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MEASURING HEART RATE VARIABILITY: INSIGHTS FOR CLINICIANS AND RESEARCHERS

Kapil Gupta, Ravi Saini, Rekchand Saini, Abhishek Sharma

SMS Medical College, 302004, Jawahar Lal Nehru Marg, Jaipur, Rajasthan, India

ABSTRACT

Background. Non-invasive studies allow for effective assessment of cardiovascular health, stress levels, and overall physiological resilience. Heart rate variability, defined as fluctuations in the time intervals between successive heartbeats, allows for the study of autonomic nervous system activity. It reflects the dynamic balance between the sympathetic and parasympathetic branches of the autonomic nervous system, providing information that is a valuable biomarker in various fields, including cardiology, sports science, psychology, and occupational health.
Aim. To analyze the effective use of heart rate variability and summarize the obtained information to better inform physicians.
Materials and methods. A literature review was conducted using well-known databases such as the Russian Science Citation Index and PubMed covering a 10-year period.
Results. Heart rate variability is the variation in the time intervals between successive heartbeats and is a noninvasive indicator of autonomic nervous system activity. It reflects the dynamic balance between the sympathetic and parasympathetic branches of the autonomic nervous system, providing information about cardiovascular health, stress levels, and overall physiological resilience. Heart rate variability has become a valuable biomarker in various fields, including cardiology, sports science, psychology, and occupational health. High heart rate variability is generally associated with good health and adaptability, while low heart rate variability may indicate stress, fatigue, or pathological conditions.
Conclusion. Advances in wearable technologies and data analysis have facilitated real-time heart rate variability monitoring, opening up broader possibilities for clinical and personal healthcare applications. This article reviews the physiological basis of heart rate variability, common measurement methods, clinical significance, and current trends in heart rate variability research and application.

Key words: *heart rate, electrocardiogram, computer analysis, autonomic nervous system, risk assessment*

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ИЗМЕРЕНИЕ ВАРИАБЕЛЬНОСТИ СЕРДЕЧНОГО РИТМА: ИНФОРМАЦИЯ ДЛЯ ВРАЧЕЙ И ИССЛЕДОВАТЕЛЕЙ

Гупта К., Саини Р., Саини Р., Шарма А.

Медицинский колледж Савай Ман Сингх, 302004, Джавахар Лал Неру Марг, Джайпур, Раджастхан, Индия

АННОТАЦИЯ

Актуальность. Неинвазивные исследования позволяют эффективно оценивать состояние сердечно-сосудистой системы, уровень стресса и общую физиологическую устойчивость организма. Вариабельность сердечного ритма, определяемая по колебаниям временных интервалов между последовательными сердечными сокращениями, позволяет исследовать активность вегетативной нервной системы. Она отражает динамическое равновесие между симпатической и парасимпатической ветвями вегетативной нервной системы, предоставляя информацию, которая является ценным биомаркером в различных областях, включая кардиологию, спортивную науку, психологию и гигиену труда.

Цель. Провести анализ эффективного применения вариабельности сердечного ритма и обобщить полученную информацию для лучшего информирования врачей.

Материалы и методы. Проведён обзор источников литературы с использованием известных баз данных, таких как Российский индекс научного цитирования, PubMed, за последние 10 лет.

Результаты. Вариабельность сердечного ритма – колебание временных интервалов между последовательными сердечными сокращениями, представляющее собой неинвазивный показатель активности вегетативной нервной системы. Она отражает динамическое равновесие между симпатической и парасимпатической ветвями вегетативной нервной системы, предоставляя информацию о состоянии сердечно-сосудистой системы, уровне стресса и общей физиологической устойчивости. Вариабельность сердечного ритма стала ценным биомаркером в различных областях, включая кардиологию, спортивную науку, психологию и гигиену труда. Высокая вариабельность сердечного ритма обычно ассоциируется с хорошим здоровьем и адаптивностью, в то время как пониженная вариабельность сердечного ритма может указывать на стресс, усталость или патологические состояния.

Заключение. Достижения в области носимых технологий и анализа данных способствовали мониторингу вариабельности сердечного ритма в режиме реального времени, что открывает более широкие возможности для клинического и личного применения в области здравоохранения. В данной статье рассматриваются физиологические основы вариабельности сердечного ритма, распространённые методы измерения, клиническая значимость и современные тенденции в исследованиях и применении вариабельности сердечного ритма.

Ключевые слова: *частота сердечных сокращений, электрокардиограмма, компьютерный анализ, автономная нервная система, оценка риска*

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INTRODUCTION

Over the past two decades, the correlation between the autonomic nervous system and cardiovascular mortality – particularly the incidence of sudden cardiac death – has become increasingly evident. A multitude of experimental investigations reveal that aberrant patterns in autonomic activity – whether characterized by excessive sympathetic stimulation or a diminished vagal influence – can significantly elevate the risk of fatal arrhythmias. This understanding has catalysed the advancement of objective methodologies to quantify autonomic function.

Among these, heart rate variability (HRV) has emerged as one of the most promising indicators. Due to the ease with which HRV can be derived – often automatically by commercial electrocardiogram (ECG) devices – it has gained popularity in both clinical and research settings. However, interpreting HRV data correctly is more complicated than it may appear. Misunderstandings or over-interpretation of the various HRV metrics are common [1–3].

AIM

To analyze the effective use of heart rate variability and summarize the obtained information to better inform physicians.

MATERIALS AND METHODS

A literature review was conducted using well-known databases such as the Russian Science Citation Index and PubMed covering a 10-year period.

RESULTS

Defining heart rate variability (HRV)

It focuses on the fluctuations in the time intervals between consecutive heartbeats, known as RR intervals, as well as changes in moment-to-moment heart rate. Although other terms – like "cycle length variability" or "heart period variability" – have appeared in literature, "Heart Rate Variability" (HRV) is the most widely adopted [4].

Later in the 1970s, researchers found that our heart rate contains built-in rhythms that reflect how the body's nervous system is working. Around that time, simple bedside tests were created to check short-term heart rate changes in people with diabetes, which helped detect damage to their nerves [5].

In 1977, scientists discovered that patients who had a heart attack and showed lower HRV were more likely to die afterward. This made HRV a powerful tool for predicting heart problems. Then in 1981, a method called power spectral analysis was introduced. It breaks down heart rate signals into different frequency ranges and gives a better understanding of how the nervous system controls the heart from beat to beat. By the late 1980s, it became clear that HRV could predict who might be at higher risk of death after a heart attack. Thanks to new digital devices that can record heart activity for 24 hours, HRV became even more useful for doctors and researchers to study heart health in everyday life [6].

Measuring HRV: time domain methods

One of the easiest ways to measure HRV is by looking at how the heart rate changes over time – this is called time domain analysis. In a continuous heart recording (like an ECG), each heartbeat creates a spike (called the QRS complex). We measure the time between these spikes – specifically the time between two normal heartbeats, called the NN interval (short for "normal-to-normal").

From this, we can calculate simple things, like: the average time between heartbeats (mean NN); the average heart rate; the difference between the longest and shortest NN intervals; the difference between heart rate at night and during the day (Table 1).

Some tests involve changing body position or breathing patterns (like the Valsalva maneuver, deep breathing, or tilting the body) to see how the heart responds in different conditions [7].

Statistical methods

If we record heartbeats over a longer time (usually 24 hours), we can do more detailed statistical analysis. Based on the actual time between beats (NN intervals), based on the differences between each beat and the next beat (Fig. 1, Table 1).

Geometric methods

Another way to analyze HRV is by looking at the shape and patterns made by the heartbeat intervals. These are called geometric methods. In these methods, the time between each heartbeat (the NN intervals) is turned into a visual shape, like a histogram (a bar graph of interval lengths) (Fig. 2), Lorenz plot (a type of scatter plot showing how each beat compares to the next), triangle (used to estimate overall variability) [8].

Common geometric HRV measures

HRV Triangular Index counts the total number of NN intervals and divides it by the height of the most common interval (the tallest part of the histogram). It is simple and works well with long-term recordings.

Pros and cons of geometric methods

These methods are less sensitive to noise and small errors in data. They are easy to use with large datasets or low-quality recordings. Although, they do not work well with short recordings; one would need enough data points (heartbeats) to form clear pattern.

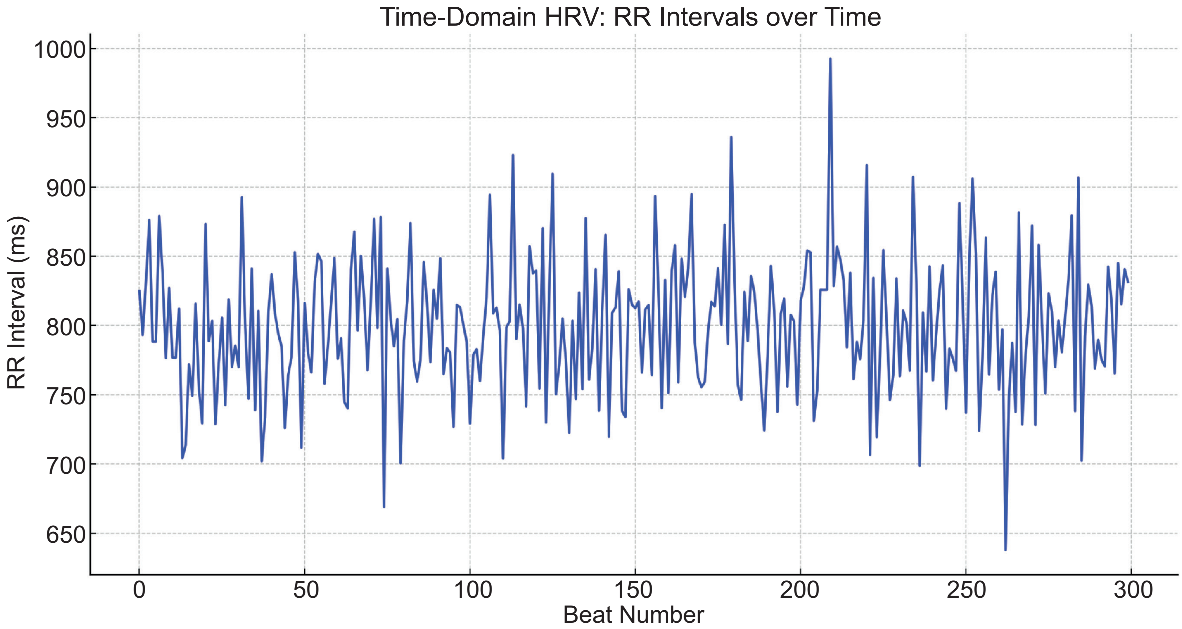

Fig. 1. *Time-domain analysis of heart rate variability, showing RR intervals across consecutive heartbeats*

Рис. 1. *Анализ вариабельности сердечного ритма во временной области, показывающий RR-интервалы между последовательными сердечными сокращениями*

TABLE 1
TIME DOMAIN MEASURES

ТАБЛИЦА 1
ПОКАЗАТЕЛИ ВРЕМЕННОЙ ОБЛАСТИ

SDNN	Shows overall heart rate variability, works best with long (24-hour) recordings
HRV Triangular Index	Measures overall HRV
TINN (Triangular Interpolation of NN Interval Histogram)	Measures the base width of a triangle fitted over the histogram of intervals
SDANN	Focuses on long-term changes (like over several minutes or hours)
RMSSD	Focuses on short-term changes (like beat-to-beat differences)
NN50	Counts how many times the time between beats changes by more than 50 milliseconds
pNN50	The percentage of these larger changes compared to the total number of beats

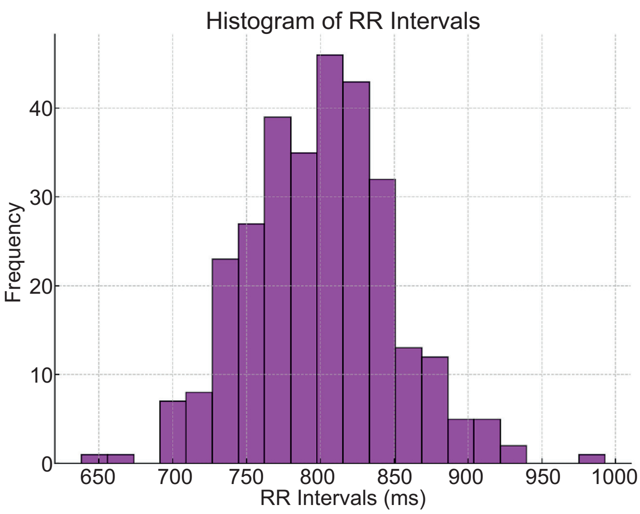

Fig. 2. *Histogram, showing the distribution of RR intervals obtained from time-domain HRV analysis*

Рис. 2. *Гистограмма, показывающая распределение RR-интервалов, полученных в результате анализа вариабельности сердечного ритма во временной области*

Measuring HRV: frequency domain methods

Besides measuring HRV over time, another popular way is to break it down by frequency – in other words, how fast or slow certain patterns in heart rate happen [9]. This is called frequency domain analysis. Frequency analysis looks at how much "power" (or energy) is in each range of heart rate changes (Fig. 3):

- high-frequency (HF): fast changes (like those caused by breathing);
- low-frequency (LF): medium-speed changes (often affected by both sympathetic and parasympathetic nervous systems);
- very-low-frequency (VLF): slower changes (meaning is still not fully understood);
- ultra-low-frequency (ULF): very slow changes (found only in long-term, 24-hour recordings).

There are two main types of methods:

1. Nonparametric (e.g., FFT – Fast Fourier Transform) – simple and fast, commonly used in many devices.
2. Parametric (e.g., AR models – Auto-Regressive models) – more complex, gives smoother results and works

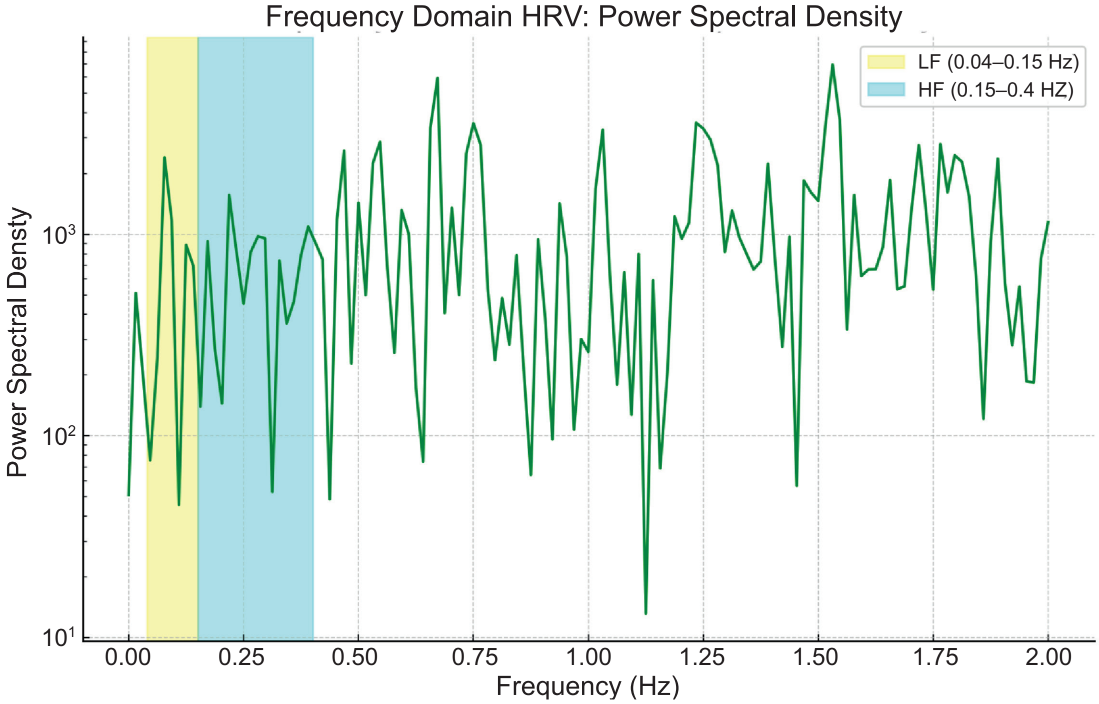

Fig. 3. *Frequency-domain analysis of HRV showing the power spectral density distribution*

Рис. 3. *Анализ вариабельности сердечного ритма в частотной области, показывающий распределение спектральной плотности мощности*

well even with short recordings, requires choosing the right model and checking how accurate it is [10].

Normalized units

Sometimes, LF and HF are shown as percentages of total power (ignoring VLF). This helps show the balance between sympathetic and parasympathetic systems more clearly.

There are a few different ways to prepare the heartbeat data for frequency analysis:

1. RR interval tachogram: plots the time between each heartbeat over time; good for both parametric and nonparametric spectral analysis.
2. Interpolated series: converts irregular heartbeats into regularly spaced data points; needed for some spectral methods, especially the FFT (Fast Fourier Transform).
3. Counts per Time Unit: measures how many beats happen in each second, minute, etc.

Standards for software algorithms

For nonparametric methods (like FFT), the software should report: the number of points used; the interpolation formula; the frequency range sampled; the windowing method used (e.g., Hann, Hamming).

For parametric methods (like AR models), the software should include: the model types; the order of the model (usually between 8–20); tests showing the model is reliable (e.g., prediction error whiteness test (PEWT) and optimal order test (OOT)).

Without this information, it is hard to know if the HRV analysis is accurate or meaningful.

HOW TIME AND FREQUENCY HRV MEASURES ARE CONNECTED [11]

Short-term recordings

When one measures HRV over a short period (like 5 minutes), frequency domain methods (LF, HF, etc.) often give more detailed insight than time domain methods. That is because they break the signal into parts tied directly to nervous system activity (Table 2).

Long-term recordings (24 hours)

When one measures over 24 hours, both time domain (like Standard Deviation of Normal-to-Normal intervals (SDNN)) and frequency domain (like LF, HF, VLF, ULF) often tell very similar stories. They are strongly correlated – meaning they tend to rise and fall together – because of how the body behaves over a whole day. That is why simple time domain methods like SDNN are usually enough for long-term HRV analysis. Spectral (frequency) analysis of a full 24-hour period does not provide much more useful info unless you are looking at specific changes, like log-log slope (a special analysis of very slow rhythms).

Peak-valley methods

They find the highest and lowest points in heart rate changes and are useful to detect short bursts of fast or slow heart rate.

Block-based analysis

It groups heartbeats into “chunks” with similar rhythms, analyzes how blocks relate, ignoring smaller internal variations.

TABLE 2

FREQUENCY DOMAIN MEASURES [13]

ТАБЛИЦА 2

ИЗМЕРЕНИЯ В ЧАСТОТНОЙ ОБЛАСТИ [13]

HF (High Frequency)	Linked to breathing and vagal (parasympathetic) activity
LF (Low Frequency)	May reflect both sympathetic and parasympathetic input, sometimes used to measure sympathetic activity, especially when expressed in "normalized units"
VLF (Very Low Frequency)	Unclear

Complex demodulation

It is a more advanced method that tracks how amplitude and phase (timing) of frequency components change over time [12]. It helps detect short-term heart changes.

These methods can be especially helpful when studying how heart rate responds to breathing, blood pressure, or sudden events like stress or arrhythmia.

Nonlinear HRV methods

The heart's rhythm is not purely mechanical – it involves complex biological systems. So, researchers have tried to use nonlinear math (from chaos theory and complex systems science) to dig deeper into HRV (Fig. 4).

Techniques include:

• Poincaré plots (show how each beat compares to the last one) (Fig. 5);

• Fractal analysis (like 1/f scaling);

• Lyapunov exponents and entropy (measure unpredictability);

• Scaling indexes (track how patterns repeat over time).

Understanding the physiology behind frequency domain measures of HRV

HRV is influenced by how the autonomic nervous system controls your heart. This system has two main parts: sympathetic system – speeds up the heart ("fight or flight"); parasympathetic system (vagal nerve) – slows down the heart ("rest and digest").

Parasympathetic (vagal) activity

• works by releasing acetylcholine, which slows down the heart;

• this effect happens quickly and fades fast, which allows beat-to-beat control;

• mainly responsible for high-frequency (HF) HRV.

Sympathetic activity

• releases adrenaline (epinephrine) and noradrenaline (norepinephrine);

• speeds up the heart and affects it over longer time scales;

• related to low-frequency (LF) HRV, although not only sympathetic in origin.

At rest, the vagal system dominates, which is why healthy HRV is often a sign of strong parasympathetic (vagal) tone.

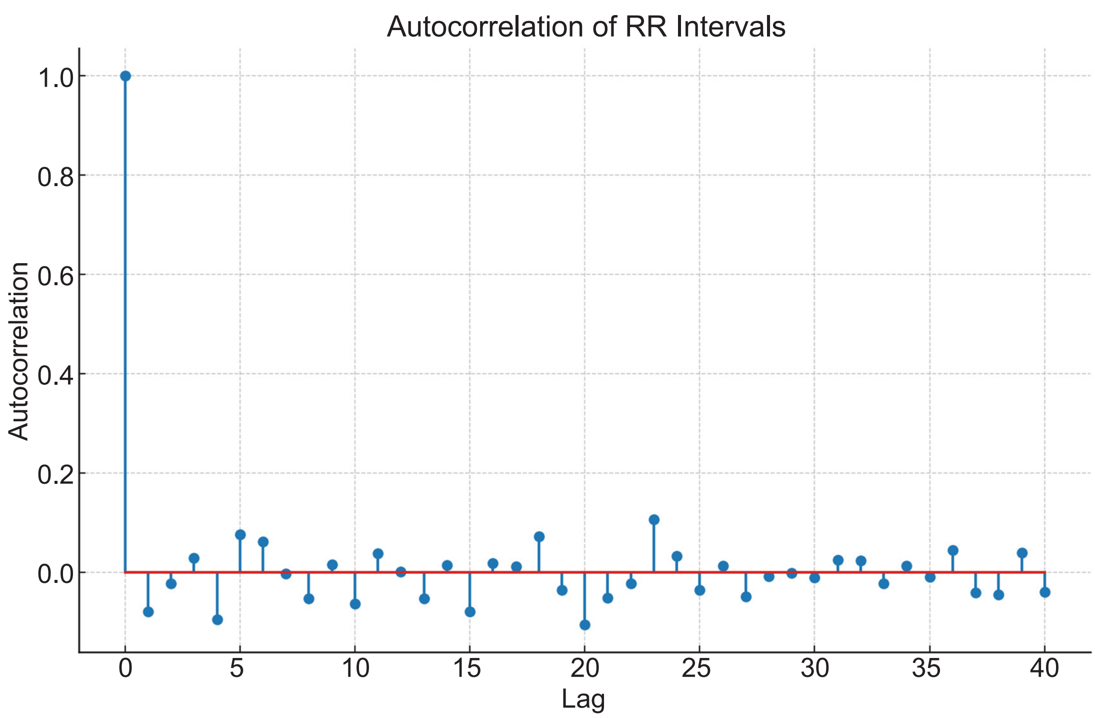

Fig. 4. *Auto correlation of RR intervals*

Рис. 4. *Автокорреляция RR-интервалов*

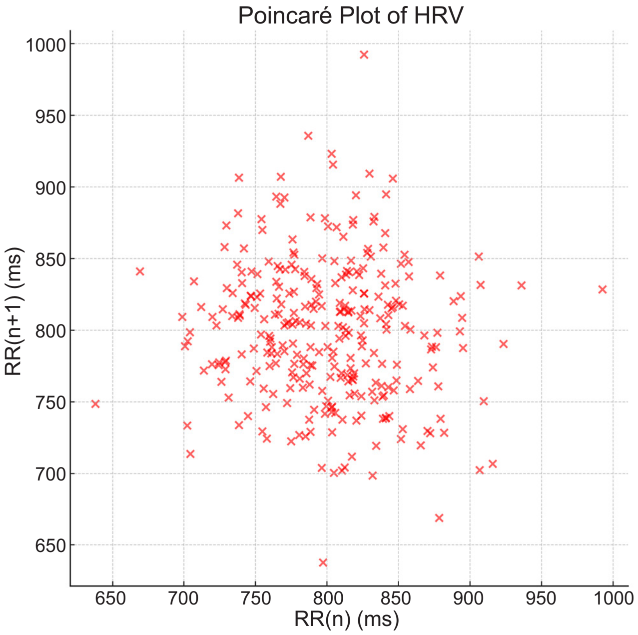

***Fig. 5.** Poincare plot of HRV*

***Рис. 5.** Диаграмма Пуанкаре вариабельности сердечного ритма*

HRV FREQUENCY BANDS [14]

High frequency (HF)

- controlled almost entirely by the vagal nerve;
- strongly linked to breathing rhythm;
- goes up when relaxed or doing slow, deep breathing.

Low frequency (LF)

- more complex;
- some scientists say it shows both sympathetic and parasympathetic effects;
- others believe it is mostly sympathetic, especially when measured in normalized units.

LF is often misunderstood. During stress, total HRV can drop, making it look like LF stays the same – even though sympathetic activity is rising.

Very low frequency (VLF) and ultra-low frequency (ULF)

- make up most of the total power in 24-hour HRV;
- still not well understood;
- might relate to hormones, temperature, or very slow body rhythms.

CHANGES IN HRV DURING THE DAY

- HF is higher at night (more vagal activity);
- LF is higher during the day (more sympathetic influence);
- these patterns disappear in people with poor autonomic function (like after a heart attack).

Increases in LF (normalized units):

- standing up (tilt test);
- mental stress;
- moderate exercise;
- low blood pressure;
- blockage of blood flow (e.g., coronary artery).

Increases in HF:

- deep breathing;
- cold stimulation on the face;
- rotational motion.

HRV tells us about fluctuations in nervous system activity – not the total amount. A heart can have low HRV both if it is overly stressed or if it has no activity at all.

MAIN CLINICAL USES OF HRV [15]

HRV has been studied in many health conditions, but right now, there are two key areas where it is widely accepted and used in clinical practice:

1. Predicting risk after a heart attack (myocardial infarction).

After a heart attack, some people are at higher risk of death – especially from dangerous arrhythmias. HRV helps identify who is most at risk.

- SDNN < 50 ms or HRV Triangular Index < 15 = very high risk;
- SDNN < 100 ms or HRV Triangular Index < 20 = moderate risk.

When to measure:

- best time is around 1 week after the heart attack, usually before hospital discharge;
- HRV measured early (within a few days), late (months later), or both, can all give valuable information.

24-hour vs. short-term HRV:

- 24-hour recordings are more reliable for predicting risk.
- short-term tests are helpful for initial screening, especially if resources are limited.

2. Early detection of diabetic neuropathy

In diabetes, damage to the nerves that control the heart can happen before symptoms appear. This is called diabetic autonomic neuropathy (DAN).

HRV can detect nerve damage early, even before the person feels any symptoms. It helps prevent serious complications like sudden death, blood pressure drops, digestive issues, bladder problems.

OTHER CLINICAL AND RESEARCH POSSIBILITIES FOR HRV

1. Building normal HRV standards according different ages, men and women, different lifestyles and health conditions. Recent studies (like from the Framingham Heart Study) show that HRV can predict death even in healthy older adults. But more population studies are needed to build reliable normal ranges [16, 17].

2. Sleep and circadian rhythms

HRV changes depending on day vs. night cycles, different stages of sleep, especially REM and deep sleep, shift work and jet lag. In healthy people, vagal activity (HF) increases during deep (non-REM) sleep. But in people with heart disease, this nighttime increase may be missing [18, 19].

3. Exercise and recovery

HRV may help track physical conditioning during training, recovery after illness or heart attack, deconditioning due to bed rest or space travel [20, 21].

4. Medication effects

HRV can help doctors understand how drugs affect the nervous system. For example, high-dose atropine decreases HRV (blocks vagal activity), low-dose scopolamine increases HRV (boosts vagal tone), beta-blockers usually increase HRV and reduce sympathetic activity. Many other drugs (like calcium channel blockers, sedatives, and chemotherapy) have not been studied enough for their effect on HRV [22, 23].

5. Sudden death risk in other conditions

HRV might help predict death risk in people with heart failure, heart valve problems, genetic arrhythmia disorders (like long QT syndrome), neurological conditions (like Parkinson's, multiple sclerosis, or spinal cord injury) [24, 25].

6. Fetal and infant monitoring now allow detailed fetal HRV analysis – helping doctors understand how the baby's autonomic system is developing.

FUTURE DIRECTIONS AND RESEARCH GOALS FOR HRV [26]

Although HRV has already proven useful, there is still a lot to learn and improve. Here are the top goals for future research: improve HRV recording and analysis tools; make devices more accurate, affordable, and easy to use; build better editing software to clean ECG signals and remove errors like ectopic beats; improve algorithms for automated HRV analysis in real time; collect more population data; study large groups of healthy people to define what "normal" HRV looks like at different ages, genders, activity levels; expand use in disease prediction and management, standardize clinical use; explore new HRV methods etc.

CONCLUSION

HRV is a powerful, non-invasive tool that reflects how well the nervous system is controlling the heart. It has clear value in risk assessment after heart attacks, early detection of diabetic nerve damage, potential future roles in many other diseases and conditions. To use HRV effectively, we need to standardize how it is measured and analysed, train clinicians and researchers on how to interpret it, keep improving the tools and science behind it. With further research and better technology, HRV could become a routine part of medical care.

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Information about the authors

Kapil Gupta – Professor at the Department of Physiology, SMS Medical College, 302004, Jawahar Lal Nehru Marg, Jaipur, Rajasthan, India. ORCID: https://orcid.org/0000-0002-6505-4216

Ravi Saini – PhD, Department of Physiology, SMS Medical College, 302004, Jawahar Lal Nehru Marg, Jaipur, Rajasthan, India. ORCID: https://orcid.org/0000-0001-8154-9385

Rekchand Saini – MSc student, Department of Physiology, SMS Medical College, 302004, Jawahar Lal Nehru Marg, Jaipur, Rajasthan, India.

Abhishek Sharma – PG Resident at the Department of Physiology, SMS Medical College, 302004, Jawahar Lal Nehru Marg, Jaipur, Rajasthan, India.

Corresponding author

Ravi Saini, sainiravi414@gmail.com

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Информация об авторах

Капил Гупта – профессор кафедры физиологии, Медицинский колледж Савай Ман Сингх, 302004, Джавахар Лал Неру Марг, Джайпур, Раджастан, Индия. ORCID: https://orcid.org/0000-0002-6505-4216

Рави Саини – доктор философии, кафедра физиологии, Медицинский колледж Савай Ман Сингх, 302004, Джавахар Лал Неру Марг, Джайпур, Раджастан, Индия. ORCID: https://orcid.org/0000-0001-8154-9385

Рекчанд Саини – студент магистратуры, кафедра физиологии, Медицинский колледж Савай Ман Сингх, 302004, Джавахар Лал Неру Марг, Джайпур, Раджастан, Индия.

Абхишек Шарма – аспирант кафедры физиологии, Медицинский колледж Савай Ман Сингх, 302004, Джавахар Лал Неру Марг, Джайпур, Раджастан, Индия.

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Рави Саини, sainiravi414@gmail.com

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