF/HF – the ratio of the powers of LF to HF; Nd – the contribution of HR decelerations in number of all changing RR intervals; pNN50 – percentage of successive RR intervals that differ by more than 50 ms; PP – pulse pressure; SD1 – the square root of the short-term RR intervals variance; SD1a – the square root of the short-term RR intervals variance derived from accelerations; SD1d – the square root of the short-term RR intervals variance derived from decelerations; SD2 – the square root of the long-term RR intervals variance; SD2/SD1 – the ratio of SD1 to SD2; SD2a – the square root of the long-term RR intervals variance derived from accelerations; SD2d – the square root of the long-term RR intervals variance derived from decelerations; SDNN – the square root of the total RR intervals variance; SDNNa – the square root of the total RR intervals variance derived from accelerations; SDNNd – the square root of the total RR intervals variance derived from decelerations; TP – the total power in the whole frequency range of RR intervals; VLF – the power of very low frequency of RR intervals.

tinct signals, methods and sampling frequencies. For ECG, the sampling frequency in our database is 1600 Hz or 2048 Hz, depending on the version of the A/D converter. For pressure waveforms, these frequencies are 100 Hz or 200 Hz when recorded by Portapres 2 or Finapres Nova. In addition, the peaks of the R waves in the ECG are sharp. In contrast, the peaks of the arterial pressure waveforms are broader and not as well defined. The HYPOL database allows comparing RR and IB intervals in the same individuals.

Figure 3 shows the correlation between RR intervals and IBI, and **Figure 4** shows RR and IB intervals changing over time and the differences in their duration (RRI – IBI). These differences are clearly visible and not interchangeable. Nevertheless, interbeat intervals can provide valuable clinical information. As they are more readily available from sports watches, smart watches or other mobile devices, their usefulness in various clinical scenarios is being investigated. One example is the detection of atrial fibrillation [69,70].

This database has several limitations. Firstly, the data come from people of Polish ethnicity, so it is better to refer to this database in comparative studies, and any findings should be limited to a European ethnic group. Second, because of the narrow age range between 18 and 30 years, no findings should be extrapolated to children under 18 or adults over 30. Thirdly, these recordings were made under laboratory conditions in people in the supine position. The real-life recordings made outside the laboratory environment, in conditions other than those described, or in people using different pharmacological agents may differ. Fourth, the sampling frequencies of the ECGs were either 1600 Hz or 2048 Hz, which are typical for laboratories but not for other systems. Some other laboratories record ECGs at even higher sampling frequencies than we do.

The HYPOL database is primarily intended for use in the ESGCO 2024 Challenge. However, other scientists can also use the database for their studies. Use of the database is free of charge, and we would like to be acknowledged as the team that created and shared the database. A reference to the current paper would be appropriate.

The data will be available on the Poznan University of Medical Sciences website, hypol.ump.edu.pl, after potential users provide their details.

Acknowledgements

This paper has been prepared within the tasks of the project "Development of the University Centre for Sports and Medical Studies in Poznan, Poland" (Number: NdS/544750/2021/2022) with Principal Investigator Prof. Przemysław Guzik. The Ministry of Education and Science, Warsaw, Poland, funded the project within the "Science for Society" Program.

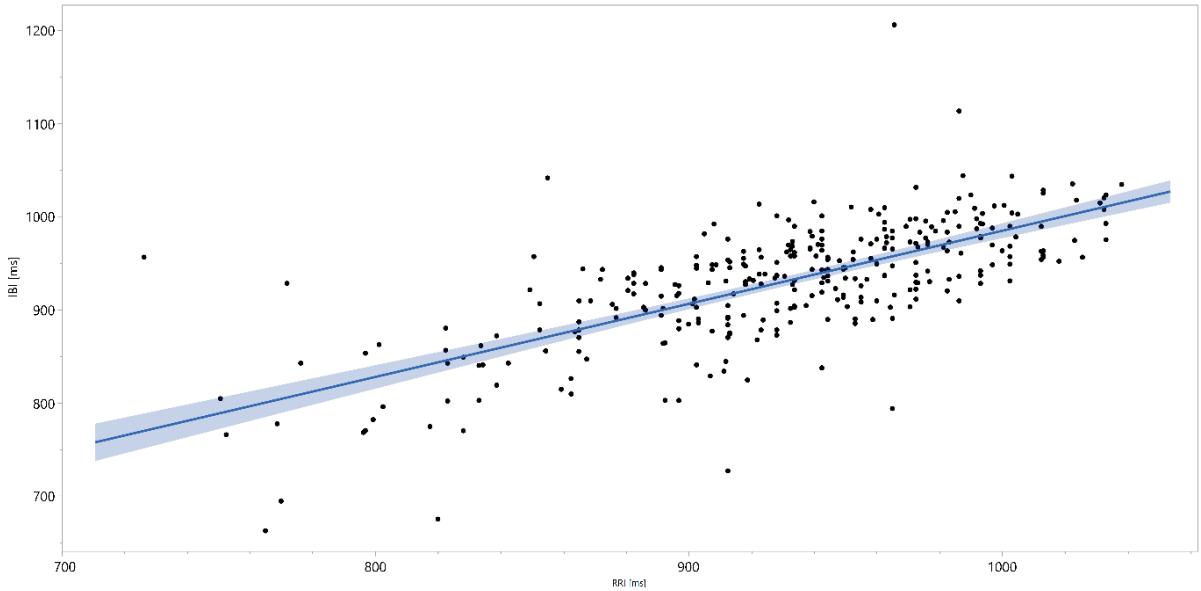

Figure 3. A simple regression line over RR intervals (RRI) from ECG and paired interbeat intervals (IBI) from finger arterial pressure waveform from the same person for the first 5 of the 30-minute recording. The value of R^2 for this regression line is 0.49 ($p < 0.0001$).

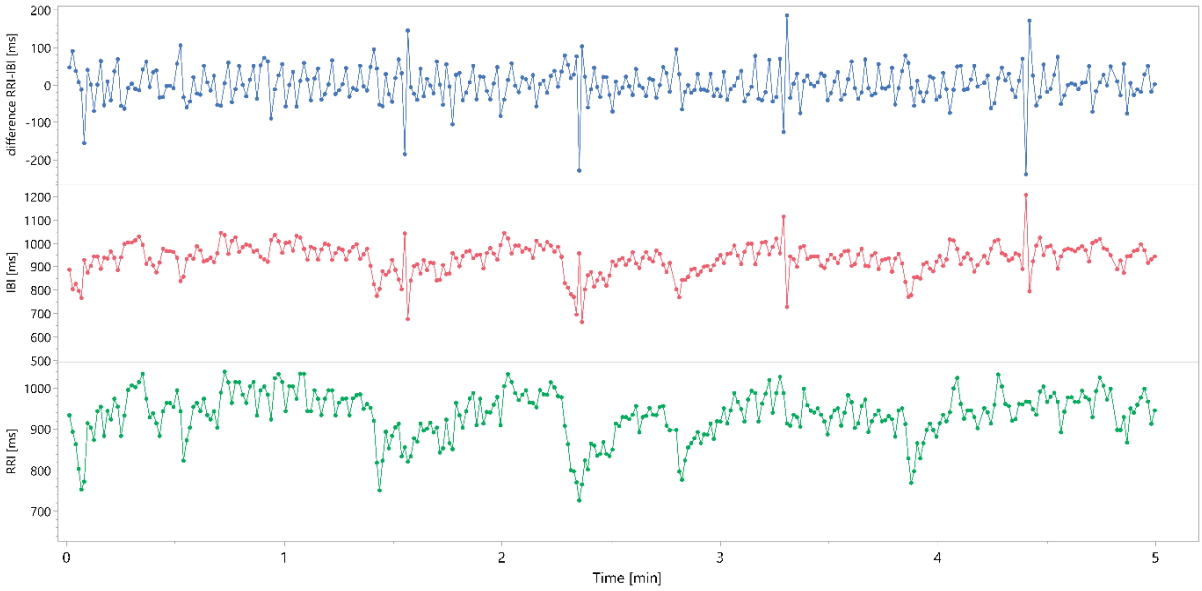

Figure 4. Local tachograms from the same healthy subject as in **Figure 3**. The lower tachogram shows all RR intervals (RRI) for each cardiac cycle recorded over 5 minutes. The middle tachogram displays the interbeat intervals (IBI) for identical heartbeats. From time to time, there are visible rapid changes in the duration of the IBIs; after a single beat prolongation, there is a sudden decrease in the duration of the IBI. A similar phenomenon does not occur in ECG and RR intervals. However, these sudden changes in the IBI are transferred to the differences in the duration of the RR and interbeat intervals, as shown in the upper tachogram. The HRV analysis results for the 30-minute recordings showed that the mean RR and IB intervals were almost identical (914.51 vs. 914.01 ms). However, other parameters differed, some substantially (SDNN – 59.12 vs. 69.37 ms; SD1 – 25.85 vs. 52.32 ms; SD2 – 79.51 vs. 82.98 ms; pNN50 – 15.94 vs. 22.67%).

All data come from several projects funded by internal research grants from Poznan University of Medical Sciences, Poznan, Poland. The numbers of the decisions and the dates of their issuance by the Bioethics Committee at Poznan University of Medical Sciences are as follows: 1144/05 of 08.09.2005, 1251/05 of 08.09.2005, 89/09 of 05.02.2009, 538/10 of 17.06.2010, 975/15 of 05.11.2015, 708/18 of 14.06.2018 and 953/19 of 03.10.2019.

Conflict of interest statement
The authors declare no conflict of interest.

Funding sources
There are no sources of funding to declare.

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